Electronic Word of Mouth in Online Social Networks: Strategies for Coping with Opportunities and Challenges

Doctoral Dissertation

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Alper Beşer

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Anneme ve Babama

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List of Abbreviations

AC	Activity check
AD	Advertising
AI	Artificial intelligence
App	Application
Ber	Bernoulli
CTR	Click-through rate
CYC	Cyclic pricing scheme
ECIS	European Conference on Information Systems
ES	Evolution strategy
EWOM	Electronic word of mouth
FT	Full price transparency
HF	High visit frequency
HLA	High loss aversion
HT	High price transparency
IBM	International Business Machines Corporation
ICIS	International Conference on Information Systems
ICT	Information and communication technologies
IDC	International Data Corporation
IGTV	Instagram TV
INF	Influencer
LF	Low visit frequency
LLA	Low loss aversion
LT	Low price transparency
MF	Medium visit frequency
MLA	Medium loss aversion
MQ	Medium quick PWOM message
MT	Medium price transparency
NT	No price transparency

NWOM	Negative electronic word of mouth
OPT	Optimum
OSN	Online social network
PD	Price discrimination
PD1	Price discrimination with one price per customer group
PD3	Price discrimination with three prices per customer group
PD6	Price discrimination with six prices per customer group
PU	Personal utility
PUL	Pull up pricing scheme
PWOM	Positive electronic word of mouth
RQ	Research question
SD	Strong delayed PWOM message
SE	Standard error
SLO	Successive lowering pricing scheme
ST	Strong ties
STU	Strong-tie utility
UGC	User-generated content
UP	Uniform pricing
VHB	Verband der Hochschullehrer für Betriebswirtschaft e.V.
WOM	Word of mouth
WT	Weak ties
WTU	Weak-tie utility
WWW	World Wide Web

List of Symbols

$\alpha^{decrease}$	Slope of the linear decrease of the willingness-to-pay WTP_{it}
$\alpha^{increase}$	Slope of the linear increase of the willingness-to-pay WTP_{it}
α^{limit}	Limiting factor that denotes the difference between the reference price RP_{it} and willingness-to-pay WTP_{it} up to which an OSN member is willing to increase his willingness-to-pay
β	Market parameter
β_i	Individual market parameter perceived by OSN member i that is used for weighting the normative social influence NSI_{it}^m and informational social influence ISI_{it}^m in the evaluation of the message credibility C_{it}^m
β^{STU}	Initial level of excitement an OSN member experiences regarding the strong-tie utility when he gets aware of the social media app or service for the first time
β^{WTU}	Initial level of excitement an OSN member experiences regarding the weak-tie utility when he gets aware of the social media app or service for the first time
γ_i	Individual parameter of OSN member i that is used for weighting the argument quality AQ^m and expressiveness EX^m in the evaluation of the informational social influence ISI_{it}^m
δ	Steepness of the logistic sigmoid function for determining the perceived normative social influence NSI_{it}^m
δ^{STU}	Steepness of the logistic sigmoid function for determining the valuation of the strong-tie utility based on the share of adopters
δ^{WTU}	Steepness of the logistic sigmoid function for determining the valuation of the weak-tie utility based on the share of adopters
ΔB_T	Final change in the share of buyers evoked by the countermeasure at time step T
ΔWTP_{it}	Change in the willingness-to-pay of OSN member i at time step t
$\tilde{\varepsilon}_{it}$	Random flexibility of OSN member i regarding small differences between the offered price p_{it} and his willingness-to-pay WTP_{it} during the online store visit at time step t
ζ	Expected delay until an OSN member will evaluate the information about the social media app or service that has been sent to him via EWOM
η_i	Individual counterbalancing factor of OSN member i that is used in the forwarding probability FP_{ijt}^m for weighting the additive and multiplicative effects of the message credibility C_{it}^m and the perceived tie strength w_{ij} to a potential receiver

θ_i	Utility threshold of OSN member i for the social media app or service
ϑ_i	Individual parameter that denotes OSN member i's range of indifference in his credibility decision CD_{it}^m
κ^{STU}	Steepness of the excitement decay regarding the strong-tie utility
κ^{WTU}	Steepness of the excitement decay regarding the weak-tie utility
λ	Base level for the expected duration until the next online store visit
λ^{ES}	Evolution strategy: number of children in a generation
λ^{+}	Parameter for exponentially increasing the purchase probability PP_{it} depending on the perceived credibility of the PWOM message C_{it}^{+}
λ^{-}	Parameter for exponentially decreasing the purchase probability PP_{it} depending on the perceived credibility of the NWOM message C_{it}^{-}
λ_{it}	Individually modified expected duration until the next online store visit of OSN member i depending on the weighted difference between the reference price RP_{it} and willingness-to-pay WTP_{it} at time step t
Λ	Distance (longest possible walk) in the OSN originating from a random OSN member that denotes the spread of the price information he shares via EWOM
μ	Mean of the selected distribution
μ^{ES}	Evolution strategy: number of parents in a generation
ξ	Expected duration until the next usage of the social media app or service
Π	Profit of the firm/seller
ρ	Correlation coefficient
ϱ_i	Price sensitivity of OSN member i that is used for weighting the external reference price ERP_{it} and internal reference price IRP_{it} in cases where OSN member i is disadvantaged by price discrimination
σ	Standard deviation of the selected distribution
σ^{ES}	Evolution strategy: step size for generating new children by mutation
ς^{STU}	Excitement decay parameter that denotes after how many time steps an OSN member's initial excitement about the strong-tie utility offered by the social media app or service is completely depleted
ς^{WTU}	Excitement decay parameter that denotes after how many time steps an OSN member's initial excitement about the weak-tie utility offered by the social media app or service is completely depleted
τ	Auxiliary time index
ϕ_i^m	Credibility threshold of OSN member i for message m

ϕ_i^+	Credibility threshold of OSN member i for the PWOM message
ϕ_i^-	Credibility threshold of OSN member i for the NWOM message
ψ_i	Memory factor of OSN member i for exponentially smoothing past prices
ω	Midpoint position of the logistic sigmoid function for determining the perceived normative social influence NSI_{it}^m
ω^{STU}	Midpoint position of the logistic sigmoid function for determining the valuation of the strong-tie utility based on the share of adopters
ω^{WTU}	Midpoint position of the logistic sigmoid function for determining the valuation of the weak-tie utility based on the share of adopters
Ω	Edge pass-through probability that denotes the likelihood that price information is forwarded to a directly connected neighbour
A	Group (set) of OSN members who are characterised by a high willingness-to-pay
a_{it}	Binary activity indicator that denotes if OSN member i is active in the social media app or service at time step t
A_t	Share of OSN members who are active in the social media app or service at time step t
AB	Advertising budget that denotes the number of unique OSN members who are reached by advertising
AF_{it}	Individually perceived ageing factor that denotes the exponentially decreasing age of both the NWOM and PWOM message at time step t
AF_t^m	Ageing factor that denotes the exponentially decreasing age of message m at time step t
ak_{it}	Binary EWOM activation indicator that denotes if OSN member i has already received price information via EWOM at least once until time step t inclusively
APL	Average path length
AQ^m	Argument quality of message m
AQ^+	Argument quality of the PWOM message
AQ^-	Argument quality of the NWOM message
AS	Advertising schedule that depicts the splitting of the available budget into multiple advertising impulses
as_t	Advertising schedule element that denotes the partial budget to be spent at time step t
av_{it}	Binary visit indicator that denotes if OSN member i has already visited the online store at least once until time step t inclusively

B	Group (set) of OSN members who are characterised by a moderate willingness-to-pay
b_{it}	Binary purchase indicator that denotes if OSN member i buys the product at time step t
b_{it}^{STU}	Valuation of OSN member i for the strong-tie utility based on the initial excitement at time step t
b_{it}^{WTU}	Valuation of OSN member i for the weak-tie utility based on the initial excitement at time step t
B_t	Share of buyers in the OSN at time step t
BC_i	Betweenness centrality of OSN member i
c	Marginal costs for each sold product
C	Group (set) of OSN members who are characterised by a low willingness-to-pay
C_{it}^{m}	Credibility of message m perceived by OSN member i at time step t
C_{it}^{+}	Credibility of the PWOM message perceived by OSN member i at time step t
C_{it}^{-}	Credibility of the NWOM message perceived by OSN member i at time step t
C_{SQ_k}	Activation costs of a seed belonging to the kth seed quality class
C_{SQ^+}	Activation costs of a seed belonging to the selected PWOM seed quality class SQ^+
CC_i	Closeness centrality of OSN member i
CD_{it}^{m}	Binary credibility decision of OSN member i regarding message m at time step t
CTR^{AD}	Click-through rate for advertising
CTR^{EWOM}	Click-through rate for EWOM messages
CTR^{INF}	Click-through rate for influencer marketing
D	Delay between the launch time of the NWOM and PWOM message in the OSN
d_{ij}	Geodesic distance between distinct OSN members i and j
d_{it}	Time factor that denotes the duration at time step t since OSN member i has been informed about the social media app or service for the first time
DC_i	Degree centrality of OSN member i
e	Euler’s number
E	Set of edges in the graph G

E_i	Number of edges that exist in OSN member i's social neighbourhood
ERP_{it}	External reference price of OSN member i at time step t
EX^m	Expressiveness of message m
EX^+	Expressiveness of the PWOM message
EX^-	Expressiveness of the NWOM message
f	Function that calculates the time that is required for composing a PWOM message of argument quality $AQ^+$and expressiveness EX^+
FD_{ijt}	Binary forwarding decision of OSN member i regarding the sending of information about the social media app or service to a contact j at time step t
FD_{it}^m	Binary forwarding decision of OSN member i regarding the sending of message m to all of his followers at time step t
FD_{ijt}^m	Binary forwarding decision of OSN member i regarding the sending of message m to a follower j at time step t
FP_{it}^m	OSN member i's forwarding probability of message m to all of his followers at time step t
FP_{ijt}^m	OSN member i's forwarding probability of message m to a follower j at time step t
G	Graph
GCC	Global clustering coefficient
h	OSN member index
HR	Hourly rate for composing a PWOM message
i	OSN member index
I	Number of OSN members
IRP_{it}	Internal reference price of OSN member i at time step t
ISI_{it}^m	Informational social influence of message m perceived by OSN member i at time step t
j	OSN member index
k	Seed quality class index
K	Number of seed quality classes
k_{it}	Binary EWOM activation indicator that denotes if OSN member i knows about at least one other price paid in the OSN at time step t
k_{ijt}	Binary EWOM activation indicator that denotes if OSN member i knows about the price paid by OSN member j at time step t

LCC_i	Local clustering coefficient of OSN member i's social neighbourhood
m	Message
$\overline{m}$	Opposing message
M	Set of messages in the graph G
n	Maximum number of changes an OSN member is allowed to make to his willingness-to-pay
n_{it}	Number of changes made to the willingness-to-pay of OSN member i until time step t exclusively
n_{it}^{STU}	Valuation of OSN member i for the strong-tie utility based on the share of adopters among his strong ties at time step t
n_{it}^{WTU}	Valuation of OSN member i for the weak-tie utility based on the share of adopters among his weak ties at time step t
N_i	Set of OSN member i's contacts in an undirected graph G
$N_i^{followers}$	Set of OSN members who follow member i
$N_i^{following}$	Set of OSN members whom member i follows
N_i^{ST}	Set of OSN members who belong to the strong ties of member i
N_i^{WT}	Set of OSN members who belong to the weak ties of member i
NSI_{it}^{m}	Normative social influence of message m perceived by OSN member i at time step t
Ø	Average
p	Significance level
P	Product contribution margin
p_{it}	Price offered to OSN member i at time step t
PD_{it}	Binary purchase decision of OSN member i at time step t
PL	Price level
PM	Price matrix
pm_{xy}	Price element of the price matrix PM that depicts the price that is offered to a member of group x on his yth visit
$PP_i^{initial}$	Initial purchase probability of OSN member i
PP_i^{max}	Maximum purchase probability of OSN member i
PP_i^{min}	Minimum purchase probability of OSN member i
PP_{it}	Purchase probability of OSN member i at time step t

PU The maximum personal utility an OSN member can obtain by using the social media app or service

PU_i Personal utility of the social media app or service perceived by OSN member i

r_{it} Binary reception indicator that denotes if OSN member i has been informed about the social media app or service until time step t inclusively

r_{it}^{AD} Binary reception indicator that denotes if OSN member i has been informed about the social media app or service by advertising at time step t

r_{it}^{EWOM} Binary reception indicator that denotes if OSN member i has been informed about the social media app or service by EWOM at time step t

r_{it}^{INF} Binary reception indicator that denotes if OSN member i has been informed about the social media app or service by influencer marketing at time step t

r_{it}^{m} Binary reception indicator that denotes if OSN member i has received message m until time step t inclusively

r_{ijt}^{m} Binary reception indicator that denotes if OSN member i has received message m from his contact j at time step t

$\mathbb{R}_{+}^{XxY}$ Set of positive real numbers denoting the solution space for the price matrix PM with the dimensions X and Y

RP_{it} Reference price of OSN member i at time step t

s_{xz} Similarity between customer groups x and z

S_t^m Spread of message m in the OSN at time step t

SN^+ Number of activated PWOM seeds

sp_{hj} Number of all shortest paths between distinct OSN members h and j

$sp_{hj}(i)$ Number of all shortest paths between distinct OSN members h and j that include member i

SP_{it}^m Social pressure OSN member i perceives regarding message m at time step t

SQ_k kth seed quality class

SQ^+ Selected PWOM seed quality class

STU The maximum strong-tie utility an OSN member can obtain by using the social media app or service

STU_{it} Strong-tie utility of the social media app or service perceived by OSN member i at time step t

t Time index

T Time horizon

T^{AD}	Time horizon for advertising
T^{m}	Launch time of message m in the OSN
T^{+}	Launch time of the PWOM message in the OSN
T^{-}	Launch time of the NWOM message in the OSN
$T_{1/2}^{m}$	Half-life of message m
$T_{1/2}^{+}$	Half-life of the PWOM message
$T_{1/2}^{-}$	Half-life of the NWOM message
U_{it}	Total utility of the social media app or service perceived by OSN member i at time step t
V	Set of vertices in the graph G
v_{i}^{PU}	Valuation of OSN member i for the personal utility offered by the social media app or service
v_{it}	Binary visit indicator that denotes if OSN member i is visiting the online store at time step t
v_{it}^{STU}	Valuation of OSN member i for the strong-tie utility offered by the social media app or service
v_{it}^{WTU}	Valuation of OSN member i for the weak-tie utility offered by the social media app or service
$V^{m,seeds}$	Set of seeds who initially launch message m in the OSN
$V^{\overline{m},seeds}$	Set of seeds who initially launch message $\overline{m}$ in the OSN
V_{t}^{AC}	Set of OSN members who evaluate the offered utility of the social media app or service and decide whether to actively use it at time step t
V_{t}^{AD}	Set of OSN members reached by advertising at time step t
V_{t}^{EWOM}	Set of OSN members reached by EWOM at time step t
V_{t}^{INF}	Set of OSN members reached by influencer marketing at time step t
$V_{t}^{m,senders}$	Set of potential senders of message m in the OSN at time step t
$V_{t}^{senders}$	Set of OSN members who will potentially forward the information about the social media app or service to their contacts at time step t
W	Function that assigns a weight to the edges in the graph G
w_{ij}	Weight of the edge between distinct OSN members i and j that represents the perceived social tie strength to j from the perspective of i
WTP_{i0}	Initial willingness-to-pay of OSN member i

WTP_{it}	Willingness-to-pay of OSN member i at time step t
WTP_i^{max}	Upper limit of the willingness-to-pay of OSN member i
WTU	The maximum weak-tie utility an OSN member can obtain by using the social media app or service
WTU_{it}	Weak-tie utility of the social media app or service perceived by OSN member i at time step t
x	Customer group index
X	Number of customer groups
x_i	Index of OSN member i's customer group
y	Index that denotes the number of online store visits
Y	Number of available prices per customer group that are offered to group members depending on the number of their previous online store visits
y_{it}	Number of OSN member i's total visits until time step t inclusively
z	Customer group index

Chapter 1:

Introduction

1 Introduction

1.1 Social Media and Online Social Networks

Technological advances in the past decades and declining prices have enabled information and communication technologies (ICT) such as personal computers, smartphones, and tablets to become an enduring and indispensable part of people's everyday lives (Chun et al. 2010, p. 1; Fatehkia et al. 2018, p. 189; Oberst et al. 2017, p. 51; Stephen 2016, p. 17). High-speed Internet and more people getting access to it at affordable prices further accelerated the market diffusion of ICT and increased the interconnectedness between people around the world (Bouras et al. 2011, p. 134; Lamberton and Stephen 2016, p. 146). In the early years, the Internet and World Wide Web (WWW) were mostly used by technically adept early adopters (Farrell and Nezlek 2007, p. 413; Morahan-Martin and Schumacher 2003, p. 660) but over time developed into a mass phenomenon affecting all sections of society. While in 2005 only 16.8% of the world population had access to the Internet, in 2018 the share of Internet users surpassed 50% on a global level and reached 84.9% in developed countries (Statista 2019d). Today, there are 4.57 billion active Internet users, corresponding to 59% of the global population (Statista 2020c). The increasing popularity of the Internet is also reflected in the time users spend online on a daily basis. In 2011, the average Internet usage time was 75 minutes per day, which more than doubled to 161 minutes in 2018 (Statista 2019a).

In 2004, the term *Web 2.0* emerged that described a shift in the usage of the Internet by both developers and end-users (Kaplan and Haenlein 2010, pp. 60-61). Prior to Web 2.0, regular Internet users predominantly took on the role of consumers of content that was usually created and made available online by professional publishers (Büscher and Igoe 2013, p. 284; Ghani et al. 2019, p. 417; Kaplan and Haenlein 2010, pp. 60-61). Only experienced and well-versed users were able to create their own websites for distributing personal content. By providing new technologies and platforms such as blogs and wikis, Web 2.0 altered the role of Internet users and transformed them from consumers to so-called "prosumers" who create content with added value for other users (Ghani et al. 2019, p. 417; Kaplan and Haenlein 2010, pp. 60-61; Pierson 2012, p. 100). This is called user-generated content (UGC) and refers to any kind of information conveyed to a multitude of people digitally in the form of text, pictures, or videos (Daugherty et al. 2008, p. 16; Gandomi and Haider 2015, p. 142; Kaplan and Haenlein 2010, p. 61). With the technologies of Web 2.0, UGC can be modified in participation and collaboration with others (Kaplan and Haenlein 2010, pp. 60-61; Pierson 2012, p. 100). Because of this, Web 2.0 is also referred to as the *participatory web* or *participatory media* (Collis and Moonen 2008, p. 94; Pierson 2012, pp. 99-100; van Noort and Willemsen 2012, pp. 132-133).

The emergence and success of online social networks (OSN) like MySpace and Facebook gave rise to the term *social media* that has become popular shortly after the Web 2.0 term in 2005 (Kaplan and Haenlein 2010, pp. 60-61). Web 2.0 can be seen as the technological basis from which social media has evolved (Berthon et al. 2012, pp. 262-263; Huang and Benyoucef 2013, p. 246; Kaplan and Haenlein 2010, pp. 60-61; Weinberg and Pehlivan 2011, pp. 275-276). While primarily UGC was paramount to the success of Web 2.0 and in its centre of attention (Lee et al. 2008, p. 340; Yang et al. 2008, p. 3), it can be argued that social media puts more emphasis on the social relationships that accrue among users and the exchange of personal information, which is facilitated by OSN (Alves et al. 2016, p. 1029; Gikas and Grant 2013, p. 19; Penni 2017, p. 499; Sahoo and Krotov 2008, p. 250; Tsimonis and Dimitriadis 2014, p. 330). OSN can therefore be seen as a concrete form of social media (Ghali et al. 2016, p. 25; Greenhow and Askari 2017, p. 624). However, the boundaries between the terms Web 2.0 and social media are blurred and prevent a clear distinction. According to some classifications, OSN also belong to Web 2.0 (e.g. Eid and Ward 2009, p. 1; Harris and Rea 2009, p. 138). Web 2.0, on the other hand, was initially associated with blogs, wikis, and video sharing platforms (e.g. Ajjan and Hartshorne 2008, p. 72; Bower 2016, pp. 184-186; Harris and Rea 2009, p. 138), which are also attributed to social media (e.g. Ceyp and Scupin 2013, p. 23; Hanna et al. 2011, p. 266; Hemsley and Mason 2012, p. 3928). The terms are therefore often used interchangeably (Berthon et al. 2012, pp. 262-263; Pierson 2012, pp. 99-100; Weinberg and Pehlivan 2011, pp. 275-276).

People use social media and OSN for various reasons. These include sharing of experiences, gathering knowledge, and connecting to people for personal, educational, or business reasons (Eid and Ward 2009, p. 1; Mitrou et al. 2014, p. 2; Sobaih et al. 2016, p. 296; Teng et al. 2017, p. 76; Vorderer et al. 2016, p. 694). In OSN, users usually have a public or semi-public profile and can connect and relate to each other (Boyd and Ellison 2007, p. 211; Ghani et al. 2019, p. 418; Greenhow and Askari 2017, p. 624; Oberst et al. 2017, p. 52). These can be used for self-presentation, self-disclosure, and building social identities as well as reputation among peers (Kaplan and Haenlein 2010, p. 61; Ngai et al. 2015, p. 33; Oberst et al. 2017, p. 52). Due to these usage patterns, social media and OSN have become an essential part of the daily lives of Internet users. On average, users spent 144 minutes per day on social media in 2019, constituting more than 84% of the daily spent time on the Internet (Statista 2019a, 2020a). Figure 1 shows the currently most popular social media platforms ranked by the number of monthly active users. It demonstrates that the platforms that primarily focus on facilitating social interactions among their users (e.g. Facebook and WhatsApp) are in sum more popular than the platforms where the creation and sharing of UGC is the main purpose (e.g. YouTube and Pinterest). From this, it can be concluded that OSN are crucial to social media's success and constitute its most important concrete form.

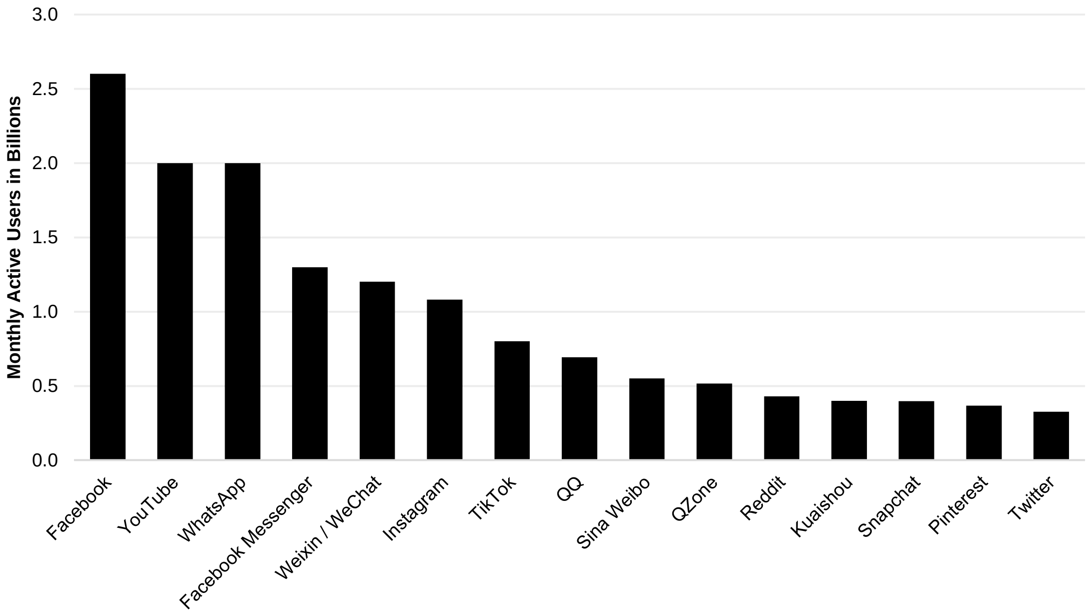

Figure 1. Most popular social media platforms as of July 2020 (Statista 2020d).

Offline or traditional word of mouth (WOM) is regarded as a reliable and trustworthy form of communication (Chung and Darke 2006, p. 270; Jung and Kim 2012, p. 343; Schijns and van Bruggen 2018, p. 95). Web 2.0, social media, and OSN have induced changes in the way people communicate with each other (Hanna et al. 2011, p. 266; Hennig-Thurau et al. 2010, p. 311; Ngai et al. 2015, p. 33) because their widespread success and ubiquitous availability provide the basis for electronic word of mouth (EWOM) (Chu and Kim 2011, p. 49; Teng et al. 2017, p. 76). EWOM can be seen as a digital enhancement of traditional WOM that makes communication more efficient and involves less effort by its users (Cheung et al. 2008, pp. 230-231; Kim et al. 2016, p. 511). Information of any kind and form can travel faster and reach a higher spread with EWOM (Kumar and Purbey 2018, p. 3592; Lis and Neßler 2014, p. 63; Yoo et al. 2013, p. 669). The resulting information transparency has an impact both on economic and social developments in a society (Eid and Ward 2009, p. 1; Shabir et al. 2014, p. 132). According to theories on social change, the predominant communication medium significantly influences the perception and understanding of the world (Eid and Ward 2009, p. 1). Thereby, social media, OSN, and the related digitisation of communication by EWOM have caused transformative changes in consumer behaviour in all types of markets (Lamberton and Stephen 2016, p. 146). For adequately dealing with the newly emerged circumstances, the development of new business strategies are required (Fu et al. 2015, p. 616; Ngai et al. 2015, p. 33).

In the following, at first three related subject areas in the context of EWOM and OSN are outlined and discussed. Afterwards, research questions are derived for the subject areas concerning the investigation of capable strategies for coping with the emerged opportunities and challenges of EWOM in OSN.

1.1.1 Electronic Word of Mouth in E-Commerce

Traditional WOM is an important source for customers to gather relevant information for making purchase decisions (Cheung et al. 2008, p. 230; Hennig-Thurau et al. 2004, p. 39; Viglia et al. 2016, p. 2036) and is therefore acknowledged by researchers and practitioners as a far-reaching and effective marketing tool (Beneke et al. 2015, p. 69; Cheung et al. 2008, p. 230; Cheung and Thadani 2012, p. 462). The communication via traditional WOM exhibits a private and informal nature (Anderson 1998, p. 6; East et al. 2008, p. 215; Schmäh et al. 2017, p. 148), which increases the perceived credibility of the conveyed information (Beneke et al. 2015, p. 69). This is reflected in an early definition provided by Arndt (1967, p. 3), in which the author describes traditional WOM as "*oral, person to person communication between a receiver and a communicator whom the receiver perceives as non-commercial, concerning a brand, a product, or a service*".

Due to the widespread success and popularity of the Internet, new ways and channels opened up for customer-to-customer interaction and communication (Beneke et al. 2015, p. 68; Jung and Kim 2012, p. 343). Customers can use online communities, blogs, and various social media platforms like OSN for sharing experiences and opinions about brands, products, and services with other customers via EWOM (Chang et al. 2015, p. 48; Jung and Kim 2012, p. 343; Kunz et al. 2012, p. 472; Yoo et al. 2013, p. 669). EWOM is more measurable and observable than traditional WOM because of the persistence and increased accessibility of the shared information (Baber et al. 2016, p. 390; Cheung and Thadani 2012, p. 462). The communication via EWOM is asynchronous, which enables participants to send and receive information at their convenience at any given time (Cheung et al. 2009, p. 11; Rothe and Wicke 2018, p. 1638). Traditional WOM is, by contrast, usually carried out as synchronous one-to-one or one-to-many communication in small groups (Cheung and Thadani 2012, p. 462). Due to limitation in space, time, and the number of participants, the spread of information disseminated via traditional WOM is much lower than the sharing via EWOM (van Noort and Willemsen 2012, p. 131; Yoo et al. 2013, p. 669). Depending on the social media platform and its offered social media services, EWOM can be used for either one-to-one, one-to-many, or many-to-many communication at a much larger scale and thereby reach substantially more people than traditional WOM (Cheung et al. 2009, p. 11; Cheung and Thadani 2012, p. 462; Rothe and Wicke 2018, p. 1638; van Noort and Willemsen 2012, p. 131; Yoo et al. 2013, p. 669). An often-cited definition that emphasises the large scale feature of EWOM, and which this dissertation will follow, is provided by Hennig-Thurau et al. (2004, p. 39), who define EWOM as "*any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet*".

The increased relevance of EWOM is reflected in the attention it has received from researchers, particularly since the emergence of social media (Cheung and Thadani 2012, p. 462; Hussain et al. 2016, p. 493; Kim et al. 2016, p. 511; Schmäh et al. 2017, p. 148). Systematic literature reviews on the topic of EWOM summarising research from 2000 to 2010 and from 2010 to 2016 are provided by Cheung and Thadani (2012) and Schmäh et al. (2017) respectively. EWOM has also gained practical importance in e-commerce, both for firms and customers (Lis and Neßler 2014, pp. 64-65). Because of EWOM and the enhanced possibilities for exchanging information, e-commerce has undergone a transformation where the focus shifted from the offered products and services to customers and the relationship to them (Ho and Rezaei 2018, p. 205; Huang and Benyoucef 2013, p. 246; Zhou et al. 2013, pp. 61-62). In 2018, 52% of online shoppers were influenced in their online shopping behaviour by reading and relying on social media content (Statista 2018c). This is because one substantial problem in e-commerce from the perspective of customers concerns the non-availability of physical product examinations before making a purchase (Guo et al. 2018, p. 63). In Germany, 53% of online orders were returned to the seller in 2018 (Statista 2018d). The return rates were particularly high for experience goods such as clothes (32%) and shoes (17%) (Statista 2019e). For this kind of products, it is difficult to assess the quality solely based on reading reviews since it depends heavily on the customer's personal experience with the purchased good (Li and Wu 2018, p. 1336; Steffes and Burgee 2009, p. 44). By contrast, the return rates were considerably lower for search goods such as consumer electronics (6%), for which the pre-purchase assessment of quality is easier and more accurate due to researchable characteristics like hardware specifications that depend less on personal experiences (Li and Wu 2018, p. 1336; Nakayama and Wan 2017, p. 9; Statista 2019e; Steffes and Burgee 2009, p. 44). Thus, in order to reduce the risk of bad purchases, customers seek to gather a sufficient amount of information before ordering products online (Kumar and Purbey 2018, p. 3594; Wang and Yu 2017, p. 179; Yoo et al. 2013, p. 670). In this regard, customers pay less attention to the information provided by sellers, manufacturers, and professional reviewers (Viglia et al. 2016, pp. 2035-2036; Yoo et al. 2013, p. 670). Information shared via traditional WOM and EWOM are perceived to be more persuasive (Kumar and Purbey 2018, p. 3594; Pajuniemi 2009, p. 72; Viglia et al. 2016, p. 2036) as they enable the customer to gauge the quality of the offered product based on real experiences made by other customers (Balaji et al. 2016, p. 528; Hyrynsalmi et al. 2015, p. 2; Viglia et al. 2016, pp. 2037-2038; Zhao and Peng 2019, p. 2). Thereby, customers benefit from EWOM because it helps them to make better purchase decisions by facilitating and expediting the exchange of real experiences (Hussain et al. 2016, p. 494; Kim et al. 2016, p. 511; Schmäh et al. 2017, p. 154; Yoo et al. 2013, p. 669). By making use of EWOM, customers gain more power in the purchase process because prior to EWOM an information asymmetry prevailed that allowed the seller to better control which product-related information potential buyers were exposed to (Das 2016, p. 212; Thomas et al. 2012, pp. 88-90; van Noort and Willemsen 2012, p. 131).

Firms are aware of the fact that customers increasingly rely on EWOM in their purchase decision-making (Rathore et al. 2018, pp. 255-256; Xu et al. 2012, p. 318), which opens up new opportunities for customer relationship management and direct marketing (Hennig-Thurau et al. 2010, p. 311; Huang and Benyoucef 2013, p. 246). EWOM has evolved into an important marketing tool that is utilised by firms to advertise their products and services online (Cheung et al. 2008, p. 231; Das 2016, p. 212; Hussain et al. 2016, p. 493; Pfeffer et al. 2014, p. 118). Research shows that EWOM has a significant impact on various elements in e-commerce such as product preferences, brand awareness, perceived trustworthiness of the seller, and sales (Fu et al. 2015, p. 616; Kim et al. 2016, p. 512; Li and Wu 2018, pp. 1331-1333; van Noort and Willemsen 2012, p. 131; Zhang et al. 2016, p. 198; Zhou et al. 2019, pp. 189-190). Therefore, initiating positive electronic word of mouth (PWOM) has become an important success factor that can increase sales in e-commerce (Chih et al. 2013, p. 659; Kudeshia and Kumar 2017, p. 314; Kumar and Purbey 2018, p. 3594). PWOM is proven to be more influential than traditional forms of advertising (López and Sicilia 2014, p. 29). Firms try to induce PWOM by encouraging and incentivising satisfied customers to share their positive experiences online (Yoo et al. 2013, p. 669). Customers who strongly identify with the product or brand may intrinsically disseminate sales-promoting information privately and publicly (Rialti et al. 2017, p. 149). Such brand advocates and the maintenance of relationships to them, e.g. in virtual communities, have gained importance for firms since they can act as so-called seeds who spread PWOM on their behalf in OSN (Kudeshia and Kumar 2017, p. 314; Mochalova and Nanopoulos 2014, p. 2; Pajuniemi 2009, p. 73; Rialti et al. 2017, p. 153).

Firms also face challenges in the context of EWOM that unfolded with the widespread success of social media and OSN (Kim et al. 2016, pp. 511-512; van Noort and Willemsen 2012, p. 131). Customers who are not content with the products or services offered by a firm can warn other customers by spreading negative electronic word of mouth (NWOM) (Chang et al. 2015, p. 49; Lee and Song 2010, p. 1074; van Noort and Willemsen 2012, p. 132). Often, customers use NWOM with the intention of harming the firm or taking revenge for perceived misconduct (Beneke et al. 2015, p. 70; Fu et al. 2015, p. 617; van Noort and Willemsen 2012, p. 132). Due to the so-called negativity bias (Ahluwalia 2002; Rozin and

Royzman 2001), NWOM is perceived to be more credible and thereby more influential than PWOM (Chang et al. 2015, p. 49; Chang and Wu 2014, p. 206; Kumar and Purbey 2018, p. 3593; Kunz et al. 2012, p. 472; Sen and Lerman 2007, p. 78). A possible explanation for this is that good quality can be attributed to both good and bad products, whereas bad quality is only attributable to the latter and is therefore treated as being more diagnostic (Lee et al. 2008, p. 342; Skowronski and Carlston 1989, p. 137). Current research further suggests that dissatisfaction induces more NWOM than satisfaction leads to PWOM (Kumar and Purbey 2018, p. 3594) and that NWOM decreases sales more than PWOM is able to increase them (Kim et al. 2016, p. 512).

In OSN, NWOM can spread unrestrictedly and reach a large number of potential buyers who could be deterred from making purchases (Chang and Wu 2014, p. 206; Kunz et al. 2012, p. 472; Pfeffer et al. 2014, p. 118; van Noort and Willemsen 2012, pp. 131-132). Therefore, firms have a great interest in preventing and limiting the prevalence of NWOM in OSN and its negative impact on sales. A proactive strategy can be applied by pointing out to customers that in case of post-purchase dissatisfaction, the firm's support or service team will help them in resolving their issues. Although proactive interactions are well received by customers (Shin et al. 2017, p. 176), it is not possible to completely rule out that customers use NWOM to publicly complain about product or service failures that require the firm to deploy a reactive strategy. This creates the necessity for firms to continuously monitor OSN for NWOM activities (Mochalova and Nanopoulos 2014, p. 2; Rathore et al. 2018, p. 256; van Noort and Willemsen 2012, p. 133). Many firms also maintain public support pages and accounts in OSN such as Facebook or Twitter (Bacile et al. 2017, p. 24; He et al. 2019, p. 6638). These are aimed at being a first point of contact for dissatisfied customers where a quick reaction to complaints can help to better control the dissemination of NWOM and positively influence the public perception among customers (Gunarathne et al. 2017, p. 315; Melancon and Dalakas 2018, p. 158).

1.1.2 Social Big Data and Price Differentiation in E-Commerce

The current technological progress is making both hardware and software more powerful leading to the accelerated creation, capturing, and processing of data from various sources (Korhammer and Grambow 2018, p. 252; Tanaka 2015, p. 5). At the same time, the costs of data storage decrease steadily, which also encourages the saving of less important data resulting in an even greater amount of data (Korhammer and Grambow 2018, p. 252). Such large amounts of data are referred to as *big data* (Bello-Orgaz et al. 2016, p. 45; Ghani et al. 2019, p. 417; O'Leary 2013, p. 96). There are numerous definitions of big data due to disparate interpretations from different disciplines, which can therefore be seen as an evolving term (Bello-Orgaz et al. 2016, p. 45; Gandomi and Haider 2015, p. 138; O'Leary

2013, p. 96; Tsou 2015, p. 70). A well-known and often-cited definition proposed by IBM emphasises three major characteristics of big data: volume, variety, and velocity (O'Leary 2013, p. 96; Sokol and Ames, p. 2). While volume refers to the large amount, variety and velocity describe the data's potentially unstructured nature and speed of creation respectively (Gandomi and Haider 2015, p. 138; O'Leary 2013, p. 96; Tsou 2015, p. 70). The volume of the generated data and the number of data generation sources increase exponentially (Bello-Orgaz et al. 2016, p. 45). The International Data Corporation (IDC) estimates the total amount of globally available data in 2018 to be 33 zettabytes in size, equalling 33 billion terabytes, and predicts it to increase to 175 zettabytes by 2025 (Reinsel et al., p. 3). Big data offers many opportunities for improvements and decision-making in various fields including e-commerce (Akter and Wamba 2016, p. 173; Gandomi and Haider 2015, p. 140; Hargittai 2015, pp. 63-64; Korhammer and Grambow 2018, pp. 251-252). Due to the multifaceted potentials of big data, it created a "data rush" (Felt 2016, p. 1; Mahrt and Scharkow 2013, pp. 20-21) and is also referred to as the "new oil" (Korhammer and Grambow 2018, p. 255).

Today, a significant part of the globally created data comes from social media and OSN in the form of UGC (Bello-Orgaz et al. 2016, p. 46; Ghani et al. 2019, pp. 417-418). In this respect, the intersection of the research concerning social media and big data is also called *social big data* (e.g. Alt and Reinhold 2020, pp. 7-8; Bello-Orgaz et al. 2016, p. 46; Nguyen et al. 2015, p. 223; Zhou et al. 2018, pp. 769-770) and less commonly *big social data* (e.g. Cambria et al. 2013, p. 401; Oneto et al. 2016, p. 45). In the following, the former term will be used. Although the emergence of social big data gives rise to privacy concerns because personal and behavioural data is collected about users (Hargittai 2015, p. 64; Katal et al. 2013, p. 407; Tsou 2015, p. 72), it also creates new opportunities for firms that can use social big data to uncover the needs of their customers (Chen et al. 2012, p. 1169). The collected data about users can be leveraged for making accurate predictions about their preferences by building personality profiles (Korhammer and Grambow 2018, p. 254; Ullah et al. 2014, p. 547). Thereby, social big data can help firms to identify relevant success factors for improving their products and services (Immonen et al. 2015, p. 2028; Katal et al. 2013, p. 405).

(Social) big data also offers potentials for improving pricing decisions in e-commerce (Akter and Wamba 2016, pp. 173-174). Price and thereby pricing strategies are important tools for dealing with the requirements of the market (Bitran and Caldentey 2003, p. 203; Stahl et al. 2016, p. 139) and depend on multiple factors such as the level of competition or the costs of production (Calabrese and Francesco 2014, p. 906). Pricing decisions directly influence a firm's revenue and long-term success (Calabrese and Francesco 2014, p. 907). With the invention of mass production during the industrial revolution, the concept of offering standardised prices, also called *uniform pricing*, was introduced and replaced the until then common practice of price negotiations due to impracticability in the newly created mass markets (Wurman 2001, p. 36). Another reason for the introduction and prevalence of uniform pricing is that mass production has led to standardised products with consistent quality aggravating the charging of different prices to different customers (Wyld 2003, p. 343).

With the emergence of the Internet, the offering of standardised prices to all customers is challenged (Wurman 2001, p. 36) as it is leaves economic potential untapped, particularly if a highly diversified customer base is served (Caton et al. 2015, p. 316). The advancement and increased popularity of e-commerce have led to fierce competition among online retailers and thereby increased the importance of choosing the right pricing strategy (Bitran and Caldentey 2003, pp. 203-204; Kramler 2017, p. 81; Schlosser and Boissier 2018, p. 26; Serth et al. 2017, p. 61). In this context, (social) big data can be utilised for identifying customer groups and estimating their willingness-to-pay for products and services (Bourreau et al. 2017, p. 40; Victor et al. 2019, p. 140), which denotes the price up to which a customer would buy an offered product or service (Wertenbroch and Skiera 2002, p. 228). Such estimates allow firms to deploy differential pricing strategies like *dynamic pricing* for increasing their profit by offering prices that are closer to the willingness-to-pay of their customers (Backhaus et al. 2010, p. 133; Reinartz et al. 2018, pp. 3-4). In the past decades, dynamic pricing has gained relevance in research and practice, which has led to a multitude of definitions that differ in their scope and focus (Deksnyte and Lydeka 2012, p. 213; Gönsch et al. 2009, p. 4). In most definitions, dynamic pricing is described as the dynamic adjusting of prices to supply and demand which are subject to continuous change, e.g. due to seasonal factors or situational changes in the behaviour of competitors (Deksnyte and Lydeka 2012, p. 214; Garbarino and Lee 2003, p. 495; Gönsch et al. 2009, pp. 3-4; Wurman 2001, p. 36). Because of its time-dependency, dynamic pricing is also referred to as *intertemporal price differentiation* (Reinartz et al. 2018, p. 16).

Dynamic pricing has long been common in some industries such as air travel or the hospitality sector (Backhaus et al. 2010, p. 133; Bauer and Reiss 2019, p. 20). When deploying dynamic pricing in these industries, it is not only important to determine the level of demand but also where the demand comes from. In the air travel industry, for instance, business travellers exhibit a higher willingness-to-pay and usually book flights at short notice (Bergantino and Capozza 2015, p. 703; Gönsch et al. 2009, p. 7). By contrast, most of the ordinary holiday travellers have a lower willingness-to-pay but are more flexible in terms of planning and thus purchase tickets months in advance (Bergantino and Capozza 2015, pp. 702-703; Gönsch et al. 2009, p. 7; Narahari et al. 2005, p. 234). Since these groups of customers hardly overlap in regard to the time of booking, the air travel industry is able to price differentiate between them quite easily by using dynamic pricing. However, dynamic pricing has also become an established form of pricing in e-commerce businesses where a strict timely separation of customer groups may not be common (Weisstein et al. 2013, p. 501). In order to make use of dynamic pricing in such situations, the prices need to change on a more detailed time schedule. In this regard, it has been reported that Amazon changes the prices for some products up to 300 times within a few days (Hirsch 2015). Collected data from German price search engines further revealed that in April 2017 the prices for products listed on Amazon were changed more than 3.6 million times (Statista 2017).

An important characteristic of dynamic pricing is that the varied price still applies to all customers (Penmetsa et al. 2015, p. 896). From the perspective of the seller, a more efficient way would be differentiating prices on an individual level. This is called *personalised pricing*, also referred to as *individualised pricing*, where each customer is offered prices that are tailored to him, e.g. by using available individual-level information for more precisely estimating his willingness-to-pay (Aydin and Ziya 2009, p. 1523; Ghose and Huang 2006, p. 3; Kim et al. 2019, p. 373; King 2018, p. 115; Shapiro and Varian 1998, pp. 40-42). Firms already recognised at an early development stage of e-commerce that offering the right price to the right customer is the future (Ghose et al. 2002, p. 306). Even though uniform and dynamic pricing are still widely applied in e-commerce, recent progress in technology and consumer analytical research has increased the importance of personalised pricing (Anderson et al. 2015, p. 53; Chen and Chen 2017, p. 154; Vulkan and Shem-Tov 2015, p. 179), which could be widely applied in the foreseeable future (Victor et al. 2019, p. 141). In view of these developments, both researchers and practitioners hold a debate over the advantages and disadvantages of offering individualised prices (Esteves and Resende 2017, p. 2; King 2018, pp. 115-116). Research shows that personalised pricing has the potential to increase a firm’s profit (Lee et al. 2012, p. 9255) without necessarily jeopardising the consumer surplus (Bourreau et al. 2017, p. 44), which is defined as the difference between the willingness-to-pay and the paid price of a customer (Jayaraman and Baker 2003, p. 476). The increase in profit partly stems from the skimming of the consumer surplus of customers who are offered a price closer to their willingness-to-pay (Garbarino and Lee 2003, p. 496). These customers are financially worse off, which is referred to as the appropriation effect (Bourreau et al. 2017, p. 43; Schofield 2019, p. 9). However, even though the surplus is lowered, the utility the customers derive from using the purchased good remains the same. An increase in profit is also achieved by lowering the prices offered to those customers for whom the uniform price is too high (Bourreau et al. 2017, pp. 43-44; Schofield 2019, p. 9). This leads to a growth in the number of sales, which is called the expansion effect (Bourreau et al. 2017, pp. 43-44; Schofield 2019, p. 9). Considering the obtained utility, the expansion effect can increase the overall welfare in a population as it enables the newly acquired customers to benefit from the offered good as well.

1.1.3 Social Media Apps and Services

The growth and popularity of social media and OSN are also attributable to the success of mobiles devices like smartphones with a continuous mobile Internet connection (Humphreys 2013, p. 23; Kaplan 2012, p. 137; Oberst et al. 2017, p. 53). As of July 2020, there are 3.96 billion active social media users, of whom 98.7% access social media via mobile devices (Statista 2020c). For facilitating EWOM communication and generating UGC, social media platforms like OSN offer *social media services* (e.g. message, photo, or video sharing), which can be accessed through applications (apps) for mobile devices (Penni 2017, pp. 500-501). In the following, such apps with OSN functionalities where users can connect and relate to each other will be called *social media apps* (Alostad et al. 2018, p. 176). An OSN can consist of a website and multiple social media apps that comprise its offered social media services. For instance, Facebook offers a main social media app from which it extracted the chat functionalities to a stand-alone instant messenger app that was introduced in 2011 (Kincaid 2011). Social media apps are the most frequently used apps on smartphones (Chen and Li 2017, p. 958; Penni 2017, p. 503). Thereby, social media and OSN have evolved into a ubiquitous part of the everyday lives of billions of Internet users (Chen and Li 2017, p. 958; Lamberton and Stephen 2016, p. 146; Stieger and Lewetz 2018, p. 618). Because of the increased popularity of mobile devices, some more recently founded OSN like the photo and video sharing platform Snapchat and the instant messenger WhatsApp only exist in the form of social media apps (Montag et al. 2018, p. 3; Piwek and Joinson 2016, p. 359).

The interplay between smartphones, mobile Internet, and the intensive usage of social media apps and services have further accelerated the creation of social big data (Ahmed et al. 2018, p. 103). For OSN vendors, social big data and the corresponding opportunities are of great relevance. The increased capability of accurately assessing user preferences and interests makes targeted advertising possible (Bello-Orgaz et al. 2016, pp. 53-54; Fowler et al. 2013, p. 512; Pangrazio and Selwyn 2018, p. 1). For running targeted advertising campaigns, Facebook, for instance, offers tools for defining target groups by a multitude of available user attributes such as age, location, and interests (Fatehkia et al. 2018, p. 192; Speicher et al. 2018, p. 3). Because targeted advertising is an efficient tool to directly reach potential customers with a keen interest in the offered goods (Dawson and Lamb 2015, p. 105; Wang et al. 2015, p. 17), OSN like Facebook have attracted the attention of advertising agencies and firms that use them for promoting products and services (Dawson and Lamb 2015, pp. 105-106; Lax and Russo 2019, p. 1174; Shareef et al. 2019, p. 58; Xu et al. 2012, p. 318). Due to the increased popularity of such advertising campaigns, social media and OSN have induced a transformation of marketing (Gilbert 2019, p. 357; Lamberton and Stephen 2016, p. 146).

Most of the profitability and enterprise value of social media platforms and OSN stem from the revenue generated as an advertising platform since the offered social media apps and services are usually free to use (Fatehkia et al. 2018, p. 192; Ribeiro et al. 2019, p. 140). In 2015, Facebook's advertising revenue was 17.1 billion USD, which more than quadrupled to 69.7 billion USD in 2019 (Statista 2020b). According to Metcalfe's Law, the value of a social network increases proportionally with the number of potential relationships to other users, which can be approximated by the square of the number of existing users for large networks (Metcalfe 2013, p. 26; Shapiro and Varian 1998, p. 184). In other words, the value of a social network increases quadratically with the number of its users. Metcalfe's Law is related to the marketing performance of a social network (Hanna et al. 2011, p. 267). This is evidenced by investigations carried out by Metcalfe (2013) and Zhang et al. (2015), where the authors equated the network value of Facebook to its generated revenue and compared it to the estimations according to Metcalfe's Law. They could show that Metcalfe's Law shows a good fit to the actual value growth data of Facebook (Metcalfe 2013, p. 30; Zhang et al. 2015, p. 248). Thus, in order to reach and sustain lucrativeness as an advertising platform, it is crucial for OSN vendors to reach and maintain a large, active user base.

However, like fashion trends, the interests and likings of social media and OSN users and thereby the usage patterns of the offered services are subject to continuous change (Wilkinson and Thelwall 2010, p. 2311). OSN and the offered social media apps and services that are popular today can start to lose their popularity by tomorrow (Farooqui and Baig 2017, p. 128; Garcia et al. 2013, p. 39; Torkjazi et al. 2009, p. 48). A famous example of quick degradation in popularity is MySpace, an OSN that was founded in 2003 (Wilkinson and Thelwall 2010, p. 2311). It had reached its peak in popularity in the timeframe from 2005 to early 2008, during which it was the most visited OSN on the Internet and was valued at around 12 billion USD (Nika and Sofi 2014, p. 22; Rushe 2011). In April 2008, it was surpassed by Facebook in terms of daily user accesses and from then on faced a continuous decrease in popularity (Torkjazi et al. 2009, p. 48). Three years later, MySpace was sold for 35 million USD (Gehl 2012, p. 99; Rushe 2011). Besides strategic mistakes (Sahoo and Krotov 2008, p. 254), MySpace's decline is also attributed to its lack of capability for adequately dealing with the changing needs and preferences of its members, which seemed to be better served by Facebook during that time (Arango 2011; Mui 2011).

In order to reach an active user base and increase its size, vendors should aim for the continuous development of their OSN. The offering of new functionalities can help to preserve the activity of current users and attract new ones (Torkjazi et al. 2009, p. 48). Today's OSN continuously expand their functionalities, e.g. by providing new social media apps or services that enhance the user experience. For instance, Instagram is an OSN that has been on the rise since it was founded in 2010 (Hwang and Cho 2018, pp. 1305-1306; Statista

2018b). Initially, the OSN was solely intended for taking, modifying, and sharing photos with friends and the public (Hochman and Schwartz 2012, p. 6). Over the years, Instagram added new social media services to the OSN like sharing short videos that automatically disappear after 24 hours and live video broadcasting, which added to its popularity (Chaykowski 2016; Chen and Cheung 2019, p. 67; Isaac 2016). One of Instagram's more recently added social media services is called Threads and was introduced in October 2019 (Instagram 2019; Költzsch 2019). It is offered as a separate social media app that focuses on private chats and simplifies the sharing of annotated photos and videos (Instagram 2019; Költzsch 2019).

Newly introduced social media apps and services do not succeed instantaneously but rather diffuse gradually within the OSN. Depending on the characteristics of the social media app or service, the social interactions and dynamics involved in them can influence the speed and reach of the propagation in the OSN. In this context, it is not particularly important if a social media app is provided by the OSN vendor itself or is founded and advertised by third parties like start-ups because the social effects for a successful diffusion apply in both cases. In order to adopt new social media apps and services, a potential adopter needs to derive a certain utility from using them. It is conceivable that the perceived utility of social media apps and services is not only based on the personal benefit that a user derives from using them on his own but also depends on the number of already existing users. Social media apps and services are therefore forms of network goods that are characterised by an intrinsic value and a network value (Jing 2007, pp. 8-9; Sundararajan 2004, p. 108). These values constitute a network good's utility (Ge 2002, p. 176; Katz and Shapiro 1985, p. 424; Zhao and Duan 2014, p. 56), which can be accordingly differentiated into a *personal utility* and *social utility* (He and Lee 2020, p. 29; Hu et al. 2020, p. 1165). The social utility can be further divided in regard to the relationship to other adopters. For some social media apps and services, it might be more important that a sufficient number of friends, family members, or other close contacts already use them actively. For instance, WhatsApp is a social media app that is often used for communicating with people to whom a strong-tie relationship exists (Church and de Oliveira 2013, p. 355; Nouwens et al. 2017, p. 730). Similarly, the above-mentioned Threads app by Instagram also aims to facilitate communication among close friends (Instagram 2019). In other cases, the social utility is predominantly determined by the total number of users to whom a user has no strong- but rather a weak-tie relationship. Pinterest, for instance, offers social media services for its members who can collect and organise ideas, photos, and videos on virtual pinboards that are either private or shared with the public (Ottoni et al. 2013, p. 458). For exploring new content, Pinterest users can follow other members or their shared pinboards (Ottoni et al. 2013, p. 458). The more members Pinterest has, the greater is the probability of finding interesting content and members to follow, which would justify an active usage of the OSN. Therefore, for the enduring success of such social media apps and services, the number of total users might be more important than a large number of adopters among a potential user's peers.

1.2 Research Questions

In view of the discussed subject areas, three overall research questions are derived for this cumulative dissertation. In the context of EWOM in e-commerce, online retailers are confronted with challenges caused by NWOM being disseminated in OSN that require adequate counter-strategies (Balaji et al. 2016, p. 528; Beneke et al. 2015, pp. 68-71). It is not always clear what an efficient reaction strategy should look like (Weitzl 2019, p. 331). A quick reaction can solve the issues and increase the loyalty of customers (Balaji et al. 2015, pp. 649-650; Kim et al. 2016, p. 512; van Noort and Willemsen 2012, p. 131). However, if the answer is not well-reasoned and lacks persuasiveness, the countermeasure could lead to more NWOM and result in a so-called firestorm, where a multitude of customers vent their anger and displeasure online (Drasch et al. 2015, p. 2; Mochalova and Nanopoulos 2014, p. 1; Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92; van Noort and Willemsen 2012, p. 132). In the last two decades, the risk of experiencing a corporate crisis over a period of five years rose from 20% to 82% (Chang et al. 2015, p. 49). Sometimes it might be better not to react at all to prevent a downward spiral that could result in such a crisis (Thomas et al. 2012, pp. 91-92). If the firm, however, is able to adequately respond to NWOM, the reaction can induce negatively influenced customers to change their mind and motivate them to initiate PWOM by revising formerly disseminated NWOM messages (Breitsohl et al. 2010, p. 653; Yoo 2018, p. 1). Thus, the first overall research question (RQ) concerns finding adequate countermeasure strategies for restricting and reversing the influence of NWOM in OSN:

RQ1: *How should NWOM be countered in OSN?*

For answering the first overall research question, a diffusion model for the propagation of NWOM and its countering by PWOM in OSN is developed. In order to evaluate the effectiveness of different reaction strategies, the diffusion model is solved numerically for various NWOM and PWOM scenarios by simulating the propagation of messages in artificially generated networks and extracted sub-graphs from Facebook. This dissertation mainly contributes to the current literature in the research field of EWOM by incorporating realistic aspects such as message strength, reaction delay, nodal characteristics of message seeds, and economic considerations in the proposed diffusion model. Thereby, insights are provided into how financially harmful different NWOM messages are and which countermeasure strategies are most suitable for efficiently reducing their influence in OSN.

The second subject area concerns price differentiation in e-commerce in the age of EWOM and OSN. Although today's technological progress enables the application of differential pricing strategies like personalised pricing, online retailers are mostly hesitant about their deployment (Matsumura and Matsushima 2015, p. 887; Vulkan and Shem-Tov 2015, p. 182). First experiments with personalised pricing in e-commerce were not successful and created a surge of indignation among customers (Hinz et al. 2011, p. 82; Kamishima and Akaho 2011, p. 58; Vulkan and Shem-Tov 2015, p. 182). Many customers are still reluctant to accept prices that are tailored to them based on collected information (Aydin and Ziya 2009, p. 1524; Reinartz et al. 2018, p. 13). Therefore, dynamic pricing enjoys a higher level of acceptance among customers (Koschate-Fischer and Wüllner 2017, p. 840; Reinartz et al. 2018, p. 12). Under certain circumstances, however, personalised pricing is to some extent accepted by customers. Primarily, this applies to situations where the costs of products and services are varied, e.g. due to different levels of quality or duration of consumption, or situations where social norms prevail (Garbarino and Lee 2003, p. 498). Customers, for instance, generally accept discounts for students or retirees (Aydin and Ziya 2009, p. 1524; Garbarino and Lee 2003, p. 498). Hence, the traceability of price differences can help to increase the acceptance of individualised prices (Kamishima and Akaho 2011, p. 58; Koschate-Fischer and Wüllner 2017, p. 840; Kowatsch and Maass 2011, p. 314; Schofield 2019, p. 35). But offering products at different quality levels is not always feasible, and building social norms is a long-term process that can hardly be influenced by an online store. If the constitution of prices lacks transparency and traceability, it can lead to a high degree of perceived price unfairness (Reinartz et al. 2018, p. 17; Weisstein et al. 2013, p. 502). This, in turn, could upset customers, reduce the trust in the online retailer, and ultimately result in a decrease in sales and profit (Bourreau et al. 2017, p. 45; Koschate-Fischer and Wüllner 2017, p. 841; Reinartz et al. 2018, p. 13). Since EWOM enables a fast and widespread diffusion of information in OSN (Drasch et al. 2015, p. 2; Willemsen 2013, p. 10), customers could be made aware of others being privileged by online retailers in terms of prices without reasonable justification. Therefore, EWOM and the resulting price transparency in the market bear the risk of amplifying customer dissatisfaction and its impact on sales due to individualised prices. Despite this, EWOM is also associated with advantages for the seller because low prices shared with others can attract customers and entice them to visit the online store (Chiou and Pan 2009, p. 327; Jadhav and Khanna 2016, p. 22; Schmitz and Latzer 2002, p. 164). From this, the second overall research question arises that concerns the development of pricing strategies that allow the profitable deployment of price individualisation:

RQ2: *How should individualised pricing be deployed in the age of EWOM and OSN?*

The second overall research question will be answered by developing a pricing decision model for an online store that sells a good to customers who are interconnected in an OSN. Customers can get aware of the prices paid by others via EWOM and react to price differentiation in various ways, e.g. by lowering their willingness-to-pay if they observe others paying less. The decision model is solved numerically by applying various artificial intelligence (AI) solution methods that are benchmarked against each other regarding the generated profit. EWOM and price differentiation are excessively researched topics in the economics literature (see Section 2.2 and 3.2 respectively). However, the intersection of both research areas is mostly neglected by researchers. Therefore, this dissertation contributes to the current research on price differentiation by conjointly considering the effects of individualised pricing and price transparency resulting from EWOM in OSN. The developed model can be used for deriving capable individualised pricing strategies that are able to leverage EWOM's potentials and reduce its risks for increasing the online store's profit.

The third subject area of this dissertation concerns the adoption of new social media apps and services among OSN members. There are different aspects that need to be considered when launching social media apps or services. For instance, decisions must be taken about how and when the advertising budget is spent, e.g. by determining the number of users who shall be exposed to the advertisement within a given period of time. Besides the advertising volume, the way the advertisement is distributed in the OSN may also play an important role. If, for instance, a start-up decides to advertise a social media app in an OSN, it could choose a simple targeting approach where the advertisement is shown to randomly chosen users, which will be called *random marketing* in this dissertation. The start-up could also opt for more complex targeting approaches where a defined audience is presented the advertisement. Because social interactions are crucial to the success of social media apps, the target audiences could be formed according to existing relationships among members. This would enable targeting cohesively connected areas and clusters in the OSN, which will be referred to as *cluster marketing* in this dissertation. It is conceivable that cluster marketing is particularly effective for advertising social media apps and services where strong-tie relationships prevail. In these cases, a sufficient level of perceived utility for adoption could be reached sooner because only a subset of a user's close contacts may be needed for deriving a high social utility. Another way of informing OSN users about a new social media app or service is *influencer marketing*, where influential users publish a sponsored post that is made available to their followers (Appel et al. 2020, pp. 82-83; Müller et al. 2018, pp. 1-2). Because influencers have a large number of followers and usually are in key positions in the OSN, they are able to reach a multitude of other users within a short period of time (Rothe and Wicke 2018, pp. 1637-1638). Therefore, such an advertising strategy could be more suitable for apps and services where weak-tie relationships are more important. This leads to the third overall research question that relates to the investigation of successful launch strategies for social media apps and services:

RQ3: *How should social media apps and services be launched in OSN?*

In order to answer the third overall research question, a diffusion model for social media apps and services in OSN is developed and analysed numerically by simulation. For this, a novel classification scheme is proposed that differentiates social media apps and services according to the offered personal and social utility. On a meta-level, such propagation is similar to the diffusion of network goods in a social network, which has been thoroughly researched in the past decades. However, approaches in this research field lack a sufficient consideration of realistic user behaviour in the context of social media apps and services. This dissertation addresses this issue by explicitly modelling relevant behaviour including a usage frequency and an initial excitement about the new app or service that is subject to decay. Thereby, a contribution is made to the research on network goods by applying its general principles to the topical subject of social media apps and services. The developed model is used for examining various launch strategies in the diffusion process of such products, which is underrepresented in current research (see Section 4.2). Thus, the contribution of this dissertation also consists of testing and evaluating the aforementioned strategies regarding their performance in effectively distributing social media apps and services for maximising the share of active users in an OSN. To achieve realistic diffusion results, the propagation is tested in an extracted sub-graph of Facebook with more than 3 million vertices. Furthermore, as recommendations and invitations via EWOM are vital to the steady growth and success of newly introduced social media apps and services, the role of EWOM in the context of launch strategies is investigated. This dissertation therefore also provides insights into when EWOM is useful and can be leveraged for increasing the success of a launch strategy and when it has detrimental effects.

1.3 Thesis Structure and Publication Details

In accordance with the discussed subject areas, this cumulative dissertation is structured in three main Chapters 2 to 4. Each chapter addresses the previously defined respective overall research question by splitting it into multiple subordinate research questions and consists of at least one published or working paper.

Chapter 2 comprises two published papers and a working paper in the research field of EWOM. The first paper (Beşer et al. 2016) was published in the proceedings of the International Conference on Information Systems (ICIS) 2016 and introduced a message diffusion model that will be referred to as the *base model* throughout the dissertation. The base model extends a diffusion model that was first developed and tested by simulation in my master's thesis (Beşer 2015). In the base model, an NWOM and PWOM message compete in an OSN for the favour of potential customers in terms of persuasiveness. Several reaction strategies with variations in counter-message strengths, reaction delay, and the number of PWOM seeds who initially disseminate the counter-message in the OSN are tested and evaluated according to their ability to reduce the spread and influence of NWOM.

Chapter 2's second paper (Beşer et al. 2017) was published in the proceedings of the European Conference on Information Systems (ECIS) 2017 and extended the previous paper by incorporating the purchase behaviour of customers into the model. The updated model will henceforth be referred to as the *purchase model*. In the purchase model, customers are characterised by an initial purchase probability that will be either increased or decreased depending on how much NWOM and PWOM have influenced them. The purchase model is used to analyse how financially harmful NWOM is to a firm and how much of the economic damage can be reversed by PWOM. It is further used for investigating when a reaction to NWOM is mandatory and when firms may abstain from taking any measures because of NWOM's limited impact on the economic situation.

The third paper of Chapter 2 is a working paper (Beşer et al. 2020) that is based on the purchase model and concerns finding the optimal reaction strategy in given scenarios for maximising the firm's profit by efficiently reducing the negative effects of NWOM. This model will be referred to as the *optimal reaction model*. Based on the findings of the previous papers, in the optimal reaction model two opposing message strategies are compared to each other in terms of profit maximisation: (1) a strong PWOM message that is launched with delay and (2) a medium PWOM message that is disseminated shortly after the emergence of the NWOM message in the OSN. In addition to the former models, the quality of the NWOM and PWOM seeds, representing their nodal characteristics, is considered in the reaction strategy. It is thereby differentiated between weak, medium, and strong seeds, which enables deriving more detailed managerial implications for countering NWOM.

Because the three papers of Chapter 2 are based on each other, each paper contains the model of the preceding paper. In order to reduce redundancy in Chapter 2, the introduction, literature review, and base model development section are primarily based on the content of the latest paper. Thereafter, the purchase and optimal reaction models are successively presented by their corresponding extensions and numerical analyses. The conclusion section of Chapter 2 summarises the findings across all three papers, discusses limitations, and points out future research directions.

Chapter 3 addresses RQ2 and is based on a paper (Beşer et al. 2019) that was published in the proceedings of ICIS 2019. In the paper, a pricing decision model is developed for an online store whose customers can share paid prices via EWOM in an OSN. Different AI solution methods are used to solve the model for a numerical example in order to examine the profitability of individualised pricing strategies under price transparency.

Chapter 4 aims to answer RQ3 and encompasses a working paper (Beşer and Lackes 2020) that introduces a diffusion model for social media apps and services. The model is tested by simulation for identifying factors of success and failure that determine whether a newly launched social media app or service will reach a high share of active users in an OSN.

Because Chapter 3 and 4 consist of one paper each, their content structure reflects the respective paper's structure.

Table 1 gives an overview of the underlying papers this cumulative dissertation is based on. For integrating the papers into the context of this cumulative dissertation, structural and textual changes have been made to them without altering the informational value of their content. For some experiments of the already published papers, the data representation was adjusted for increased readability, and additional analyses were carried out based on the original simulation raw data.

Chapter 5 summarises the key findings of all listed papers and answers the formulated overall research questions. It concludes with limitations and future research directions.

Table 1. Publication details of underlying papers.

Chapter and Addressed Research Question	Authors	Paper Title	Development Environment	Publication Status
Chapter 2 RQ1	Beşer et al. 2016	The Quicker One Is the Better One? – How to Fight Negative Word of Mouth	NetLogo	International Conference on Information Systems 2016 [**VHB-Jourqual 3: A**]
	Beşer et al. 2017	Silence Is Golden – When Firms Should React to Negative Word of Mouth	NetLogo	European Conference on Information Systems 2017 [**VHB-Jourqual 3: B**]
	Beşer et al. 2020	Does the Early or Strong Bird Catch the Worm? – When and How to React to Negative Electronic Word of Mouth	C++, MATLAB	Working Paper
Chapter 3 RQ2	Beşer et al. 2019	Different Prices for Different Customers – Optimising Individualised Prices in Online Stores by Artificial Intelligence	MATLAB	International Conference on Information Systems 2019 [**VHB-Jourqual 3: A**]
Chapter 4 RQ3	Beşer and Lackes 2020	The Diffusion of Social Media Apps and Services in Online Social Networks	C++, MATLAB	Working Paper

Chapter 2:

Negative Electronic Word of Mouth in Online Social Networks

2 Negative Electronic Word of Mouth in Online Social Networks

2.1 Introduction

In today's world of communication, social media and online social networks (OSN) such as Facebook, Twitter, and Instagram gain more and more in popularity. As of July 2020, there are 4.57 billion Internet users worldwide, of whom 86.7% are active social media users (Statista 2020c). The rise of the Internet and the rapidly increasing impact of social media and OSN create new ways for customer interaction, which augment traditional word of mouth (Beneke et al. 2015, p. 68; Jung and Kim 2012, p. 343; Kunz et al. 2012, p. 472). Customers use electronic word of mouth (EWOM) not only to share information of private nature but also to talk about their favourite brands or products and share the experiences they have had with them (Chang et al. 2015, p. 48; Jung and Kim 2012, p. 343; Kunz et al. 2012, p. 472; Teng et al. 2017, p. 76; Yoo et al. 2013, p. 669). Reviews shared by other customers are perceived as more reliable and trustworthy than retailer-provided information (Cheung and Thadani 2012, p. 461; Das 2016, p. 212; Kumar and Purbey 2018, p. 3594; Yoo et al. 2013, p. 670) and thereby help customers in making better purchase decisions by reducing purchase risks (Bambauer-Sachse and Mangold 2013, p. 373; Jung and Kim 2012, p. 343; Kumar and Purbey 2018, p. 3594; Wang and Yu 2017, p. 179; Yoo et al. 2015, pp. 496-497). Because EWOM has considerably simplified the process of exchanging information, the shared experiences can be easily made available to a multitude of customers (Cheung et al. 2008, pp. 229-230; Schmäh et al. 2017, p. 148; Teng et al. 2017, p. 76; Willemsen 2013, p. 10).

The lively usage of social media and OSN opens up new opportunities for firms that may use them for promoting their products or services by initiating positive electronic word of mouth (PWOM) (Canali and Lancellotti 2012, p. 28; Dawson and Lamb 2015, pp. 105-106; Lax and Russo 2019, p. 1174; Xu et al. 2012, p. 318). When compared to traditional media, social media and OSN allow reaching target groups more easily, quickly, accurately, and at lower costs (Dawson and Lamb 2015, p. 105; Wang et al. 2015, p. 17). In order to exploit the potentials of PWOM in social media and OSN, firms are usually represented on these platforms with fan or support pages (Bacile et al. 2017, p. 24; He et al. 2019, p. 6638). Direct communication with customers can help to reveal latent customer needs and improve the quality of the firm's offered products and services as well as its reputation (Hennig-Thurau et al. 2010, pp. 311-312; Huang and Benyoucef 2013, p. 246; Pfeffer et al. 2014, p. 118). However, EWOM facilitated by OSN is also associated with disadvantages for firms. Because it enables an anonymous and fast exchange of information, dissatisfied customers often utilise OSN for expressing their displeasure with a firm or its offered products and services by disseminating negative electronic word of mouth (NWOM) (Chang et al. 2015, p. 49; Lee and Song 2010, p. 1074; van Noort and Willemsen 2012, p. 132). This can irritate potential customers and deter them from making purchases (Kunz et al. 2012, p. 472; van Noort and Willemsen 2012, pp. 131-132). Firms can counter NWOM by trying to induce PWOM in the OSN (Mochalova and Nanopoulos 2014, p. 4), but due to the so-called negativity bias (Ahluwalia 2002; Rozin and Royzman 2001), NWOM messages are perceived to be more informative and persuasive than PWOM messages (Chang et al. 2015, p. 49; Chang and Wu 2014, p. 206; Kumar and Purbey 2018, p. 3593; Kunz et al. 2012, p. 472; Sen and Lerman 2007, p. 78). Customers therefore tend to rely more on NWOM messages in their decision-making when shopping online (Cheung and Thadani 2012, p. 464). In this regard, NWOM is found to reduce the purchase intention of customers more than PWOM is able to increase it (Kumar and Purbey 2018, p. 3593; Lee et al. 2008, p. 342; Park and Lee 2009, pp. 62-65). Research has also shown that NWOM messages propagate faster in OSN, which can result in so-called firestorms that may tremendously harm a firm's reputation (Beneke et al. 2015, p. 70; Cannarella and Piccioni 2008, p. 125; Mochalova and Nanopoulos 2014, pp. 1-2; Pfeffer et al. 2014, pp. 117-118). Thus, NWOM messages disseminated in OSN can lead to significant financial losses and therefore represent a great threat to a firm's success (Beneke et al. 2015, p. 68; Drasch et al. 2015, p. 2; Mochalova and Nanopoulos 2014, p. 2; van Noort and Willemsen 2012, pp. 131-132).

Firms have recognised the increased relevance of EWOM and the necessity of coping with its opportunities and challenges by both generating and monitoring it in OSN (Mochalova and Nanopoulos 2014, p. 2; van Noort and Willemsen 2012, p. 131). Although inducing PWOM enables firms to improve their reputation and increase the awareness level for their brands, the way to react to NWOM is not clear (Hennig-Thurau et al. 2010, p. 313; Pfeffer et al. 2014, pp. 119-120; van Noort and Willemsen 2012, p. 132). If an NWOM message reaches a certain spread, countering it can be challenging even if it is an unjustified customer complaint (Pfeffer et al. 2014, pp. 119-120). A quick reaction might help to resolve the issue and prevent further damage (van Noort and Willemsen 2012, p. 131). If the reaction takes too long, it might not be possible to counteract and contain the firestorm efficiently (Mochalova and Nanopoulos 2014, pp. 10-11; van Laer and de Ruyter 2010, p. 164). Therefore, it is crucial for firms to permanently monitor OSN for detecting NWOM at an early stage in order to react to it as soon as possible (Drasch et al. 2015, p. 2; Malthouse 2007, p. 385; van Noort and Willemsen 2012, p. 131).

When facing a unilateral risk, the firm has to trade off the potential damage caused by the risk against the costs of actively coping with it. In the case of NWOM, this means that a firm must weigh the loss of reputation and sales that NWOM may cause and set it off against the measures that can be taken for responding to NWOM. Because people are exposed to a huge amount of information in OSN (Canali and Lancellotti 2012, p. 28; Liang and Fu 2017, pp. 1-4; Thomas et al. 2012, p. 92), the majority of the shared information has a small reach (Cha et al. 2009, p. 722). Thus, even if NWOM is identified in an OSN, it might still be better just to observe the communication instead of initiating a countermeasure (Thomas et al. 2012, pp. 91-92).

However, if a firm opts for taking countermeasures and launches a counter-message, it might have already lost control over it and its ways of communication (Thomas et al. 2012, pp. 88-92). A publicly issued statement or a mistreated customer can provoke more NWOM that might strongly harm a brand and cause customer losses (Lee and Song 2010, p. 1076; Thomas et al. 2012, pp. 91-92; van Noort and Willemsen 2012, p. 132). This is because people can spread the initial message in OSN as well as a changed message (Botha and Reyneke 2013, p. 160; Hennig-Thurau et al. 2010, p. 313; Illia 2003, p. 327) with a tenor that possibly diverges from the original intentions of the firm. Such engendered messages usually express the dissatisfaction of customers with a firm in a harsh manner and often without substantial criticism (Pfeffer et al. 2014, p. 118). Thus, a premature and quickly sent out response that is neither well-founded nor appealing to customers could easily backfire by initiating new waves of NWOM that might increase the initial damage (Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92; van Noort and Willemsen 2012, p. 132). Therefore, a firm might be better off by taking time for designing a persuasive message. However, because of the influence of the negativity bias, NWOM messages draw more attention and diffuse further than PWOM messages (Mochalova and Nanopoulos 2014, p. 2; van Noort and Willemsen 2012, p. 132). If not countered in time, NWOM messages could penetrate remote areas of the OSN that possibly cannot be reached by the PWOM message, which would render many customers to be only aware of the NWOM message.

Derived from these considerations, this chapter aims to answer the following research questions (RQ):

RQ1.1: *How important is the reaction speed when countering NWOM?*

RQ1.2: *In which situations is it mandatory to react to NWOM, and under which circumstances is it better to resign from taking any measures?*

RQ1.3: *When should a firm focus on the quality of the response, and when should it prefer a quick reaction at the expense of quality?*

For answering these research questions, a diffusion model is developed and solved numerically by carrying out simulation experiments. Thereafter, two extensions to the model are presented that incorporate additional customer behavioural aspects and are likewise numerically analysed. The model variants will be referred to as the *base*, *purchase*, and *optimal reaction model* and individually address the research questions in consecutive order. By addressing these research questions, this study contributes in different ways to the current research on coping with the challenges and risks of NWOM in OSN.

First of all, it is crucial to analyse which kinds of messages reach a high spread in OSN (Drasch et al. 2015, pp. 2-3; Pfeffer et al. 2014, p. 118) and how they can be countered in order to prevent firestorms (Thomas et al. 2012, pp. 90-95; van Noort and Willemsen 2012, pp. 131-132). The marketing literature already investigated characteristics of messages that make them go viral and showed that emotions and content-related aspects such as the valence and style of writing are essential factors for viral marketing (e.g. Botha and Reyneke 2013, pp. 161-163; Drasch et al. 2015, p. 3; Eckler and Bolls 2011, pp. 1-4; Radighieri and Mulder 2014, p. 251; van Laer and de Ruyter 2010, p. 165). However, none of the existing papers in the relevant research field (see next section) consider the characteristics of the transmitted message. We will address this by incorporating the argument quality and expressiveness of a message that represent its rational and emotional dimension respectively (Allsop et al. 2007, p. 402; Sweeney et al. 2012, p. 238). Secondly, we take into account that there might be a delay between the initial NWOM message and a firm's reaction to it. Usually, NWOM can spread for a certain period of time without being noticed by the firm, i.e. countermeasures are only initiated after monitoring tools have raised an alarm. Until now, only a few papers (e.g. Mochalova and Nanopoulos 2014; Nguyen et al. 2012) considered such a realistic delay and did not assume an immediate response to NWOM. Thirdly, we incorporate the ageing of messages into our model because people usually forward older messages less likely than newer ones. The reason for this is twofold. Because of today's information overload that is facilitated by social media and OSN (Canali and Lancellotti 2012, p. 28; Liang and Fu 2017, pp. 1-4; Thomas et al. 2012, p. 92), messages age quickly and easily lose their topicality (Nugroho et al. 2015, pp. 142-144; Wu and Shen 2015, p. 705). Additionally, communication in OSN serves for shaping one's reputation (Cheung and Lee 2012, p. 220; Lampel and Bhalla 2007, p. 435; Sohn 2014, pp. 145-146). But the forwarding of messages that are already known to a potential sender's peers could harm his reputation (Pescher et al. 2014, p. 47), which makes the sending of outdated information more unlikely. Fourthly, we treat the opinions of OSN members as not being fixed but subject to changes as long as they receive new information in the form of messages from their peers. As a result, an OSN member's opinion can swing between NWOM and PWOM. Therefore, a member is not necessarily "immune" if PWOM reaches him before

NWOM. In this regard, we fifthly allow OSN members to remain indifferent between NWOM and PWOM if the messages are too similar in terms of persuasiveness. Sixthly, messages cannot only trigger messages of the same valence but also of the opposite. This depicts the situation when firms react to NWOM in OSN with a poorly designed PWOM message that upsets receivers and motivates them to disseminate the NWOM message instead of the PWOM message. Seventhly, the perceived credibility of a message does not only depend on the message itself but also on the contextual environment (Batra et al. 2001, pp. 116-117), which is in our study represented by the market type. In fashion markets, for instance, people are more susceptible to peer influence than in food and grocery markets, where individualism is higher valued and more tolerated (Delre et al. 2007b, p. 192). Eighthly, the source of NWOM and its position in the network is considered. As Mochalova and Nanopoulos (2014, pp. 10-12) have shown, online firestorms can be restricted by choosing OSN members who hold a position of special quality in the network. We contribute to this by defining different seed quality classes that allow the classification of NWOM disseminators in the OSN and can also be used for choosing seeds of different quality for spreading the PWOM message. Finally, for determining a firm's optimal reaction strategy to NWOM, both the strategy's revenue and costs are taken into account.

This chapter is organised as follows. The next section gives an overview of the current research on (non-)competitive (E)WOM modelling and simulation. Thereafter, the three models are successively developed and numerically analysed. The chapter concludes with a summary of each model's findings, draws managerial implications, discusses limitations, and points out future research directions.

2.2 Literature Review

Domingos and Richardson (2001) were the first who recognised the importance of the social network structure for viral marketing (Nguyen et al. 2012, p. 214). Their aim was to choose a limited set of network members for disseminating a message that reaches the highest possible spread in a given network. Kempe et al. (2003, 2005) acted on that influence maximisation problem and formulated it as a discrete optimisation problem. By using two different diffusion models, the independent cascade model and the linear threshold model, they could show that the influence maximisation problem is NP-hard but submodular. Being submodular means that the solution of the problem, although NP-hard, can be approximated with the help of a greedy hill-climbing algorithm within reasonable computational time (Budak et al. 2011, p. 668; Nguyen et al. 2012, p. 214). Because the hill-climbing algorithm developed by Kempe et al. (2003, 2005) lacks efficiency, several papers investigated efficient algorithms that scale with increasing network size (e.g. Chen et al. 2009b; Chen 2009a; Chen et al. 2010a; Chen et al. 2010b; Leskovec et al. 2007; Wang et al. 2010).

All of the aforementioned papers focus on one message whose spread is intended to be maximised within the network. This problem is motivated from a marketing point of view where a campaign with a limited budget shall address and reach a maximum number of people. Our study contributes to the research on competitive (E)WOM message diffusion where two opposing messages propagate in a network competing for the network members' conviction. Related papers in this field are listed in Table 2 and can be divided into two groups. The first group treats the two spreading messages as being equal, while the second group assumes that one message dominates the other. In contrast to the non-competitive influence maximisation problem, already small changes to the general competitive influence maximisation problem destruct the submodular property and therefore hamper an approximation of the optimal solution (Borodin et al. 2010; Chen et al. 2011).

Papers of the first group solely focus on the objective of "influence maximisation" as listed in Table 2. The general setting consists of two competing firms (= messages) where each firm aims to maximise its influence in the market (= network). One firm is the first and the other firm is the second mover that knows the steps of the first mover. The research results show that both firms can find an optimal set of seeds for maximising their influence (Bharathi et al. 2007). But being the first mover is not always advantageous. The second mover can outperform the first mover even with a limited budget (Carnes et al. 2007; Kostka et al. 2008). As only a certain number of products/messages can survive in a given market/network, the stronger is able to oust the weaker one (Pathak et al. 2010). This is challenged by the findings of Goyal and Kearns (2012), who could show that direct competition can help to increase the total diffusion of each competitor. It might therefore be advantageous for firms to operate in the same markets instead of avoiding the clash and serving different markets.

In reality, the assumption of two equivalent messages is questionable. The truth, for example, dominates a lie if it comes from authorised or verifiable sources (Nguyen et al. 2012, p. 213). In consideration of the negativity bias and its impact on the diffusion of information in a network, papers of the second group investigate how NWOM can be stopped or restricted in order to save as many people as possible from being influenced by NWOM. In Table 2, this problem is referred to as "influence blocking maximisation".

In the truth versus lie situation, the propagation of the lie can be stopped by spreading the truth because the latter can be assumed to be more persuasive than the former (Budak et al. 2011, p. 667; Nguyen et al. 2012, p. 213). If people can grasp the truth, rumours like the wrong announcement of Obama's death in July 2011 cannot survive (Nguyen et al. 2012, p. 213). In general, however, the correct assessment of such situations is not always easy from the perspective of OSN members. In the case of rumours about a product's quality or reported adverse experiences, the evaluation of messages becomes more complicated (Chen et al. 2011). Often, the truth can hardly be verified, is not unequivocal, or lies in the eye of the beholder. Strengthened by the negativity bias, the NWOM message can gain the upper hand over a PWOM message in such situations eliciting detrimental effects for firms. Trpevski et al. (2010) could show for a setting with a dominant and a non-dominant message that the latter can quickly die out leaving the field entirely to the former. Therefore, it is crucial for firms to develop strategies for adequately dealing with the overpowering influence of NWOM in OSN. He et al. (2012) and Mochalova and Nanopoulos (2014) address this problem by developing different strategies on how to select seeds in a network for disseminating the PWOM message. Both papers use localised network centrality measures for choosing seeds and outperform the greedy algorithm that Kempe et al. (2003) originally introduced for the influence maximisation problem.

This study is mostly related to the papers of He et al. (2012) and Mochalova and Nanopoulos (2014), whose research goal is to fight NWOM instead of maximising the influence of PWOM. However, it differs from the existing approaches in several ways. Besides the nodal characteristics of seeds, we also focus on the rational and emotional characteristics of the shared messages (Allsop et al. 2007, p. 402; Sweeney et al. 2012, p. 238) as well as on the number of seeds used for launching them in the OSN.

Another distinctive feature of this study pertains to the opinion change of OSN members. Except for Trpevski et al. (2010) and Irfan and Ortiz (2011), who allow the revoking of decisions, all other papers consider a so-called progressive spread (Kempe et al. 2003) where a network participant does not change his opinion once he is convinced of either the NWOM or PWOM message. We lift this restriction in our study and allow OSN members to change their minds as long as they receive new messages from their peers. Suppose, for example, that an OSN member has received the NWOM message and gets convinced by the information it provides. If, later on, this particular member encounters that more and more of his peers adopt the opposing message, he might be inclined to change his opinion and believe in the other message as well (Delre et al. 2007b, p. 192) because people are susceptible to normative social influence (Bastiaensens et al. 2016, pp. 193-195; Batra et al. 2001, pp. 116-117; Hsu and Tran 2013, p. 26).

As in the studies of Mochalova and Nanopoulos (2014) and Nguyen et al. (2012), we also consider a time delay between the initial NWOM message and the PWOM message since firms may not always be able to react immediately to NWOM. Typically, NWOM messages propagate in OSN for a while and are identified by firms only after a certain number of people have forwarded the message.

Furthermore, most of the above-mentioned studies assume that messages can only induce a forwarding of other messages that are of the same valence, e.g. PWOM messages may trigger more PWOM messages but do not affect the forwarding of NWOM messages. This assumption, however, is not a particularly realistic depiction of message forwarding behaviour in real OSN. If, for instance, a statement issued by the firm causes annoyance among OSN members, it could encourage them to spread the opposing message again leading to a second wave of NWOM (Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92; van Noort and Willemsen 2012, p. 132). In order to properly reflect this in our study, we allow the triggering of opposing messages in the OSN.

Lastly, this study is the only one that provides an economic analysis of different countermeasure strategies by weighting the potential revenues against the related costs. It is taken into account that the PWOM seed activation costs depend on the position and interconnectedness of the seeds in the OSN since well-established influencers are more likely to charge higher prices for acting on behalf of the firm than members with a limited number of contacts. Based on the economic evaluation, recommendations about the optimal reaction to NWOM are given, i.e. in which situations which countermeasure should be preferably taken by the firm.

Table 2. Related literature in the research field of competitive (E)WOM message diffusion.

Authors	**Research Objective**	**Diffusion Model**	**Messages**	**Status Switching**	**Delay**	**Findings**
Bharathi et al. (2007)	influence maximisation	independent cascade model	equal	–	delayed infection	• the first as well as second mover can efficiently find an optimal set of seeds • the costs of competition are at most a factor of two
Borodin et al. (2010)	influence maximisation	various adapted linear threshold models	equal	–	–	• adapted models are NP-hard and not submodular • the optimal solution can hardly be approximated
Budak et al. (2011)	influence blocking maximisation when information about the network is missing	independent cascade model with positive domination	dominant	–	delay	• simple graph heuristics perform similarly well to greedy heuristics in the full information case • the proposed algorithm allows 90% missing data before its performance declines
Carnes et al. (2007)	influence maximisation	distance-based model; wave propagation model	equal	–	delay	• the second mover can outperform the first mover with a limited budget

Authors	**Research Objective**	**Diffusion Model**	**Messages**	**Status Switching**	**Delay**	**Findings**
Chen et al. (2011)	influence maximisation; analysing the influence of and sensitivity to product quality	independent cascade model extended by quality	dominant	–	–	• universally good quality does not exist for optimal spreading • model extensions destruct submodular property
Goyal and Kearns (2012)	influence maximi-sation	adapted linear threshold model	equal	–	–	• competitors are better off starting to compete in nearby instead of distant areas of the network
He et al. (2012)	influence blocking maximisation	competitive linear threshold model with negative domination	dominant	–	–	• the given problem is submodular • the provided algorithm outperforms simple graph heuristics
Irfan and Ortiz (2011)	influence maximisation	game-theoretic approach	non-competitive	adoption and rejection	–	• authors develop an algorithm for identifying the most influential nodes in the network
Kostka et al. (2008)	influence maximisation	simple propagation model based on the independent cascade model	equal	–	delay	• being the first mover is not always advantageous • the second mover can outperform the first mover

Authors	Research Objective	Diffusion Model	Messages	Status Switching	Delay	Findings
Mochalova and Nanopoulos (2014)	influence blocking maximisation	independent cascade model with negativity bias	dominant preferences	–	delay	• seeds can prevent approximately the tenfold of their number from adopting a message • the earlier the counter-strategy starts, the more people are saved
Nguyen et al. (2012)	influence blocking up to a given percentage	independent cascade model and linear threshold model with positive domination	dominant	–	delay	• blocking misinformation up to a certain percentage with a minimum number of nodes is NP-hard and can hardly be approximated
Pathak et al. (2010)	influence maximisation	generalised linear threshold model	equal	–	–	• number of surviving messages is independent of the number of competing messages
Trpevski et al. (2010)	analysis of competitive message spreading	susceptible-infective-susceptible model	dominant preferences	conversion to not-infected status due to oblivion	–	• for non-dominant messages, it is difficult to survive in the network • in order to survive, the spread of the message has to exceed a certain threshold independent of the network topology and starting point in the network

2.3 Base Model

2.3.1 Network Model

In the following, we consider a market setting where a firm (hereafter referred to as *she*) offers a product or service for sale. A potential customer (hereafter referred to as *he*) can share his experience with the offered good in an OSN where he is interconnected with others. Two messages of opposing valence can co-exist in the network: (1) a negative message disseminated by an unsatisfied customer who expresses his negative experiences with the purchased good and (2) a positive message launched by the seller in which she tries to counter the negative message, e.g. by providing rebuttal arguments. Except for the seeds, all OSN members are defined as potential customers who can be affected by these messages. After receiving one of these messages, an OSN member evaluates its persuasiveness and may forward it to his own peers based on the message characteristics and his personal preferences. If the persuasiveness of a message exceeds the member's personal credibility threshold, he will be convinced of the message. Each OSN member is described by an inherent purchase probability that will be either increased or decreased depending on which message has influenced him more. For instance, if the negative message is more persuasive, his individual purchase probability will be lowered making a purchase less likely. Thus, the more OSN members are convinced of the negative message, the fewer will purchase the firm's good. The share of members who would make a purchase represents the financially valued time-dependent state of the OSN. This state depends on the diffusion of the messages in the OSN and therefore changes over time. The firm's reaction to the negative message concerns the composition of a persuasive positive message and the choice of adequate seeds for launching it in order to reverse the damages caused by the negative information in the OSN.

The underlying system for this setting consists of an OSN and a set of messages that are passed among OSN members $i = 1, \dots, I$ within a given time horizon $t = 0, \dots, T$. The OSN can be operationalised as a graph $G = (V, E, W, M)$ where V is a finite set of vertices denoting the members $V = \{1, \dots, I\}$ of the OSN, E is a set of edges representing the social relationships $E \subseteq V \times V$ between them, W is a function that assigns a weight to the edges, and M is a set of messages that circulate in the OSN. A relationship between two distinct members $i, j \in V$ is depicted by $(i, j) \in E$ where j can be seen as a follower of i. In an undirected network, i would also follow j such that $(i, j) \Rightarrow (j, i)$. In a directed network, member i's neighbourhood N_i can be divided into the members who follow him and those whom he follows. These sets of members are denoted by $N_i^{followers} = \{j \in V: (i, j) \in E\}$ and $N_i^{following} = \{j \in V: (j, i) \in E\}$ respectively. In an undirected network, these sets are congruent: $N_i = N_i^{followers} = N_i^{following}$. Each relationship (i,j) is attributed with a weight $w_{ij} = W(i,j)$ with $W:(i,j) \to [0,1]$. The weight represents the perceived social tie strength to member j from the perspective of member i. Even in an undirected graph, the tie strength weights do not have to coincide because the perceptions of the connected members may differ such that $w_{ij} \neq w_{ji}$.

The set of messages M contains two messages that differ in their valence: (1) a negative message and (2) a positive message that counters the former. Besides the valence, a message is also characterised by various attributes including its content and temporal attributes that concern its emergence and topicality in the OSN. Let $m \in \{+,-\}$ denote the valence of one of the two messages and let $\bar{m} \in \{+,-\}\backslash m$ be the valence of the opposing message. The content of a message can be described by a rational and emotional dimension (Allsop et al. 2007, p. 402; Sweeney et al. 2012, p. 238). The rational dimension shall be represented by the argument quality $AQ^m \in [0,1]$ that depicts how well-founded and persuasive the arguments included in message m are (Cheung et al. 2009, p. 15). The emotional dimension relates to the expressiveness $EX^m \in [0,1]$ of the language used in message m, e.g. evoked by dissatisfaction with the product (Buttle 1998, p. 247). A message is further characterised by the first time it shows up in the network $T^m \in \{1,\dots,T\}$ and the celerity with which it loses its topicality in the OSN depicted by its half-life $T_{1/2}^m \in \{1,\dots,T\}$. Based on these characteristics, a message of valence m can be operationalised as a tuple $(m, AQ^m, EX^m, T^m, T_{1/2}^m)$. Consequently, the set M of the two opposing messages in the OSN can be written as $M = \{(+, AQ^+, EX^+, T^+, T_{1/2}^+),\ (-, AQ^-, EX^-, T^-, T_{1/2}^-)\}$. Hereafter, the two messages will be referred to by their valence, i.e. m and $\bar{m}$. A member can act as a seed for one of the messages. Let $V^{m,seeds}, V^{\bar{m},seeds} \subset V$ define the sets of seeds for both messages that are disjoint: $V^{m,seeds} \cap V^{\bar{m},seeds} = \emptyset$. Depending on his nodal characteristics, a member is more or less suitable for disseminating a message with the aim of reaching a high spread in the OSN. To depict this suitability, each OSN member can be assigned to a so-called seed quality class SQ_k with $k = 1,\dots,K$. The seed quality classes are ordinally scaled and considered in the optimal reaction model. Their computation is described in Section 2.8.4.

2.3.2 Credibility Evaluation of Messages

Once an OSN member has received a message, he assesses its credibility. A theory for the message credibility evaluation is the dual-process theory of Deutsch and Gerard (1955) that differentiates between two types of social influence which may occur during the exchange of information between individuals: (1) informational social influence and (2) normative social influence. The informational social influence describes the tendency of a receiver to accept the content of the transmitted message as a proof of facts (Cheung et al. 2009, p. 13). The normative social influence equates to the natural predisposition of individuals to conform with the behavioural expectations of their peer group, e.g. when a consensus is formed regarding a topic (Cheung et al. 2009, p. 13; Hsu and Tran 2013, p. 26; van Eck et al. 2011, p. 189). By conforming with the general perception of his social neighbourhood, an OSN member prevents social dismissal and is awarded social approval (Chu and Kim 2011, p. 57; Hsu and Tran 2013, p. 26; Wang et al. 2012, p. 201). It has been empirically proven that both the informational and normative social influence affect a customer's behaviour in the EWOM context (Cheung et al. 2009, pp. 27-29; Chu and Kim 2011, p. 64; Lis 2013, p. 130).

The susceptibility to the normative social influence depends on the situation a person is confronted with (Batra et al. 2001, pp. 116-117) and therefore can differ for different products or markets. For instance, in markets for fashion products, people pay more attention to the opinion and behaviour of others than in food or grocery markets, where the social tolerance for diversity is comparatively higher (Delre et al. 2007b, p. 192). Because of this, the message credibility can be operationalised as a linear combination between the informational and normative social influence (Delre et al. 2007b, p. 192; Delre et al. 2007a, p. 829; van Eck et al. 2011, p. 193). Let $\beta \in [0,1]$ be a parameter that weighs the latter in relation to the former, i.e. it specifies how much OSN members rely on the behaviour of their peers instead of the message's content when assessing its credibility. In the following, β will be called the *market parameter*. Inspired by the terminology of Hofstede (1980), who coined the terms *individualistic* and *collectivistic* in the context of cultural dimensions, we will call markets where the opinions of others play a pivotal role in the credibility evaluation process *collectivistic markets*. Markets where customers are more independent of the behaviour of their peers and pay more attention to the informational value of the message will be called *individualistic markets* (Delre et al. 2007b, p. 196).

In either kind of market, the valuation for social conformity may vary among customers (Chu 2009, p. 28; Delre et al. 2007a, p. 829; van Eck et al. 2011, p. 193) due to expertise (De Bruyn and Lilien 2008, p. 152; Fan and Miao 2012, pp. 175-176), opinion (East et al. 2007, p. 179; Mochalova and Nanopoulos 2014, p. 7), and preferences (Fan and Miao 2012, p. 175; Lord et al. 2001, p. 281). Therefore, we model the market parameter on an individual level with $\beta_i \in [0,1]$. Let $r_{it}^m \in \{0,1\}$ denote if member i has received message m and is aware of it at time step t. If he is aware of it (i.e. $r_{it}^m = 1$), the credibility C_{it}^m of message m that member i perceives at time step t is defined as follows where the market parameter β_i weighs the relative impact of the perceived time-dependent normative social influence NSI_{it}^m and informational social influence ISI_{it}^m:

$$C_{it}^{m} = \beta_i \cdot NSI_{it}^{m} + (1-\beta_i) \cdot ISI_{it}^{m}, \qquad NSI_{it}^{m},\, ISI_{it}^{m} \in [0,1],$$

$$\forall i \in \{1, \dots, I : r_{it}^{m} = 1\} \tag{1}$$

An OSN member who has assessed the credibility of a received message compares it to his individual time-independent credibility threshold $\phi_i^m \in [0,1]$. If C_{it}^m surpasses member i's credibility threshold ϕ_i^m, he will believe in message m. In this regard, let the credibility decision $CD_{it}^m \in \{0,1\}$ of member i indicate if he is convinced of message m at time step t. If member i has not received message m yet, he cannot be persuaded by it: $CD_{it}^m = 0\ \ \forall i \in \{1, \dots, I : r_{it}^m = 0\}$. If he has received it, several case distinctions need to be made depending on whether he is also aware of the opposing message. If the member has not received the opposing message yet, solely the comparison between the message's credibility C_{it}^m and the corresponding threshold ϕ_i^m will determine the member's state of belief. This also applies if the opposing message has reached him but was unconvincing. If both messages are perceived as credible, the member has to decide between them by comparing them to each other in terms of credibility threshold exceedance. The member will be convinced of message m if its threshold exceedance is higher than the exceedance of the opposing message $\bar{m}$. Based on this, the credibility decision CD_{it}^m of member i regarding message m at time step t is defined as:

$$CD_{it}^{m} = \begin{cases} 1 & if \quad C_{it}^{m} \geq \phi_i^{m} \quad \wedge \quad r_{it}^{\bar{m}} = 0 \\ 1 & if \quad C_{it}^{m} \geq \phi_i^{m} \quad \wedge \quad r_{it}^{\bar{m}} = 1 \quad \wedge \quad C_{it}^{\bar{m}} < \phi_i^{\bar{m}} \\ 1 & if \quad C_{it}^{m} \geq \phi_i^{m} \quad \wedge \quad r_{it}^{\bar{m}} = 1 \quad \wedge \quad C_{it}^{\bar{m}} \geq \phi_i^{\bar{m}} \quad \wedge \quad \frac{(C_{it}^{m} - \phi_i^{m})}{(1-\phi_i^{m})} > \frac{(C_{it}^{\bar{m}} - \phi_i^{\bar{m}})}{\left(1-\phi_i^{\bar{m}}\right)} \\ 0 & else \end{cases},$$

$$\forall i \in \{1, \dots, I : r_{it}^{m} = 1\} \tag{2}$$

Although a member can believe in neither message, he cannot be convinced of both messages simultaneously by definition such that $CD_{it}^m \cdot CD_{it}^{\bar{m}} = 0$. Additionally, we do not restrict the number of possible opinion changes. A member who believes in message m can get convinced of the opposing message $\bar{m}$ and, later on, switch back to m.

The spread S_t^m of message m equals the share of members in the OSN who are convinced of it at time step t:

$$S_t^m = \frac{1}{|V|} \cdot \sum_{i \in V} CD_{it}^m \tag{3}$$

2.3.3 Normative Social Influence

The normative social influence is based on the opinions and behaviour of an OSN member's peers and represents the social pressure that could arise if a consensus is formed among them (Cheung et al. 2009, p. 13; Ryu and Han 2009, p. 404; van Eck et al. 2011, p. 192; Wang et al. 2012, p. 201). The more of his peers forward a message to him, the more he is inclined to adopt the opinion of the transmitted message (Lascu et al. 1995, p. 202). However, a member's peers are not equally important in the opinion-making process. The stronger the social relationship between a sender and receiver is, the more likely it is that the latter will get influenced by the former (Ryu and Han 2009, p. 410). Thus, we define the normative social influence a sender j can exert on the receiver i to depend on the tie strength w_{ij} perceived by the latter. The social pressure can be modelled as a continuum (van Eck et al. 2011, p. 193) where each message reception is weighted according to the perceived tie strength to the respective sender. For this, let $r_{ijt}^m \in \{0,1\}$ indicate if member i receives message m from a member $j \in N_i^{following}$ at time step t. OSN members do not forward the same message to the same receiver multiple times such that $\sum_{\tau=1}^{T} r_{ij\tau}^m \leq 1 \ \forall i \in V, j \in N_i^{following}$. Then, the social pressure SP_{it}^m perceived by member i regarding message m at time step t can be calculated as:

$$SP_{it}^m = \frac{\sum_{j \in N_i^{following}} w_{ij} \cdot \sum_{\tau=1}^{t} r_{ij\tau}^m}{\sum_{j \in N_i^{following}} w_{ij}}, \qquad \forall i \in \{1, \dots, I : r_{it}^m = 1\} \tag{4}$$

In OSN, members usually have a multitude of contacts (Statista 2018a). It is therefore conceivable that not all but only a fraction of a member's peers are sufficient to exert a relatively high social pressure on him. For operationalising the perceived normative social influence NSI_{it}^m, we therefore transform the social pressure with the help of a logistic sigmoid function where δ and ω define, as exemplarily depicted in Figure 2, the transformation curve's steepness and midpoint position respectively:

$$NSI_{it}^m = \frac{1}{1 + e^{-\delta \cdot (SP_{it}^m - \omega)}}, \qquad \forall i \in \{1, \dots, I : r_{it}^m = 1\} \tag{5}$$

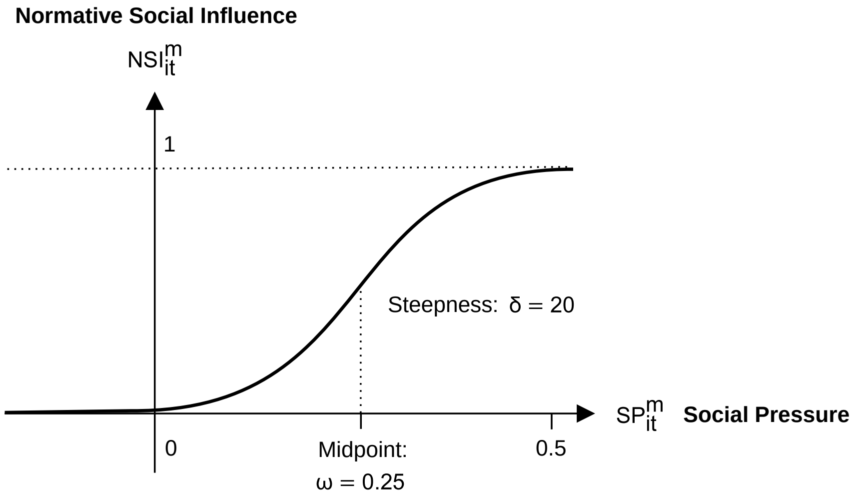

Figure 2. Exemplary transformation of the perceived social pressure by using a logistic sigmoid function with δ=20 and ω=0.25.

2.3.4 Informational Social Influence

The informational social influence refers to the content of the transmitted message, which consists of a rational and emotional dimension (Allsop et al. 2007, p. 402; Sweeney et al. 2012, p. 238). The rational dimension of message m is depicted by the argument quality AQ^m that represents its arguments and the degree to which they are convincing (Cheung et al. 2008, p. 232; Cheung and Thadani 2012, p. 465). The higher the argument quality is, the more credible the message appears to the receiver (Cheung et al. 2009, p. 15). The emotional dimension concerns the expressiveness EX^m of message m. The more (un-)satisfied a person is, the more (negative) positive and therefore emotionally expressive will his message be (Buttle 1998, p. 247). The valuation between the rational and emotional dimension can vary among OSN members because it depends on the level of their expertise (Park and Kim 2008, p. 402; Sohn 2014, p. 146). A high level of expertise enables members to process received information more comprehensively (Fan and Miao 2012, pp. 175-178; Sohn 2014, p. 146). However, if they lack expertise, they will not be able to appropriately assess the provided argument quality and instead rely more heavily on heuristic cues such as the message's expressiveness (Park and Kim 2008, p. 402; Sohn 2014, p. 146). To incorporate this, let $\gamma_i \in [0,1]$ denote how much member i values AQ^m over EX^m. Then, the informational social influence ISI_{it}^m of message m perceived by member i at time step t can be operationalised as a linear combination of the aforementioned dimensions:

$$ISI_{it}^m = \gamma_i \cdot AQ^m + (1 - \gamma_i) \cdot EX^m, \qquad \forall i \in \{1, \dots, I : r_{it}^m = 1\} \tag{6}$$

2.3.5 Forwarding of Messages: Private Messaging

Once an OSN member has received a message, he judges its credibility and decides whether to forward it to his peers. The probability of forwarding is at its highest when the message is still young and rapidly decreases afterwards as the message sharing activity in OSN usually follows an exponential distribution (Nugroho et al. 2015, p. 143; Wu and Shen 2015, p. 705). This means that the older a message is, the more unlikely it is that it gets forwarded. Therefore, we define an ageing factor $AF_t^m \in (0,1]$ for each message m that shall represent its exponentially decreasing topicality depending on the time of its first emergence T^m in the OSN and its half-life $T_{1/2}^m$: $AF_t^m = \exp(-\ln(2) \cdot (T_{1/2}^m)^{-1} \cdot (t - T^m))\ \ \forall t \geq T^m$.

Both the credibility of a message and the tie strength between the sender and receiver play an important role in the forwarding of EWOM messages (Chu and Kim 2011, p. 64; Hsu and Tran 2013, p. 31; Pescher et al. 2014, p. 47). People tend to exchange information more often with contacts to whom they have a closer social relationship (Brown et al. 2007, pp. 4-5; Chiu et al. 2006, pp. 1876-1877; Chu and Kim 2011, p. 64; Pescher et al. 2014, p. 47; Wirtz and Chew 2002, p. 142). But the interplay of the credibility and tie strength for determining the forwarding probability is complex as they are neither complete antipodes nor do they act fully complementary. Since people communicate to shape their reputation in their peer group (Cheung and Lee 2012, p. 220; Lampel and Bhalla 2007, p. 435; Sohn 2014, pp. 145-146), a less convincing message bears the risk of not being noteworthy and could harm a social relationship (Sohn 2014, pp. 145-146) or the reputation of the sender (Pescher et al. 2014, p. 47). Because of this, it is conceivable that a message with low credibility is not forwarded even if there is a strong-tie relationship. This could be reflected in the forwarding probability by multiplicatively linking both factors. On the other hand, if the credibility is very high, a message may be forwarded irrespective of the perceived strength of the social relationship. In that case, instead of lowering the forwarding probability, a low tie strength could add to its value, which would mean that credibility and tie strength act additively. Therefore, we use a parameter $\eta_i \in [0,1]$ for counterbalancing both factors for mutual dependency and enhancement instead of using a pure linear combination. Hence, member i's forwarding probability FP_{ijt}^m of message m to one of his followers $j \in N_i^{followers}$ at time step t can be operationalised as follows where the ageing factor AF_t^m is used as a weighting factor:

$$FP_{ijt}^m = \left(\eta_i \cdot w_{ij} \cdot C_{it}^m + (1-\eta_i) \cdot \left(w_{ij} + C_{it}^m - w_{ij} \cdot C_{it}^m\right)\right) \cdot AF_t^m, \tag{7}$$

$$\forall i \in \{1, \dots, I: r_{it}^m = 1\}$$

An OSN member will forward the message to each one of his peers according to the forwarding probability. However, we define two main conditions that need to be met for a member to forward the message. First, the member is required to have received the corresponding message in the preceding time step. This means that if he has received the NWOM but not the PWOM message, his forwarding decision will only concern the NWOM message and vice versa. Second, we assume that if a member is convinced of message m, he will not forward the opposing message $\bar{m}$. Only if he has not been persuaded yet or if he prefers to remain indifferent, he may forward both messages. In other words, he is only allowed to forward message m if he does not believe in the opposing message $\bar{m}$. Let $V_t^{m,senders}$ denote the set of potential senders of message m who fulfil these conditions at a given time step t: $V_t^{m,senders} = \{i \in V\colon \sum_{j \in N_i^{following}} r_{ijt-1}^m \geq 1 \,\wedge\, CD_{it}^{\bar{m}} = 0\}\ \forall t \geq 1$. For the OSN members belonging to this set, the forwarding probability is subject to a {0,1} distribution and can be defined as a Bernoulli (Ber) random variable (Aizenman et al. 2009, p. 221). Based on this, the actual forwarding decision FD_{ijt}^m of member i regarding the sending of message m to a follower $j \in N_i^{followers}$ at time step t is operationalised as:

$$FD_{ijt}^m \sim \mathrm{Ber}\left(FP_{ijt}^m\right), \qquad \forall i \in V_t^{m,senders} \tag{8}$$

Note that, as pointed out in Section 2.3.3, member i forwards message m to member j only once in order not to harm his reputation by spreading old information (Pescher et al. 2014, p. 47; Sohn 2014, pp. 145-146). Thus, we additionally require for a potential receiver that member i has not yet sent him the message: $j \in \left\{1, \ldots, I \in N_i^{followers}\colon \sum_{\tau=1}^{t-1} FD_{ij\tau}^m = 0\right\}$.

This probabilistic forwarding of messages does not apply to seeds whose forwarding decision is deterministic. They forward message m to all of their followers $j \in N_i^{followers}$ as soon as the seed activation time is reached: $FD_{ijt}^m = 1\ \forall i \in V^{m,seeds}, t = T^m$ with $FD_{ijt}^m = 0\ \forall i \in V^{m,seeds}, t \neq T^m$. The remaining members in the OSN do not forward the message at time step t: $FD_{ijt}^m = 0\ \forall i \in (V \backslash V^{m,seeds}) \backslash V_t^{m,senders}$. If member i opts for forwarding message m, the selected follower j will receive it at the subsequent time step $t+1$ such that $r_{jit+1}^m = FD_{ijt}^m\ \forall j \in N_i^{followers}$. Consequently, member i is aware of message m if he has received it from at least one contact $j \in N_i^{following}$ until time step t exclusively:

$$r_{it}^m = \begin{cases} 1 & if \quad \sum_{j \in N_i^{following}} \sum_{\tau=1}^{t-1} r_{ij\tau}^m \geq 1 \\ 0 & else \end{cases}, \qquad \forall t \geq 1 \tag{9}$$

2.4 Base Model: Numerical Analysis

2.4.1 Parameterisation

Due to the stochastic variables of the developed diffusion model that prevent an analytical solution, a numerical analysis was carried out by conducting simulations in artificially generated networks. According to Granovetter (1973, pp. 1363-1366), social networks can be characterised by two components: (1) highly clustered sub-networks where members intensively communicate with each other and (2) so-called bridges or short cuts that interconnect these sub-networks and ensure a fast diffusion of information (Chen and Li 2017, p. 959; Watts and Strogatz 1998, pp. 440-441). Onnela et al. (2007, p. 7334) found empirical evidence for this theory by analysing usage data of 4.6 million mobile phone users. For measuring the diffusion of NWOM and PWOM messages in an undirected network, we used the small-world network model developed by Watts and Strogatz (1998) that shares both of these characteristics (Watts and Strogatz 1998, p. 441; Zhang et al. 2014, p. 231).

On an aggregated structural level, social networks can be described by the average path length and the global clustering coefficient (Albert and Barabási 2002, p. 49; Watts and Strogatz 1998, pp. 440-441). The average path length describes how many edges in a graph need to be passed on average in order to get from a randomly selected first vertex to a likewise randomly selected second vertex (Wang and Chen 2003, pp. 8-9; Zaidi 2013, p. 52). It can therefore be seen as a measure for the diffusion speed within a network (Watts and Strogatz 1998, pp. 441-442). Let d_{ij} denote the geodesic distance between two distinct network participants i and j representing the number of edges that need to be passed on the shortest path between them (Strang et al. 2018, p. 2; Zhao et al. 2008, pp. 184-185). If i and j are directly connected, their distance equals one. If there is no path between them such that they cannot reach each other in the network, the distance is defined as $d_{ij} = \infty$ (Raj et al. 2018a, p. 16; Strang et al. 2018, p. 2). The average path length APL is calculated by summing up all non-infinite distances and dividing the resulting sum by the maximum number of edges that can exist, which equals $|V| \cdot (|V| - 1)/2$ in undirected networks (Bilgin et al. 2016, p. 351; Raj et al. 2018a, p. 17; Zhao et al. 2008, pp. 184-185):

$$APL = \frac{1}{|V| \cdot (|V| - 1)/2} \cdot \sum_{i \in V} \sum_{j \in V} d_{ij} \tag{10}$$

The global clustering coefficient is a measurement of the social cliquishness in a network (Watts and Strogatz 1998, p. 441). It is defined as the average of the local clustering coefficient that calculates the degree of connectivity in the neighbourhood of each network participant (Cowan and Jonard 2004, p. 1560; Raj et al. 2018b, p. 22). The local clustering coefficient measures the likelihood that two distinct neighbours of a vertex are also connected to each other (Kiesling 2011, p. 39; Watts and Strogatz 1998, p. 441). Let E_i denote the actual number of existing edges in the social neighbourhood N_i of member i. The local clustering coefficient LCC_i of his neighbourhood is calculated by dividing E_i by the theoretically attainable maximum number (Albert and Barabási 2002, p. 49; Blanco and Lioma 2012, p. 63; Watts and Strogatz 1998, p. 441):

$$LCC_i = \frac{E_i}{|N_i| \cdot (|N_i| - 1)/2} \tag{11}$$

The global clustering coefficient GCC is then given by (Albert and Barabási 2002, p. 49; Blanco and Lioma 2012, pp. 63-64; Watts and Strogatz 1998, p. 441):

$$GCC = \frac{1}{|V|} \cdot \sum_{i \in V} LCC_i \tag{12}$$

In order to obtain representative values for the numerical analysis, 500 simulation runs were executed for each simulation experiment (i.e. a certain combination of the varied model parameters) to determine the average message spread. For each run, a new small-world network with 1000 vertices was generated by following the algorithm of Watts and Strogatz (1998, p. 441) where we used a lattice parameter of six and a rewiring probability of 10%. On average, the generated networks had an average path length of $APL \approx 6.3$ and a global clustering coefficient of $GCC \approx 0.43$. Real social networks are found to provide similar values for the average path length (Albert and Barabási 2002, pp. 48-49; Milgram 1967, p. 65).

Some of the developed model's parameters were fixed for the following experiments. We assume that the parameters concerning the individual preferences of OSN members are normally distributed with a mean μ and standard deviation σ. The values were generated by using a truncated normal distribution in order to comply with their defined value range. For generating the individual market parameter, we used $\mu(\beta_i) = \beta$ and $\sigma(\beta_i) = 0.125$. Due to the lack of empirical data regarding the valuation of the argument quality and expressiveness used in a message, we chose $\mu(\gamma_i) = 0.5$ and $\sigma(\gamma_i) = 0.125$. This means that, on average, both message dimensions were perceived as equally important by OSN members. Various findings regarding the negativity bias indicate that NWOM messages are twice as powerful as PWOM messages (Amini et al. 2012, p. 304; Goldenberg et al. 2007, p. 191; Sweeney et al. 2005, pp. 334-335). Therefore, we defined the threshold for PWOM to be roughly twice as high as the threshold of NWOM with $\phi_i^+ \approx 2 \cdot \phi_i^-$, which leads to NWOM messages being more easily believed by OSN members. To accomplish this, the threshold for accepting a PWOM message was generated by using $\mu(\phi_i^+) = 0.5$ and $\sigma(\phi_i^+) = 0.125$. For the acceptance threshold of the NWOM message, we used $\mu(\phi_i^-) = 0.25$ and $\sigma(\phi_i^-) = 0.0625$. The edge weights were drawn from an exponential distribution with a mean of $\mu(w_{ij}) = 0.2$ because in OSN like Facebook the number of contacts to whom a member has a strong social relationship is rather small (Spiliotopoulos et al. 2014, p. 3). The generated edge weights were truncated at one for complying with their normalisation. For modelling a rapidly increasing normative social influence, we set the parameters for the logistic sigmoid function to $\delta = 20$ and $\omega = 0.25$. Hereby, NSI_{it}^m attained values close to one if a member felt pressure from at least half of his peers (i.e. $SP_{it}^m \geq 0.5$). Because there is a lack of empirical evidence on how tie strength and perceived message credibility influence each other, the counterbalancing factor for the forwarding probability was set to $\eta_i = 0.5$ for all OSN members. This depicts the basic case where no counterbalancing occurs, i.e. the tie strength and perceived message credibility are treated as equivalent to each other in the forwarding probability. The NWOM message's time of emergence in the OSN was fixed at $T^- = 0$, while the time step at which the PWOM message showed up in the OSN for the first time was varied in the following subsections with $T^- \leq T^+$. The simulation was stopped at time step T when all OSN members stopped forwarding the messages. In the following, comparisons between different measurements are always given in percentage points unless otherwise specified.

2.4.2 Non-Competitive Setting: Influence of Half-Life, Market, and Message Strength

For investigating the influence of the half-life $T_{1/2}^m$ and market parameter β on the message spread, we used an NWOM message with the highest possible values $AQ^- = EX^- = 1.0$ and analysed its propagation in different markets $\beta \in \{0.0, 0.1, \dots, 1.0\}$. In general, the following observations also apply to the diffusion of a PWOM message. However, the reached spread levels would be lower due to the higher credibility threshold used in the parameterisation of PWOM messages.

Figure 3 illustrates that if there is no ageing, the strong NWOM message is able to reach an NWOM spread of almost 100% in all markets. In the opposite case, when the message ages very quickly and loses 50% of its topicality in one time step (i.e. $T_{1/2}^- = 1$), the NWOM spread is quite low and ranges from approximately 1% to 3%. Between these extreme ageing factors, the NWOM spread is significantly higher in individualistic markets ($\beta \to 0$) than in collectivistic markets ($\beta \to 1$). This is due to the fact that in individualistic markets the content of a message (i.e. ISI_{it}^{m} consisting of AQ^{m} and EX^{m}) is higher valued than the opinions and behaviour of an OSN member's peers (i.e. NSI_{it}^{m}). Because of this, the message is more likely to be perceived as credible, which causes the message to be forwarded more often by OSN members resulting in a higher spread.

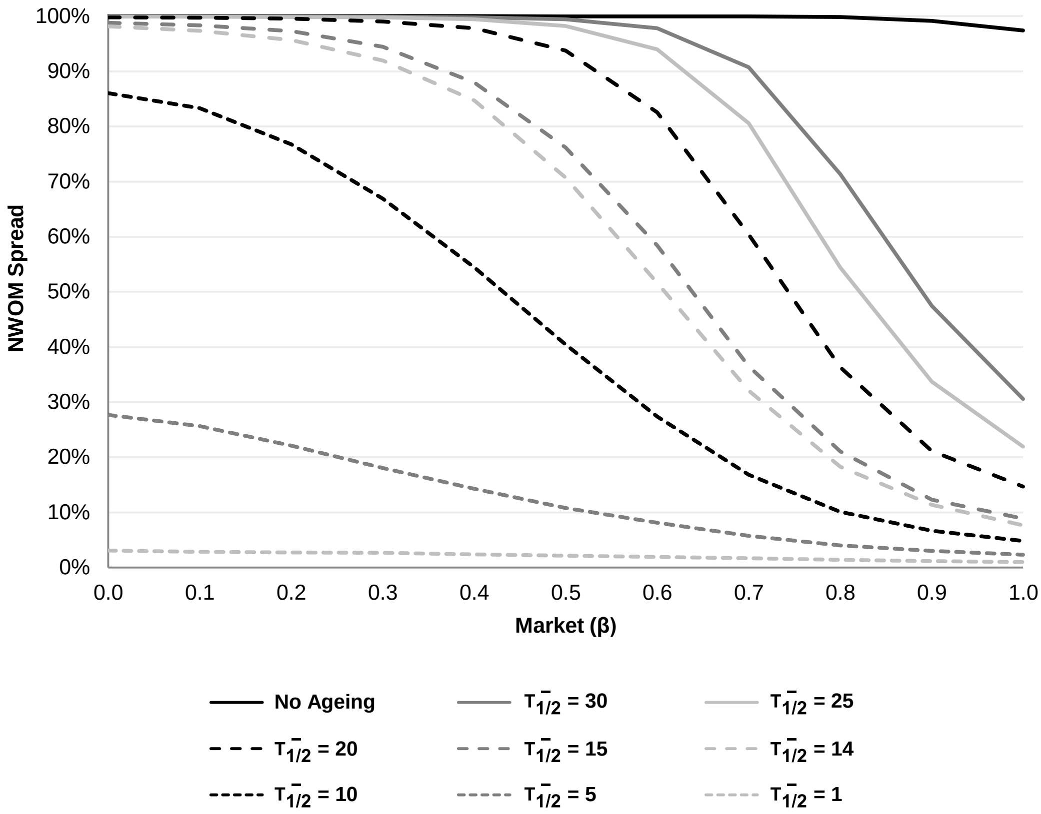

Figure 3. Variation of the half-life in different markets for AQ^{-}=EX^{-}=1.0.

In collectivistic markets, it is more difficult for messages to spread because people are more hesitant and generally oriented towards the opinions and behaviour of their peers rather than the message's content. Despite the tested message's high strength of $AQ^{-} = EX^{-} = 1.0$, the perceived credibility is very low as the message is hardly forwarded by OSN members in the beginning. Only after a certain number of an OSN member's peers have shared the message, the perceived credibility starts to increase. This entails two effects that need to be considered. First, it makes the degradation of topicality a more critical issue in collectivistic markets. If messages age quickly, they will not get forwarded very often and die out before reaching a considerable spread in the OSN. Second, the hesitant forwarding behaviour of OSN members can induce a delay in the overall diffusion process. To verify the second effect, we analysed the average duration of the diffusion until the simulation was automatically stopped at time step T. Table 3 lists for each tested constellation the simulation time and shows that particularly for greater values of the half-life (i.e. slower ageing) the NWOM message takes significantly longer in collectivistic markets to reach its final spread than in individualistic markets. The situation is reversed for smaller values of the half-life (i.e. quicker ageing), where the simulation is stopped earlier in collectivistic markets due to the first above-mentioned effect, which restricts the spread of the NWOM message.

Table 3. Simulation time for tested constellations.

	Average duration in time steps (t) until the stop criterion of the simulation was met for different markets (β) and values of the half-life										
	Highly Individualistic Markets										**Highly Collectivistic Markets**
Half-Life	**β = 0.0**	**β = 0.1**	**β = 0.2**	**β = 0.3**	**β = 0.4**	**β = 0.5**	**β = 0.6**	**β = 0.7**	**β = 0.8**	**β = 0.9**	**β = 1.0**
1	4.238	4.142	4.064	4.008	3.864	3.728	3.622	3.498	3.322	3.134	3.112
5	14.930	14.732	14.350	13.774	12.976	12.198	11.388	10.456	9.460	8.900	8.214
10	23.340	23.364	23.592	23.290	22.614	21.732	20.290	18.476	16.602	14.966	13.596
14	24.652	25.040	25.812	26.626	27.198	27.320	26.400	24.306	21.914	19.610	17.786
15	24.574	25.150	25.952	26.970	28.140	28.382	27.714	26.196	23.332	20.704	18.830
20	23.464	24.394	25.378	27.186	29.058	30.992	32.214	32.222	29.876	26.736	24.434
25	22.702	23.062	24.094	25.826	27.948	30.810	33.720	35.958	35.550	32.688	29.638
30	21.806	22.408	23.292	24.906	27.106	29.528	33.850	37.210	39.136	37.402	34.756
No Ageing	18.654	18.932	19.272	20.140	21.184	22.718	24.488	26.758	30.044	33.446	35.914

We performed the same experiments for a considerably weaker NWOM message with $AQ^- = EX^- = 0.1$, for which the results are depicted in Figure 4. Note that the tested half-life values were increased as compared to the former experiment with the strong NWOM message. If lower values had been used for the half-life, the quick ageing would have prevented the weak message from spreading at all and thereby hampered the analysis. The graphs in Figure 4 show that despite the slow ageing, the weak message hardly propagates in individualistic markets ($\beta < 0.4$) but, interestingly, has a considerably better survival rate in collectivistic markets ($\beta \geq 0.4$). This finding suggests that if there is a slow degradation of topicality, messages can reach high spreads in collectivistic markets even if they lack substantial content. This is because the message still gets forwarded by OSN members, which can accumulate over time and result in a high spread in the OSN. Individualistic markets are less prone to this effect because of the higher valued content in the credibility evaluation that impedes the forwarding and spreading of less persuasive messages.

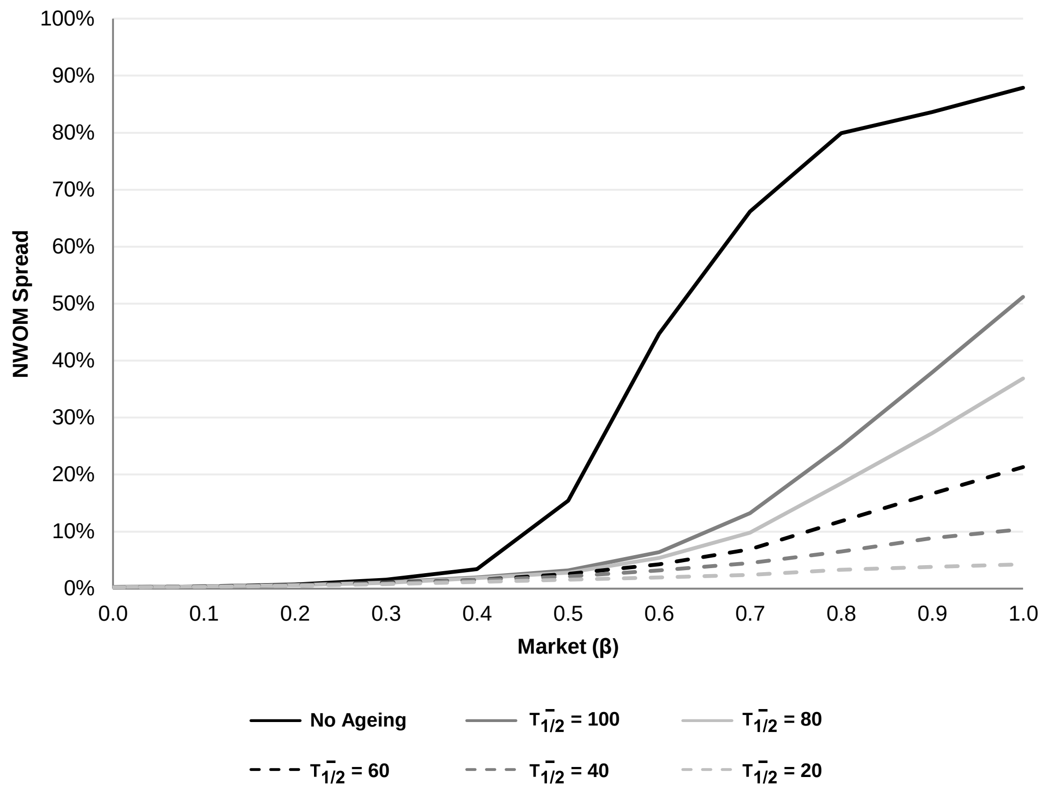

Figure 4. Variation of the half-life in different markets for AQ⁻=EX⁻=0.1.

For the following experiments, we set the half-life of both messages to $T_{1/2}^{m} = 10$. This means that messages lose 50% of their topicality after ten time steps. By choosing a relatively low half-life for inducing a quick ageing of information, the used small-world networks mimic the dynamics of much larger networks since it is highly unlikely that even a strong NWOM message can reach a spread close to 100% in large OSN such as Facebook or Twitter. Furthermore, we picked two markets for closer examination: (1) an *individualistic market* ($\beta = 0.1$) and (2) a *collectivistic market* ($\beta = 0.4$). In these two markets, we examined the influence of the message credibility by testing the diffusion of various NWOM messages that were varied in terms of argument quality and expressiveness. Due to the parameterisation provided in Section 2.4.1, the argument quality AQ^{m} and expressiveness EX^{m} are, on average, perceived by OSN members as being equally important. This makes any combination of AQ^{m} and EX^{m} interchangeable, because of which we assigned the same value to them. The level of AQ^{m} and EX^{m} will in the following also be referred to as the *message strength* or *informational value* of a message. We varied the informational value of the NWOM message in equal steps of 0.1: $AQ^{-} = EX^{-} \in \{0.0, 0.1, \ldots, 1.0\}$. The resulting diffusion data is given in Table 4, and the corresponding plots are depicted in Figure 5.

Table 4. NWOM spread for different values of AQ^{-} and EX^{-}.

		Mean and standard deviation of the reached NWOM spread for different message strengths			
		Individualistic Market (β=0.1)		**Collectivistic Market (β=0.4)**	
	Message Strength	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
AQ^{-} and EX^{-}	**0.0**	0.150%	0.080%	0.567%	0.354%
	0.1	0.300%	0.171%	0.858%	0.482%
	0.2	0.926%	0.509%	1.519%	0.821%
	0.3	**2.799%**	**1.592%**	**2.509%**	**1.315%**
	0.4	6.289%	3.538%	4.596%	2.582%
	0.5	10.780%	6.002%	8.011%	4.360%
	0.6	**19.200%**	**9.317%**	**12.924%**	**6.601%**
	0.7	33.412%	12.644%	20.169%	8.826%
	0.8	52.007%	14.148%	29.161%	11.426%
	0.9	68.162%	13.621%	41.050%	13.781%
	1.0	**82.790%**	**10.322%**	**54.752%**	**14.673%**

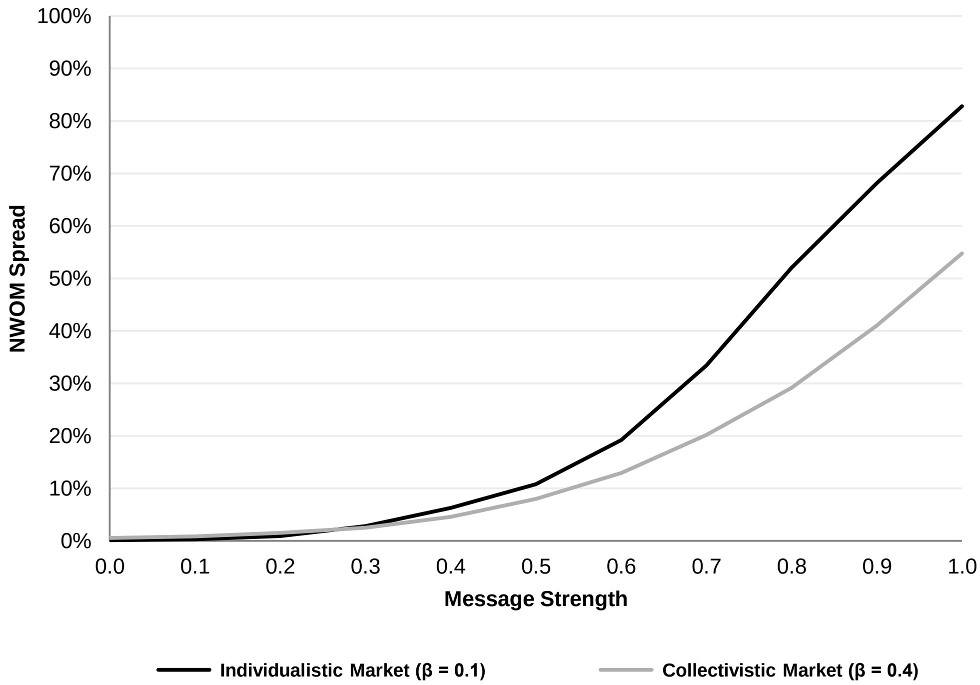

Figure 5. NWOM spread for different values of AQ^{-} and EX^{-}.

The data in Table 4 reveals that even messages with no strength (i.e. $AQ^{-} = EX^{-} = 0.0$) can propagate and reach a certain spread in the tested networks. This can be explained by the diversity in the generated populations regarding the susceptibility to social pressure. Some OSN members think and act in a very collectivistic way, i.e. they do not attach weight to the conveyed information, which might motivate them to forward and believe in the message despite its unconvincing nature. The listed results further show that for $AQ^{-} = EX^{-} \leq 0.3$ the reached NWOM spreads in the individualistic and collectivistic market are quite similar in terms of mean and standard deviation. The differences between the markets increase for $0.3 < AQ^{-} = EX^{-}$.

In order to examine the similarities and differences between both markets in terms of spread dynamics in the presence of PWOM, in the following subsections three NWOM message cases are analysed in greater depth that are highlighted in bold in Table 4: a *weak NWOM message* ($AQ^{-} = EX^{-} = 0.3$), *medium NWOM message* ($AQ^{-} = EX^{-} = 0.6$), and *strong NWOM message* ($AQ^{-} = EX^{-} = 1.0$).

2.4.3 Competitive Setting: Influence of Message Strength and Delay

In the competitive setting, a PWOM message is launched as a countermeasure by the firm to restrict the prevalence of the NWOM message in the OSN. Several parameters of the PWOM message can be influenced by the firm. These include its argument quality AQ^{+}, expressiveness EX^{+}, and the response delay between the first occurrence of the NWOM message T^{-} and the launch time of the PWOM message T^{+}. The response delay represents the reaction time of the firm and is given by $D = T^{+} - T^{-}$ in time steps (t). For investigating the influence of the PWOM message strength and the response delay on the NWOM spread, we conducted a sensitivity analysis for these parameters. The argument quality and expressiveness of the PWOM message were changed in equal steps of 0.1: $AQ^{+} = EX^{+} \in \{0.1, 0.2, \dots, 1.0\}$. In order to reduce the computing time, we doubled the values of the response delay: $D \in \{0, 1, 2, 4, 8, 16, 32\}$. The resulting NWOM spreads for the value combinations are depicted in Figure 6.

If the NWOM message is weak as in the cases of Figure 6a/b, the reaction time hardly affects the effectiveness of the countermeasure because a reaction time of $D = 32t$ results in almost the same NWOM spread that is also reached by a non-delayed countermeasure with $D = 0t$. The PWOM message strength, by contrast, plays a more important role. As the graphs show, the reached level of the diffusion is lowered with increasing PWOM message strength. However, PWOM can only restrict NWOM if the informational value of the PWOM message exceeds a certain value. For instance, in the individualistic market case shown in Figure 6a, AQ^{+} and EX^{+} need to be greater than 0.6 and therefore more than twice as strong as the NWOM message's dimensions to achieve a considerable reduction of the

NWOM spread. In this context, the remaining graphs in Figure 6 indicate that the strength of the NWOM message moderates the impact of the PWOM message. The stronger the NWOM message is, the higher is the critical value that needs to be surpassed by the PWOM message in order to exert an influence on the NWOM spread. In other words, with increasing NWOM message strength, most of the PWOM messages are rendered ineffective except for the very persuasive ones.

The results in Figure 6 further disclose that the NWOM message strength also has a moderating effect on the reaction time. As Figure 6c/d suggest for a medium NWOM message, the effectiveness of most of the tested PWOM messages will decrease and potentially get nullified if the firm's response takes too long. The impact on the NWOM spread is reduced in a degressive way where particularly short delays significantly decrease the countermeasure's performance. The stronger the PWOM message is, the smaller are the effectiveness losses caused by longer reaction times, which particularly applies to the individualistic market case in Figure 6c. Also note that short reaction times can hardly outweigh the gains of a higher informational value used in the counter-message. If the strength of the PWOM message is increased, with a few exceptions, it restricts the NWOM spread more effectively than weaker counter-messages that are released earlier. But if the firm is confronted with a very convincing NWOM message as in the cases depicted in Figure 6e/f, even the strongest PWOM message can lose all of its reduction effects due to a delayed response. Particularly in the collectivistic market case in Figure 6f, the firm might be better off with a quick response instead of aiming for a maximum PWOM message strength that could cause a delay in the reaction time.

In general, these observations hold both in the individualistic and collectivistic market. The main difference is that in the collectivistic market the NWOM spread is comparatively lower, which also applies to the countermeasure effectiveness of the PWOM message. For instance, as Figure 6e/f reveal, PWOM messages that are as strong as the countered NWOM message (e.g. $AQ^{+} = EX^{+} = AQ^{-} = EX^{-} = 1.0$) reduce the NWOM spread in the collectivistic market less than in the individualistic market, both in absolute and relative terms. These results indicate that countering NWOM is a more challenging task in collectivistic markets.

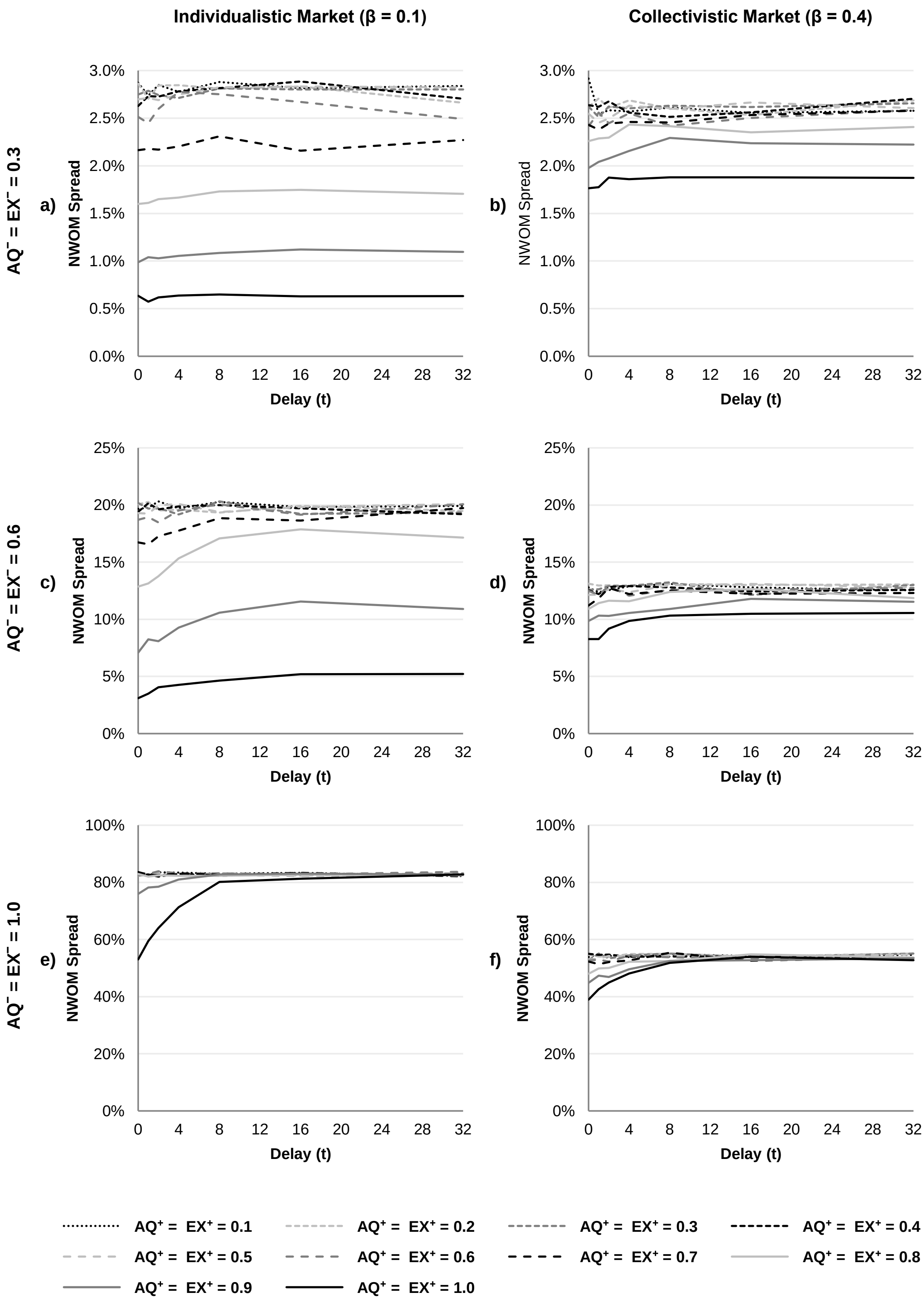

Figure 6. NWOM spread for different reaction times and one PWOM seed.

2.4.4 Competitive Setting: Influence of Seed Quantity

Besides the characteristics of the PWOM message, another countermeasure strategy parameter that can be influenced by the firm concerns the number of seeds who initially disseminate the PWOM message in the OSN. As the experiments of the previous subsection revealed, PWOM messages should be, as far as possible, of higher informational value than the NWOM messages that are being countered. For testing the influence of the seed quantity, we therefore defined the following PWOM message cases for the previously tested three NWOM message cases:

(1) Weak NWOM message ($AQ^- = EX^- = 0.3$): $AQ^+ = EX^+ \in \{0.3, 0.7, 1.0\}$
(2) Medium NWOM message ($AQ^- = EX^- = 0.6$): $AQ^+ = EX^+ \in \{0.6, 0.8, 1.0\}$
(3) Strong NWOM message ($AQ^- = EX^- = 1.0$): $AQ^+ = EX^+ \in \{0.8, 0.9, 1.0\}$

The results are depicted in Figure 7, Figure 8, and Figure 9 respectively. The numerical data for these experiments with the mean and standard deviation is provided in Table 5, Table 6, and Table 7 respectively.

Figure 7a/b show for a weak NWOM message that an increased number of seeds will not yield better results in restricting the NWOM spread if the PWOM message is likewise weak. The weak PWOM message hardly shows any reducing effects in both markets. If, however, the PWOM message is stronger than the NWOM message, the usage of multiple seeds leads to an additional decrease in the NWOM spread as revealed by Figure 7c/d/e/f and Figure 8c/d/e/f. In these cases, a greater response delay does not reduce the relative effectiveness gains between different seed quantities, i.e. activating more seeds will also result in a higher reduction of the NWOM spread irrespective of the reaction time. This does not hold in the strong NWOM message cases depicted in Figure 9, where the gains of activating more seeds decline and almost completely vanish with increasing reaction time.

The results further show that the deployment of multiple seeds seems to have a greater impact in individualistic markets if the NWOM message is weak or medium. This is rather surprising since one would expect that multiple seeds are more powerful in collectivistic markets due to the greater influence of social pressure. A reason for their lower performance is that seeds were randomly chosen in our experiments. Because of this, the likelihood that multiple seeds were activated in the same neighbourhood or cluster in the OSN was quite low, which prevented the seeds from fully unfolding their potential by exerting high levels of social pressure. In individualistic markets, where OSN members pay more attention to the content of a message, the activation of multiple seeds serves a different purpose. Instead of exerting social pressure, which is less valued in these markets, multiple seeds facilitate the diffusion of the strong PWOM message by making it available to more people. Because the diffusion in individualistic markets is not slowed down and restricted by collectivistic behaviour, multiple starting points of the PWOM message lead to an increased spread in the OSN. However, the doubling of the seed quantity does not always produce the same effect. For instance, increasing the number of seeds from eight to 16 brings only little gains in Figure 7e and Figure 8e, where a saturation seems to be reached. This is attributable to the high discrepancy between the PWOM and NWOM message strength in these cases, which mitigates the negativity bias and allows the PWOM message to effectively alleviate the impact of NWOM already with a limited number of seeds.

As depicted in Figure 9, the situation changes when a strong NWOM message is to be countered, which seems to lessen the effectiveness of using multiple seeds in the individualistic market more than in the collectivistic market. Because of the high persuasiveness of the NWOM message and the negativity bias, the NWOM message dominates the PWOM message in the OSN. If the strong NWOM message reaches areas and clusters in the OSN that are already positively influenced by the PWOM message, it is still able to influence and convince them of the opposite due to the higher valuation of the message content. This only applies to a limited extent to the collectivistic market, where the PWOM message can lead to the creation of convinced groups of OSN members that show a certain robustness against NWOM messages. Peer pressure saves these groups from believing in the opposing message when it reaches them and thereby serves as a kind of "immunity" against later arriving NWOM messages.

These results demonstrate that multiple seeds can yield an advantage in reducing the NWOM spread only if the PWOM message provides a sufficiently high informational value. If the NWOM message is weak or medium, the reaction time plays a minor role in the effectiveness of the additionally activated seeds. Hence, the firm can confidently abstain from hurried decisions and responses in these cases. However, if the NWOM message is strong, the firm is compelled to react as quickly as possible in order to avoid effectiveness losses that could render the activation of multiple seeds worthless.

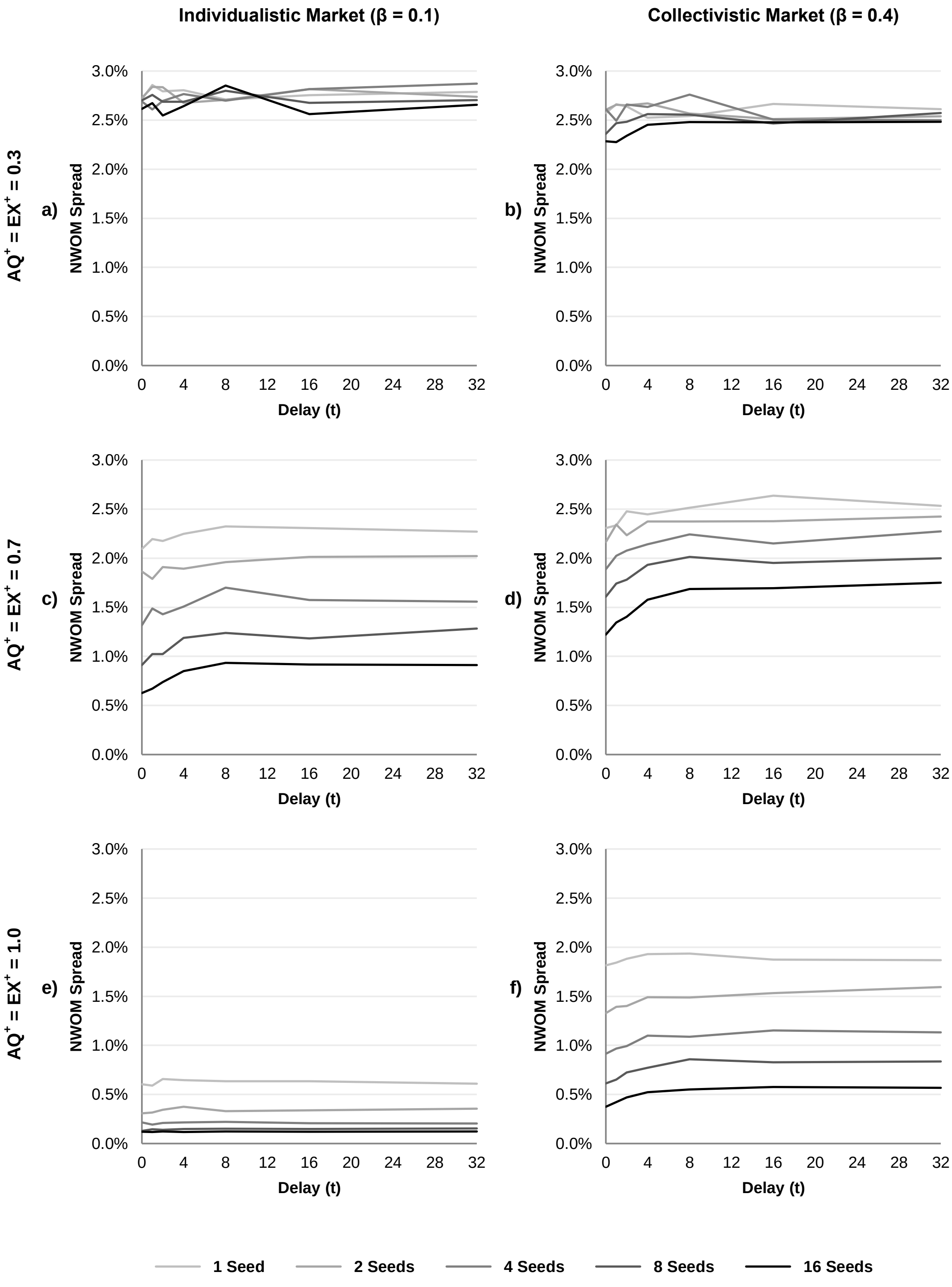

Figure 7. NWOM spread for $AQ^{-}=EX^{-}=0.3$ and varied quantity of PWOM seeds.

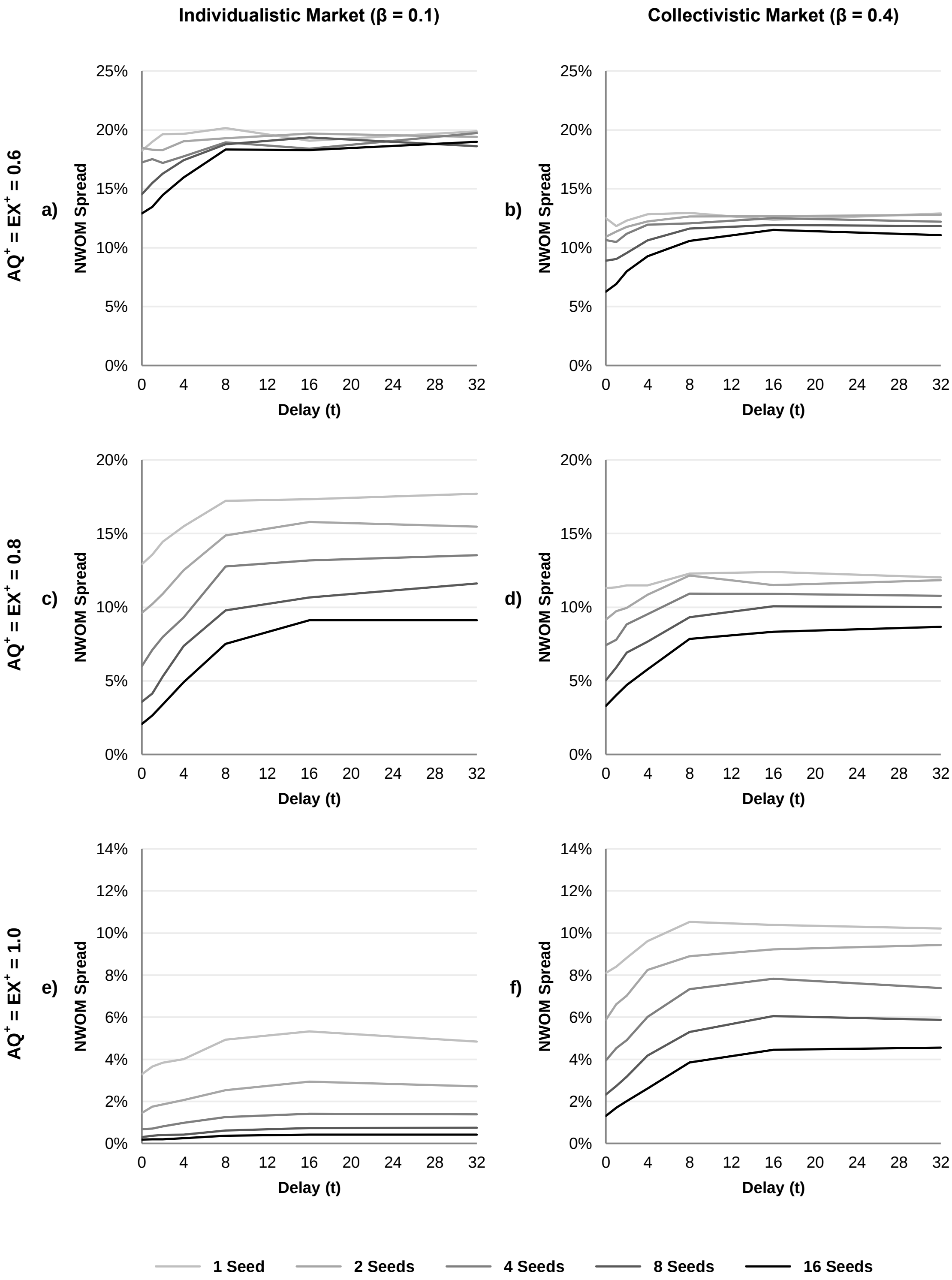

Figure 8. NWOM spread for AQ^{-}=EX^{-}=0.6 and varied quantity of PWOM seeds.

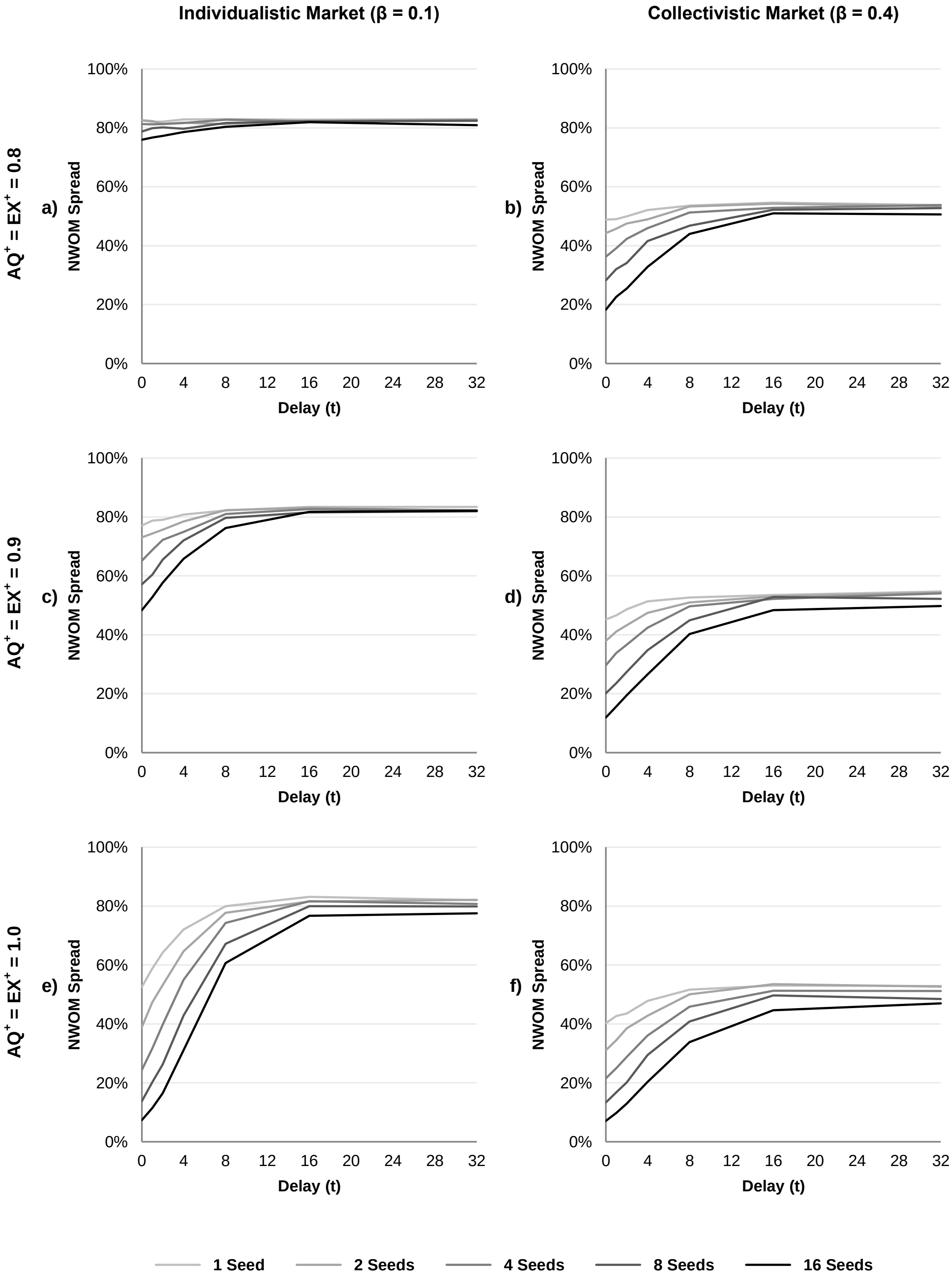

Figure 9. NWOM spread for AQ^{-}=EX^{-}=1.0 and varied quantity of PWOM seeds.

Table 5. Mean (standard deviation) of the NWOM spread for $AQ^{-}=EX^{-}=0.3$.

		NWOM spread after the dissemination of a PWOM message														
		$AQ^{+}=EX^{+}=0.3$					$AQ^{+}=EX^{+}=0.7$					$AQ^{+}=EX^{+}=1.0$				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	2.712% (1.463%)	2.727% (1.520%)	2.691% (1.492%)	2.701% (1.557%)	2.614% (1.423%)	2.096% (1.198%)	1.865% (1.133%)	1.317% (0.812%)	0.912% (0.597%)	**0.627% (0.413%)**	0.603% (0.570%)	0.307% (0.299%)	0.214% (0.203%)	0.129% (0.077%)	0.121% (0.079%)
	1	2.858% (1.512%)	2.837% (1.608%)	2.608% (1.399%)	2.757% (1.493%)	2.672% (1.530%)	2.195% (1.263%)	1.789% (1.089%)	1.489% (0.921%)	1.024% (0.654%)	0.672% (0.456%)	0.590% (0.550%)	0.316% (0.301%)	0.194% (0.164%)	0.144% (0.102%)	0.118% (0.059%)
	2	2.794% (1.461%)	2.836% (1.540%)	2.695% (1.536%)	2.686% (1.477%)	2.548% (1.421%)	2.177% (1.261%)	1.910% (1.098%)	1.430% (0.877%)	1.024% (0.603%)	0.739% (0.493%)	0.659% (0.602%)	0.345% (0.292%)	0.211% (0.193%)	0.140% (0.097%)	0.123% (0.079%)
	4	2.806% (1.490%)	2.677% (1.474%)	2.765% (1.508%)	2.687% (1.507%)	2.642% (1.377%)	2.247% (1.249%)	1.892% (1.128%)	1.508% (0.943%)	1.188% (0.722%)	0.849% (0.540%)	0.647% (0.584%)	0.374% (0.374%)	0.216% (0.192%)	0.149% (0.105%)	0.118% (0.067%)
	8	2.710% (1.488%)	2.707% (1.405%)	2.699% (1.433%)	2.798% (1.508%)	2.852% (1.654%)	2.323% (1.379%)	1.959% (1.173%)	1.699% (1.038%)	1.240% (0.769%)	0.934% (0.603%)	0.634% (0.544%)	0.329% (0.291%)	0.220% (0.193%)	0.151% (0.105%)	0.122% (0.063%)
	16	2.753% (1.585%)	2.816% (1.665%)	2.816% (1.596%)	2.677% (1.494%)	2.560% (1.335%)	2.307% (1.334%)	2.013% (1.167%)	1.574% (1.031%)	1.183% (0.769%)	0.917% (0.619%)	0.635% (0.637%)	0.339% (0.308%)	0.206% (0.187%)	0.148% (0.104%)	0.119% (0.062%)
	32	2.787% (1.539%)	2.736% (1.642%)	2.871% (1.555%)	2.703% (1.449%)	2.656% (1.479%)	2.270% (1.319%)	2.021% (1.170%)	1.557% (0.921%)	1.285% (0.862%)	0.912% (0.543%)	**0.610% (0.534%)**	0.355% (0.354%)	0.204% (0.165%)	0.155% (0.122%)	0.123% (0.078%)
Collectivistic Market (β=0.4)	**0**	2.573% (1.509%)	2.606% (1.411%)	2.613% (1.475%)	2.360% (1.324%)	2.286% (1.248%)	2.306% (1.318%)	2.163% (1.152%)	**1.886% (1.007%)**	1.607% (0.896%)	1.222% (0.698%)	1.815% (1.163%)	1.328% (0.844%)	0.915% (0.592%)	0.612% (0.487%)	0.376% (0.298%)
	1	2.661% (1.420%)	2.656% (1.425%)	2.495% (1.367%)	2.468% (1.279%)	2.275% (1.263%)	2.335% (1.262%)	2.344% (1.262%)	2.024% (1.144%)	1.743% (1.026%)	1.346% (0.806%)	1.842% (1.106%)	1.392% (0.841%)	0.969% (0.636%)	0.652% (0.477%)	0.423% (0.359%)
	2	2.639% (1.497%)	2.652% (1.461%)	2.658% (1.376%)	2.482% (1.376%)	2.340% (1.333%)	2.478% (1.348%)	2.235% (1.243%)	2.079% (1.128%)	1.780% (1.012%)	1.404% (0.718%)	1.882% (1.074%)	1.400% (0.845%)	0.992% (0.648%)	0.724% (0.528%)	0.471% (0.388%)
	4	2.524% (1.410%)	2.671% (1.472%)	2.635% (1.477%)	2.562% (1.361%)	2.453% (1.285%)	2.448% (1.221%)	2.375% (1.293%)	2.141% (1.165%)	**1.933% (1.058%)**	1.577% (0.853%)	1.931% (1.115%)	1.490% (0.909%)	1.098% (0.696%)	0.772% (0.551%)	0.523% (0.412%)
	8	2.542% (1.435%)	2.566% (1.440%)	2.760% (1.534%)	2.557% (1.372%)	2.480% (1.405%)	2.515% (1.363%)	2.374% (1.371%)	2.242% (1.256%)	2.014% (1.175%)	1.685% (1.001%)	1.935% (1.143%)	1.487% (0.952%)	1.087% (0.728%)	0.858% (0.615%)	0.552% (0.410%)
	16	2.664% (1.525%)	2.512% (1.436%)	2.505% (1.405%)	2.467% (1.360%)	2.478% (1.504%)	2.637% (1.399%)	2.377% (1.323%)	2.150% (1.219%)	1.951% (1.113%)	1.693% (1.004%)	1.875% (1.100%)	1.533% (1.026%)	1.151% (0.736%)	0.827% (0.541%)	0.576% (0.481%)
	32	2.611% (1.460%)	2.539% (1.418%)	2.501% (1.431%)	2.573% (1.422%)	2.483% (1.464%)	2.534% (1.418%)	2.423% (1.363%)	2.273% (1.234%)	2.000% (1.154%)	1.749% (0.984%)	**1.867% (1.068%)**	1.595% (0.993%)	1.134% (0.796%)	0.837% (0.574%)	0.567% (0.431%)

Table 6. Mean (standard deviation) of the NWOM spread for $AQ^{-}=EX^{-}=0.6$.

		NWOM spread after the dissemination of a PWOM message														
		$AQ^{+}=EX^{+}=0.6$					**$AQ^{+}=EX^{+}=0.8$**					**$AQ^{+}=EX^{+}=1.0$**				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	18.249% (8.336%)	18.481% (8.433%)	17.233% (7.777%)	14.534% (7.669%)	12.920% (6.503%)	12.928% (6.904%)	9.617% (5.332%)	**6.007%** **(3.724%)**	3.572% (2.048%)	2.062% (1.274%)	3.294% (2.705%)	1.450% (1.316%)	0.675% (0.595%)	0.301% (0.291%)	0.178% (0.186%)
	1	18.990% (8.897%)	18.305% (8.461%)	17.529% (8.483%)	15.498% (7.500%)	13.477% (7.192%)	13.563% (7.181%)	10.217% (5.605%)	7.099% (3.760%)	4.144% (2.396%)	2.645% (1.450%)	3.653% (3.050%)	1.753% (1.621%)	0.709% (0.624%)	0.372% (0.383%)	0.197% (0.164%)
	2	19.638% (9.037%)	18.282% (8.636%)	17.203% (8.227%)	16.297% (7.540%)	14.464% (7.511%)	14.450% (7.496%)	10.905% (5.575%)	7.983% (4.091%)	**5.304%** **(2.968%)**	3.394% (1.870%)	3.836% (2.989%)	1.858% (1.473%)	0.806% (0.663%)	0.402% (0.358%)	0.197% (0.168%)
	4	19.673% (9.199%)	19.037% (9.348%)	17.768% (8.436%)	17.432% (8.517%)	15.952% (7.768%)	15.489% (7.617%)	12.514% (6.697%)	9.309% (4.828%)	7.356% (3.752%)	**4.913%** **(2.580%)**	4.002% (3.305%)	2.067% (1.541%)	0.980% (0.761%)	0.425% (0.368%)	0.255% (0.213%)
	8	20.154% (9.588%)	19.289% (9.113%)	18.951% (9.116%)	18.776% (9.185%)	18.342% (8.617%)	17.230% (8.622%)	14.880% (7.578%)	12.769% (7.041%)	9.785% (5.165%)	7.508% (3.860%)	4.939% (3.764%)	2.526% (1.724%)	1.254% (0.886%)	0.614% (0.460%)	0.360% (0.277%)
	16	19.091% (8.978%)	19.694% (8.869%)	18.407% (8.511%)	19.372% (9.398%)	18.282% (9.088%)	17.332% (8.670%)	15.787% (7.822%)	13.177% (6.741%)	10.671% (5.840%)	9.122% (5.113%)	5.320% (4.307%)	2.936% (2.095%)	1.414% (1.048%)	0.731% (0.560%)	0.419% (0.307%)
	32	19.877% (8.849%)	19.415% (9.239%)	19.726% (8.680%)	18.626% (8.724%)	18.998% (9.250%)	17.701% (8.570%)	15.466% (8.056%)	13.538% (7.018%)	11.619% (6.412%)	9.115% (4.783%)	**4.842%** **(3.090%)**	2.717% (1.997%)	1.380% (0.994%)	0.742% (0.552%)	0.421% (0.343%)
Collectivistic Market (β=0.4)	**0**	12.509% (6.265%)	10.925% (5.673%)	10.643% (5.296%)	8.898% (4.635%)	6.258% (3.391%)	**11.303%** **(5.741%)**	9.161% (4.651%)	7.422% (3.889%)	5.037% (2.792%)	3.293% (1.665%)	8.097% (4.499%)	5.872% (3.516%)	3.940% (2.427%)	2.326% (1.397%)	1.302% (0.923%)
	1	11.827% (6.069%)	11.374% (6.144%)	10.496% (5.204%)	9.034% (4.579%)	6.921% (3.354%)	11.353% (5.451%)	**9.727%** **(4.999%)**	7.789% (4.197%)	5.915% (3.212%)	4.030% (2.216%)	8.408% (4.509%)	6.621% (3.627%)	4.528% (2.556%)	2.725% (1.573%)	1.698% (1.031%)
	2	12.302% (5.917%)	11.776% (5.999%)	11.188% (5.858%)	9.545% (5.028%)	7.983% (4.295%)	11.475% (5.798%)	9.948% (4.971%)	8.832% (4.567%)	6.912% (3.699%)	4.721% (2.499%)	8.825% (4.438%)	7.024% (3.930%)	4.911% (2.637%)	3.174% (1.798%)	2.009% (1.180%)
	4	12.847% (6.373%)	12.224% (6.124%)	11.944% (6.181%)	10.627% (5.018%)	9.284% (4.838%)	11.475% (6.113%)	**10.841%** **(5.507%)**	**9.534%** **(5.185%)**	7.663% (4.047%)	5.779% (3.201%)	9.613% (5.122%)	8.246% (4.342%)	6.014% (3.343%)	4.174% (2.371%)	2.604% (1.622%)
	8	12.963% (6.102%)	12.649% (6.478%)	12.076% (5.942%)	11.627% (5.994%)	10.577% (5.378%)	12.281% (6.289%)	12.162% (5.911%)	**10.934%** **(5.685%)**	9.326% (4.928%)	7.852% (4.125%)	10.528% (5.521%)	8.902% (4.848%)	7.328% (4.140%)	5.301% (3.086%)	3.852% (2.193%)
	16	12.379% (6.198%)	12.676% (6.229%)	12.518% (6.021%)	11.938% (6.613%)	11.523% (5.681%)	12.403% (6.117%)	11.511% (5.995%)	10.914% (5.855%)	10.062% (5.617%)	8.335% (4.725%)	10.390% (5.711%)	9.231% (5.146%)	7.826% (4.225%)	6.059% (3.507%)	4.447% (2.642%)
	32	12.902% (6.320%)	12.787% (6.141%)	12.211% (6.294%)	11.833% (6.191%)	11.074% (5.663%)	12.018% (5.781%)	11.842% (6.116%)	10.780% (5.682%)	10.018% (5.384%)	8.661% (4.534%)	**10.212%** **(5.812%)**	**9.429%** **(5.188%)**	7.393% (4.341%)	5.874% (3.384%)	4.552% (2.691%)

Table 7. Mean (standard deviation) of the NWOM spread for $AQ^{-}=EX^{-}=1.0$.

		NWOM spread after the dissemination of a PWOM message														
		$AQ^{+}=EX^{+}=0.8$					**$AQ^{+}=EX^{+}=0.9$**					**$AQ^{+}=EX^{+}=1.0$**				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	82.475% (10.380%)	**82.611% (9.202%)**	81.257% (9.936%)	78.803% (11.986%)	**76.008% (12.435%)**	77.093% (11.423%)	**73.031% (11.906%)**	65.187% (13.607%)	57.096% (13.672%)	48.395% (14.087%)	52.544% (16.416%)	38.973% (13.917%)	24.452% (9.977%)	13.811% (6.715%)	7.333% (3.555%)
	1	82.009% (9.995%)	82.291% (9.637%)	81.143% (11.123%)	79.861% (10.516%)	76.684% (12.212%)	78.780% (10.792%)	74.425% (12.575%)	68.805% (13.370%)	60.357% (14.441%)	52.714% (13.788%)	58.837% (16.388%)	47.354% (15.191%)	31.649% (11.814%)	20.269% (8.808%)	11.485% (5.361%)
	2	82.093% (11.664%)	81.393% (11.091%)	81.321% (10.755%)	80.157% (10.194%)	77.286% (11.447%)	79.022% (11.159%)	75.708% (10.978%)	72.231% (12.522%)	65.519% (13.384%)	57.673% (13.882%)	64.257% (14.876%)	53.201% (15.400%)	39.768% (13.985%)	26.270% (10.233%)	16.473% (7.025%)
	4	82.905% (9.766%)	81.712% (10.588%)	81.667% (10.552%)	79.702% (11.082%)	78.592% (10.623%)	80.840% (11.111%)	78.486% (12.112%)	74.979% (12.683%)	72.072% (11.927%)	65.770% (13.822%)	**72.092% (13.869%)**	64.683% (14.832%)	54.989% (14.942%)	42.836% (14.394%)	31.145% (11.338%)
	8	82.952% (9.847%)	81.293% (11.811%)	82.812% (9.782%)	81.652% (10.606%)	80.309% (10.477%)	82.179% (10.727%)	**82.340% (10.390%)**	80.978% (10.945%)	79.664% (10.819%)	76.257% (12.016%)	79.954% (11.463%)	77.697% (12.546%)	74.301% (13.766%)	67.205% (15.909%)	60.661% (15.772%)
	16	82.810% (9.747%)	82.512% (11.124%)	82.213% (10.678%)	82.245% (10.522%)	81.969% (10.099%)	83.416% (9.279%)	83.114% (9.572%)	82.636% (9.787%)	81.557% (10.505%)	81.742% (9.640%)	83.107% (10.302%)	81.529% (10.629%)	81.651% (10.073%)	79.940% (11.489%)	76.667% (12.027%)
	32	82.960% (9.718%)	82.653% (10.258%)	82.603% (9.978%)	82.360% (9.472%)	80.894% (10.011%)	83.376% (9.110%)	82.158% (10.200%)	82.313% (9.721%)	81.917% (10.594%)	82.108% (9.573%)	**81.985% (10.411%)**	82.142% (9.942%)	80.763% (11.088%)	79.892% (10.325%)	77.542% (11.464%)
Collectivistic Market (β=0.4)	**0**	48.823% (13.652%)	**44.257% (13.942%)**	36.306% (13.526%)	28.225% (10.975%)	18.242% (8.341%)	**45.190% (14.313%)**	37.926% (13.806%)	29.611% (12.357%)	20.120% (8.690%)	11.919% (5.950%)	40.293% (13.478%)	31.042% (12.154%)	21.519% (9.312%)	13.337% (6.410%)	7.094% (4.287%)
	1	49.023% (15.068%)	45.769% (14.174%)	39.161% (13.744%)	32.106% (12.422%)	22.686% (9.022%)	46.587% (15.069%)	41.153% (13.815%)	33.815% (12.319%)	23.628% (9.648%)	15.670% (6.670%)	42.701% (13.793%)	34.498% (12.597%)	25.015% (11.105%)	16.824% (7.273%)	9.817% (4.498%)
	2	49.953% (14.737%)	47.528% (13.805%)	42.349% (13.120%)	34.124% (12.404%)	25.494% (10.241%)	48.665% (14.590%)	43.242% (13.982%)	36.621% (12.720%)	27.381% (10.753%)	19.505% (8.124%)	**43.543% (14.616%)**	38.472% (13.551%)	28.785% (11.867%)	20.178% (8.594%)	12.929% (5.844%)
	4	52.069% (14.351%)	48.957% (14.900%)	46.000% (13.790%)	41.542% (13.761%)	32.823% (12.647%)	51.376% (15.304%)	47.404% (14.662%)	42.371% (13.808%)	34.767% (12.796%)	26.615% (11.233%)	47.801% (14.972%)	42.825% (14.340%)	36.108% (13.334%)	29.475% (12.316%)	20.370% (9.022%)
	8	**53.631% (14.106%)**	53.361% (15.074%)	51.271% (14.553%)	46.827% (15.708%)	43.976% (14.919%)	**52.624% (14.486%)**	51.002% (15.141%)	49.706% (14.837%)	44.955% (14.653%)	40.270% (14.547%)	51.668% (14.717%)	50.057% (14.772%)	45.903% (15.153%)	40.859% (13.917%)	33.874% (13.078%)
	16	54.657% (14.546%)	54.280% (14.747%)	52.868% (15.201%)	52.240% (14.677%)	51.008% (14.915%)	53.522% (14.848%)	53.024% (14.971%)	52.220% (15.165%)	52.832% (14.068%)	48.335% (15.067%)	52.992% (14.903%)	53.532% (14.698%)	51.229% (15.087%)	49.652% (16.025%)	44.690% (15.148%)
	32	53.753% (14.565%)	53.418% (15.011%)	53.765% (14.543%)	52.801% (14.973%)	50.649% (15.448%)	54.734% (14.115%)	54.330% (15.444%)	54.087% (14.616%)	52.183% (15.579%)	49.761% (14.898%)	**52.827% (14.972%)**	52.634% (14.923%)	51.196% (15.798%)	48.428% (15.887%)	47.023% (14.886%)

The numerical data listed in Table 5, Table 6, and Table 7 reveals another interesting finding: a strong PWOM message that is launched with delay by one seed usually outperforms weaker PWOM messages that are disseminated with no or short delay in the OSN. To some extent, this holds even if the weaker PWOM messages are launched by multiple seeds. The following paragraphs will elaborate on this effect in more detail by referencing numbers that are highlighted in bold in the aforementioned tables.

In the case of a weak NWOM message (Table 5), this effect can be observed for the individualistic market where the best PWOM message (i.e. $AQ^{+} = EX^{+} = 1.0$) launched by one seed and a reaction time of $D = 32t$ restricts the NWOM spread more than the second-best message (i.e. $AQ^{+} = EX^{+} = 0.7$) launched immediately by 16 seeds (0.610% versus 0.627%). In the collectivistic market, the strong PWOM message launched by one seed with a delay of $D = 32t$ still outperforms the medium message launched immediately by four seeds (1.867% versus 1.886%). The delayed strong PWOM message also performs better than the medium PWOM message launched by eight seeds, but only if it is disseminated with a delay equal to or greater than $D = 4t$ (1.933%).

Similar observations can be made in the case of a medium NWOM message (Table 6). In the individualistic market, the best PWOM message with $D = 32t$ and one seed outperforms the second-best message launched immediately by four seeds (4.842% versus 6.007%), after two time steps by eight seeds (5.304%), and after four time steps by 16 seeds (4.913%). In the collectivistic market, the strong PWOM message outperforms the second-best message launched immediately by one seed (10.212% versus 11.303%), after four time steps by two seeds (10.841%), and after eight time steps by four seeds (10.934%). If two seeds are used for the delayed best message, it yields better results than the second-best message launched after one time step by two seeds (9.429% versus 9.727%) and after four time steps by four seeds (9.534%).

Even for the strong NWOM message (Table 7) this effect can be observed. Note that the second- and third-best PWOM messages are only slightly weaker than the best PWOM message. If the strongest PWOM message is launched with $D = 32t$ in the individualistic market, it outperforms the second-best message launched by two seeds after eight time steps (81.985% versus 82.340%) and the third-best message launched immediately by two seeds (82.611%). If the best message is launched with a short delay of $D = 4t$, it achieves better results than the second-best message launched immediately by two seeds (72.092% versus 73.031%) and strongly outperforms the third-best message launched immediately by 16 seeds (76.008%). In the collectivistic market, the best PWOM message launched with $D = 32t$ is better than the third-best message launched by one seed after eight time steps (52.827% versus 53.631%) and achieves almost the same result as the second-best message launched after eight time steps (52.624%). If the best message is launched with a delay of $D = 2t$, it outperforms the second-best message launched immediately by one seed (43.543% versus 45.190%) and the third-best message launched immediately by two seeds (44.257%).

In order to test the observed effect for statistical significance, the performance of the strong delayed PWOM message (i.e. $AQ^{+} = EX^{+} = 1.0$ and $D = 32t$) in comparison to the second- and third-best PWOM message was analysed by conducting a two-sample heteroscedastic t-test (Welch's t-test). A two-sample t-test was used because the populations to be compared were randomly generated and diverged in individual characteristics. The heteroscedastic property stems from the fact that different simulation scenarios with different reaction parameters can result in unequal variances regarding the measured value, which would prevent the application of the Student's t-test that assumes equal variances (Hoag and Kuo 2017, p. 42). Simulation studies on the robustness and reliability of Welch's t-test have revealed that it performs equally well as the Student's t-test if variances are equal and outperforms it if they are unequal (Delacre et al. 2017, p. 99; Rasch et al. 2011, pp. 230-231). Another parametric assumption that is required for the application of a two-sample t-test is the normal distribution of the data in the analysed samples (Mellenbergh 2019, p. 188; Verma 2013, p. 181). However, simulation studies further suggest that for sufficiently large sample sizes, two-sample t-tests are robust against the violation of this assumption (Hoag and Kuo 2017, p. 55; Lumley et al. 2002, p. 166; Poncet et al. 2016, p. 66; Rasch et al. 2011, pp. 230-231). According to the results of Rasch et al. (2011, p. 222) and Poncet et al. (2016, p. 66), who could prove this for sample sizes between 10 and 100 as well as 10 and 500 respectively, this condition is fulfilled for our experiments due to the numerical data being based on 500 simulation repetitions. The conducted t-tests can therefore be expected to be robust against any deviations from normality.

The two-sample heteroscedastic t-test is applied to all the following significance tests of this chapter unless otherwise specified. The results of the significance tests for the weak, medium, and strong NWOM message are presented in Table 8, Table 9, and Table 10 respectively. The cases where the strong delayed PWOM message does not perform better than the compared message strategy are shaded grey. The results suggest that the stronger the NWOM message is, the more the strong delayed PWOM message forfeits its advantage over the other strategies. As discussed before, this is because the strong NWOM message requires a quick reaction. If the firm waits too long, even a strong PWOM message can face difficulties in restricting the NWOM spread in the OSN.

In sum, the results of this subsection indicate that using more seeds can hardly compensate for a lack of persuasiveness in the firm's response. If a sufficiently strong counter-message is used, an increased seed quantity can make up for an increased response delay, but usually only if the NWOM message is weak or medium. A highly convincing PWOM message, by contrast, can in most of the tested cases compensate for both a response delay and a reduced number of seeds.

Table 8. Statistical analysis of the strong delayed PWOM message's performance in regard to the reduction of the NWOM spread for $AQ^{-}=EX^{-}=0.3$.

		Changes in the NWOM spread (the less, the better) evoked by the strong delayed PWOM message launched by one seed									
		In comparison to the second-best PWOM message					**In comparison to the third-best PWOM message**				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	-1.486%***	-1.256%***	-0.707%***	-0.303%***	-0.017%^{ns}	-2.102%***	-2.118%***	-2.081%***	-2.091%***	-2.004%***
	1	-1.586%***	-1.179%***	-0.879%***	-0.414%***	-0.062%*	-2.249%***	-2.227%***	-1.999%***	-2.148%***	-2.062%***
	2	-1.567%***	-1.300%***	-0.821%***	-0.415%***	-0.130%***	-2.184%***	-2.227%***	-2.086%***	-2.077%***	-1.939%***
	4	-1.637%***	-1.283%***	-0.898%***	-0.579%***	-0.239%***	-2.196%***	-2.068%***	-2.156%***	-2.078%***	-2.032%***
	8	-1.714%***	-1.349%***	-1.090%***	-0.630%***	-0.325%***	-2.101%***	-2.098%***	-2.089%***	-2.189%***	-2.242%***
	16	-1.697%***	-1.403%***	-0.965%***	-0.573%***	-0.307%***	-2.143%***	-2.207%***	-2.207%***	-2.067%***	-1.951%***
	32	-1.661%***	-1.411%***	-0.947%***	-0.675%***	-0.303%***	-2.177%***	-2.127%***	-2.261%***	-2.093%***	-2.047%***
Collectivistic Market (β=0.4)	**0**	-0.439%***	-0.296%***	-0.019%^{ns}	+0.261%***	+0.645%***	-0.705%***	-0.738%***	-0.746%***	-0.493%***	-0.419%***
	1	-0.468%***	-0.477%***	-0.157%*	+0.124%*	+0.522%***	-0.794%***	-0.789%***	-0.627%***	-0.601%***	-0.408%***
	2	-0.610%***	-0.368%***	-0.211%**	+0.087%^{ns}	+0.464%***	-0.772%***	-0.785%***	-0.791%***	-0.615%***	-0.473%***
	4	-0.581%***	-0.508%***	-0.274%***	-0.066%^{ns}	+0.290%***	-0.657%***	-0.804%***	-0.768%***	-0.695%***	-0.586%***
	8	-0.648%***	-0.507%***	-0.374%***	-0.147%*	+0.182%**	-0.675%***	-0.699%***	-0.892%***	-0.690%***	-0.613%***
	16	-0.770%***	-0.509%***	-0.282%***	-0.084%^{ns}	+0.174%**	-0.797%***	-0.645%***	-0.638%***	-0.600%***	-0.610%***
	32	-0.667%***	-0.556%***	-0.406%***	-0.133%*	+0.118%*	-0.744%***	-0.672%***	-0.634%***	-0.706%***	-0.616%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 9. Statistical analysis of the strong delayed PWOM message's performance in regard to the reduction of the NWOM spread for $AQ^{-}=EX^{-}=0.6$.

		Changes in the NWOM spread (the less, the better) evoked by the strong delayed PWOM message launched by one seed									
		In comparison to the second-best PWOM message					**In comparison to the third-best PWOM message**				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	-8.086%***	-4.775%***	-1.165%***	+1.270%***	+2.780%***	-13.407%***	-13.639%***	-12.391%***	-9.692%***	-8.079%***
	1	-8.722%***	-5.375%***	-2.257%***	+0.698%***	+2.197%***	-14.148%***	-13.464%***	-12.687%***	-10.656%***	-8.635%***
	2	-9.608%***	-6.063%***	-3.142%***	-0.462%**	+1.448%***	-14.796%***	-13.440%***	-12.361%***	-11.455%***	-9.622%***
	4	-10.647%***	-7.672%***	-4.467%***	-2.514%***	-0.071%^{ns}	-14.831%***	-14.195%***	-12.926%***	-12.590%***	-11.111%***
	8	-12.388%***	-10.038%***	-7.927%***	-4.943%***	-2.666%***	-15.312%***	-14.447%***	-14.109%***	-13.934%***	-13.501%***
	16	-12.490%***	-10.946%***	-8.335%***	-5.830%***	-4.280%***	-14.249%***	-14.852%***	-13.565%***	-14.530%***	-13.440%***
	32	-12.859%***	-10.624%***	-8.697%***	-6.778%***	-4.274%***	-15.035%***	-14.573%***	-14.885%***	-13.784%***	-14.157%***
Collectivistic Market (β=0.4)	**0**	-1.091%**	+1.051%***	+2.790%***	+5.175%***	+6.919%***	-2.297%***	-0.713%*	-0.431%^{ns}	+1.314%***	+3.954%***
	1	-1.141%***	+0.485%^{ns}	+2.423%***	+4.297%***	+6.182%***	-1.615%***	-1.162%**	-0.284%^{ns}	+1.178%***	+3.291%***
	2	-1.263%***	+0.264%^{ns}	+1.380%***	+3.300%***	+5.491%***	-2.090%***	-1.564%***	-0.976%**	+0.667%*	+2.229%***
	4	-1.263%***	-0.629%*	+0.678%*	+2.549%***	+4.433%***	-2.635%***	-2.012%***	-1.732%***	-0.415%^{ns}	+0.928%**
	8	-2.069%***	-1.950%***	-0.722%*	+0.886%**	+2.360%***	-2.751%***	-2.437%***	-1.864%***	-1.415%***	-0.365%^{ns}
	16	-2.191%***	-1.299%***	-0.702%*	+0.150%^{ns}	+1.877%***	-2.167%***	-2.464%***	-2.306%***	-1.726%***	-1.311%***
	32	-1.806%***	-1.630%***	-0.568%^{ns}	+0.194%^{ns}	+1.551%***	-2.690%***	-2.575%***	-1.999%***	-1.621%***	-0.862%**

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 10. Statistical analysis of the strong delayed PWOM message's performance in regard to the reduction of the NWOM spread for $AQ^{-}=EX^{-}=1.0$.

		Changes in the NWOM spread (the less, the better) evoked by the strong delayed PWOM message launched by one seed									
		In comparison to the second-best PWOM message					**In comparison to the third-best PWOM message**				
Market (β)	**Delay (t)**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**	**1 Seed**	**2 Seeds**	**4 Seeds**	**8 Seeds**	**16 Seeds**
Individualistic Market (β=0.1)	**0**	+4.892%***	+8.955%***	+16.798%***	+24.889%***	+33.590%***	-0.490%^{ns}	-0.626%^{ns}	+0.728%^{ns}	+3.183%***	+5.977%***
	1	+3.205%***	+7.560%***	+13.180%***	+21.628%***	+29.271%***	-0.023%^{ns}	-0.306%^{ns}	+0.842%^{ns}	+2.124%***	+5.301%***
	2	+2.963%***	+6.278%***	+9.754%***	+16.466%***	+24.312%***	-0.108%^{ns}	+0.592%^{ns}	+0.664%^{ns}	+1.828%**	+4.699%***
	4	+1.146%*	+3.499%***	+7.006%***	+9.914%***	+16.215%***	-0.920%^{ns}	+0.274%^{ns}	+0.318%^{ns}	+2.284%***	+3.394%***
	8	-0.194%^{ns}	-0.355%^{ns}	+1.007%^{ns}	+2.321%***	+5.728%***	-0.967%^{ns}	+0.692%^{ns}	-0.826%^{ns}	+0.334%^{ns}	+1.676%**
	16	-1.431%*	-1.129%*	-0.651%^{ns}	+0.428%^{ns}	+0.243%^{ns}	-0.825%^{ns}	-0.527%^{ns}	-0.228%^{ns}	-0.259%^{ns}	+0.016%^{ns}
	32	-1.390%*	-0.173%^{ns}	-0.328%^{ns}	+0.068%^{ns}	-0.123%^{ns}	-0.975%^{ns}	-0.668%^{ns}	-0.617%^{ns}	-0.375%^{ns}	1.091%*
Collectivistic Market (β=0.4)	**0**	+7.637%***	+14.901%***	+23.216%***	+32.707%***	+40.908%***	+4.003%***	+8.570%***	+16.520%***	+24.602%***	+34.585%***
	1	+6.240%***	+11.673%***	+19.012%***	+29.199%***	+37.157%***	+3.804%***	+7.058%***	+13.666%***	+20.720%***	+30.141%***
	2	+4.162%***	+9.584%***	+16.206%***	+25.446%***	+33.322%***	+2.874%**	+5.299%***	+10.477%***	+18.702%***	+27.333%***
	4	+1.450%^{ns}	+5.423%***	+10.456%***	+18.060%***	+26.211%***	+0.758%^{ns}	+3.870%***	+6.827%***	+11.285%***	+20.003%***
	8	+0.203%^{ns}	+1.824%*	+3.121%***	+7.872%***	+12.557%***	-0.804%^{ns}	-0.534%^{ns}	+1.556%*	+5.999%***	+8.850%***
	16	-0.696%^{ns}	-0.198%^{ns}	+0.606%^{ns}	-0.005%^{ns}	+4.491%***	-1.830%*	-1.453%^{ns}	-0.042%^{ns}	+0.587%^{ns}	+1.818%*
	32	-1.908%*	-1.504%^{ns}	-1.261%^{ns}	+0.644%^{ns}	+3.065%***	-0.927%^{ns}	-0.591%^{ns}	-0.938%^{ns}	+0.025%^{ns}	+2.177%*

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

2.5 Purchase Model: Extensions

2.5.1 Credibility Evaluation of Messages with Range of Indifference

In the base model, OSN members who have received both the NWOM and PWOM message decide between them depending on which threshold is exceeded more in relative terms. However, it is conceivable that members will tend to remain indifferent between the two messages if both exceedances are about the same size. To consider this in the credibility evaluation of messages, we introduce a range of indifference $\vartheta_i \in [0,1]$ by which the threshold exceedance of message m needs to be greater than the exceedance of its counterpart $\overline{m}$ in order to convince member i of its truthfulness. If the difference between the exceedances is too small, i.e. less than ϑ_i, member i will stay indecisive. The higher ϑ_i is, the greater the difference needs to be in order to make member i believe in the stronger message. Hence, a higher ϑ_i resembles situations where OSN members act more cautiously and believe in neither message if they are too similar in terms of threshold exceedance. As a result, the credibility decision CD_{it}^{m} of member i regarding message m at time step t is extended to:

$$CD_{it}^{m} = \begin{cases} 1 & if \quad C_{it}^{m} \geq \phi_i^m \quad \wedge \quad r_{it}^{\overline{m}} = 0 \\ 1 & if \quad C_{it}^{m} \geq \phi_i^m \quad \wedge \quad r_{it}^{\overline{m}} = 1 \quad \wedge \quad C_{it}^{\overline{m}} < \phi_i^{\overline{m}} \\ 1 & if \quad C_{it}^{m} \geq \phi_i^m \quad \wedge \quad r_{it}^{\overline{m}} = 1 \quad \wedge \quad C_{it}^{\overline{m}} \geq \phi_i^{\overline{m}} \quad \wedge \quad \frac{(C_{it}^{m} - \phi_i^m)}{(1-\phi_i^m)} - \frac{(C_{it}^{\overline{m}} - \phi_i^{\overline{m}})}{(1-\phi_i^{\overline{m}})} > \vartheta_i \\ 0 & else \end{cases} \tag{13}$$

$$\forall i \in \{1, \dots, I : r_{it}^{m} = 1\}$$

2.5.2 Forwarding of Messages: Private Messaging with Rejuvenation

Sometimes a reaction to NWOM triggers a new wave of negative information that can increase the overall spread of NWOM in the OSN (Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92; van Noort and Willemsen 2012, p. 132). Unlike in the base model, this effect should be considered in the purchase model. For this, a rejuvenation of the messages' topicality is needed. When member i receives the opposing message $\overline{m}$, the overarching topic of both messages regarding the product or service experience will gain in topicality for him because it might provoke new discussions among OSN members. Therefore, member i will forward a message with the ageing factor of the younger message as soon as he has received it.

To incorporate this into the model, we define an individually perceived ageing factor AF_{it} for member i that determines the messages' topicality for him at time step t:

$$AF_{it} = \begin{cases} AF_t^m & if \quad r_{it}^m = 1 \quad \wedge \quad r_{it}^{\bar{m}} = 0 \\ AF_t^{\bar{m}} & if \quad r_{it}^m = 0 \quad \wedge \quad r_{it}^{\bar{m}} = 1 \\ AF_t^m & if \quad r_{it}^m = 1 \quad \wedge \quad r_{it}^{\bar{m}} = 1 \quad \wedge \quad T^m \geq T^{\bar{m}} \\ AF_t^{\bar{m}} & if \quad r_{it}^m = 1 \quad \wedge \quad r_{it}^{\bar{m}} = 1 \quad \wedge \quad T^m < T^{\bar{m}} \end{cases}, \tag{14}$$

$$\forall i \in \left\{1, \dots, I: r_{it}^m = 1 \vee r_{it}^{\bar{m}} = 1\right\}$$

Then, member i's forwarding probability FP_{ijt}^m of message m to one of his followers $j \in N_i^{followers}$ at time step t is given by:

$$FP_{ijt}^m = \left(\eta \cdot w_{ij} \cdot C_{it}^m + (1 - \eta) \cdot \left(w_{ij} + C_{it}^m - w_{ij} \cdot C_{it}^m\right)\right) \cdot AF_{it}, \tag{15}$$

$$\forall i \in \{1, \dots, I: r_{it}^m = 1\}$$

The prerequisites for forwarding the message are the same as before. An OSN member can only forward message m if he is not convinced of the opposing message $\bar{m}$ and is not allowed to forward the message twice to the same contact. As an exception and difference to the base model, we lift the restriction that message m can only be forwarded if it has been received in the preceding time step. Any message, irrespective of the valence, can trigger the forwarding of message m. Hence, the set of potential senders $V_t^{m,senders}$ of message m at time step t is changed to: $V_t^{m,senders} = \{i \in V: \sum_{j \in N_i^{following}} r_{ijt-1}^{\{+,-\}} \geq 1 \ \wedge \ CD_{it}^{\bar{m}} = 0\} \ \forall t \geq 1$.

2.5.3 Purchase Behaviour

Depending on the valence of the shared messages, communication in OSN can influence members in their purchase behaviour by either increasing or decreasing their purchase intentions (Cheung and Thadani 2012, p. 464; Kumar and Purbey 2018, p. 3593; Lee et al. 2008, p. 342; Park and Lee 2009, pp. 62-65). The prospect theory of Kahneman and Tversky (1979) states that people attach greater weight to losses in comparison to gains, which explains the general loss aversion of people. For comparing gains and losses, people place them in relation to a reference point. According to the prospect theory, the valuation curve is usually concave above and convex below the reference point (Kahneman and Tversky 1979, p. 279). Because particularly smaller losses are given a greater weighting than gains of equal amount, the valuation curve is also steeper in its convex part (Kahneman and Tversky 1979,

p. 279; Mengov 2015, p. 58). Applied to the online context, this means that an NWOM message has a greater impact on changing a member's purchase behaviour than a PWOM message of equal strength (Kim et al. 2016, p. 512). In this regard, let $PP_i^{initial} \in [0,1]$ denote member i's initial purchase probability that shall represent his reference point. He will make a purchase based on this probability if he remains unaffected by the messages. In order to comply with the prospect theory, the initial purchase probability will be exponentially increased or decreased depending on which message member i believes in. Furthermore, let $PP_i^{min} \in [0, PP_i^{initial})$ and $PP_i^{max} \in (PP_i^{initial}, 1]$ specify boundaries that the purchase probability cannot undercut and exceed respectively. The purchase probability PP_{it} of member i at time step t is then calculated as:

$$PP_{it} = \begin{cases} PP_i^{initial} + \left(PP_i^{max} - PP_i^{initial}\right) \cdot \left(1 - e^{-\lambda^+ \cdot C_{it}^+}\right) & if \quad CD_{it}^+ = 1 \\ PP_i^{initial} - \left(PP_i^{initial} - PP_i^{min}\right) \cdot \left(1 - e^{-\lambda^- \cdot C_{it}^-}\right) & if \quad CD_{it}^- = 1 \\ PP_i^{initial} & else \end{cases} \tag{16}$$

Figure 10 illustrates how the initial purchase probability is modified according to the perceived credibility of the message member i is convinced of:

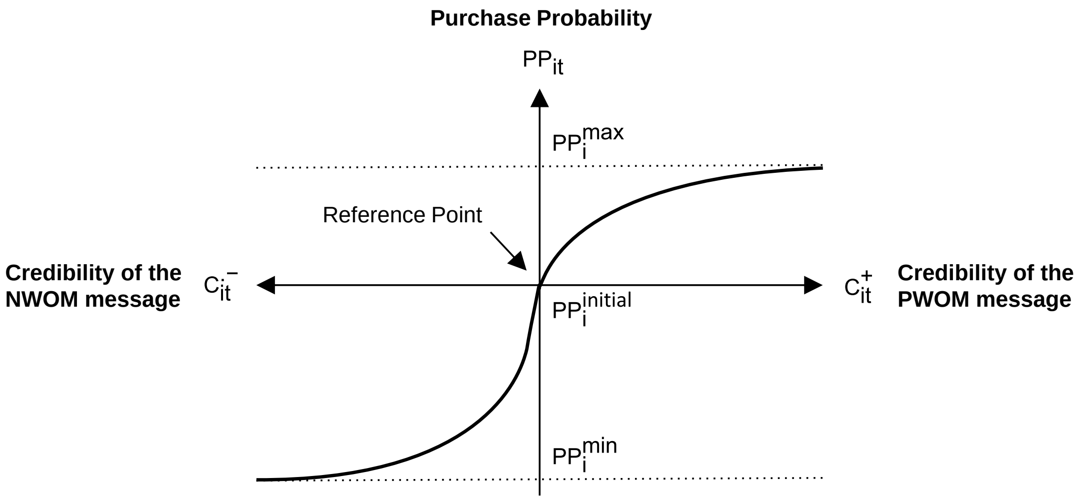

Figure 10. Prospect theory of Kahneman and Tversky (1979) applied to the purchase probability of customers.

Based on the purchase probability, the binary purchase decision PD_{it} of member i that indicates that he would make a purchase at time step t can be formulated as:

$$PD_{it} \sim \mathrm{Ber}(PP_{it}) \tag{17}$$

By summing up the purchase decisions of all members and dividing the resulting sum by the network size, the share of buyers B_t in the OSN can be determined for each time step t:

$$B_t = \frac{1}{|V|} \cdot \sum_{i \in V} PD_{it} \tag{18}$$

2.6 Purchase Model: Numerical Analysis

2.6.1 Parameterisation

Like the base model, the purchase model was also numerically analysed by simulating the diffusion of messages in artificially generated small-world networks that consisted of 1000 vertices. The parameterisation for generating the networks was adopted from the base model's parameterisation that is provided in Section 2.4.1. This also applies to the other variables of the purchase model that were already part of the base model. For all the following purchase model experiments, the half-life of both messages was set to $T_{1/2}^{m} = 10$. The newly introduced range of indifference was fixed at $\vartheta_i = 0.1$ for all OSN members. A rather small value was chosen because at higher values OSN members would tend to stay indecisive if they received both messages. As additionally carried out experiments revealed, this particularly applies to cases where both the NWOM and PWOM message have a high spread in the OSN, which renders the majority of the members to be indifferent. Choosing higher values for ϑ_i would have therefore impeded an adequate examination of the messages' impact. The purchase probability of all OSN members was set to $PP_i^{initial} = 0.1$, meaning that 10% of the OSN members would buy the product in the first place without the existence of the NWOM and PWOM message. Due to the loss aversion of people, it is conceivable that an NWOM message decreases the purchase probability more than a PWOM message can increase it (Kumar and Purbey 2018, p. 3593; Lee et al. 2008, p. 342; Park and Lee 2009, pp. 62-65). We therefore set the boundaries for limiting the purchase probability modifications to $PP_i^{min} = 0.05$ and $PP_i^{max} = 0.125$. To make the exponential NWOM modification curve steeper, we chose $\lambda^{-} = 2.5$ and $\lambda^{+} = 5.0$. The following experiments were also conducted with other values of the purchase probability, but no significant differences in the simulation outcomes could be observed. Although the values of the share of buyers were scaled by the purchase probability, the relations between the different parameter variations remained the same.

2.6.2 Non-Competitive Setting: NWOM Spread in Different Markets

In order to analyse the effectiveness of different countermeasure strategies in the context of the purchase model, at first the diffusion of NWOM messages in the OSN without the deployment of any measures needs to be determined. For this, we varied the argument quality and expressiveness of an NWOM message $AQ^{-} = EX^{-} \in \{0.1, 0.2, \ldots, 1.0\}$ for testing its diffusion in different markets $\beta \in \{0.0, 0.1, \ldots, 1.0\}$. Figure 11 depicts the final values of the NWOM spread and share of buyers for these constellations:

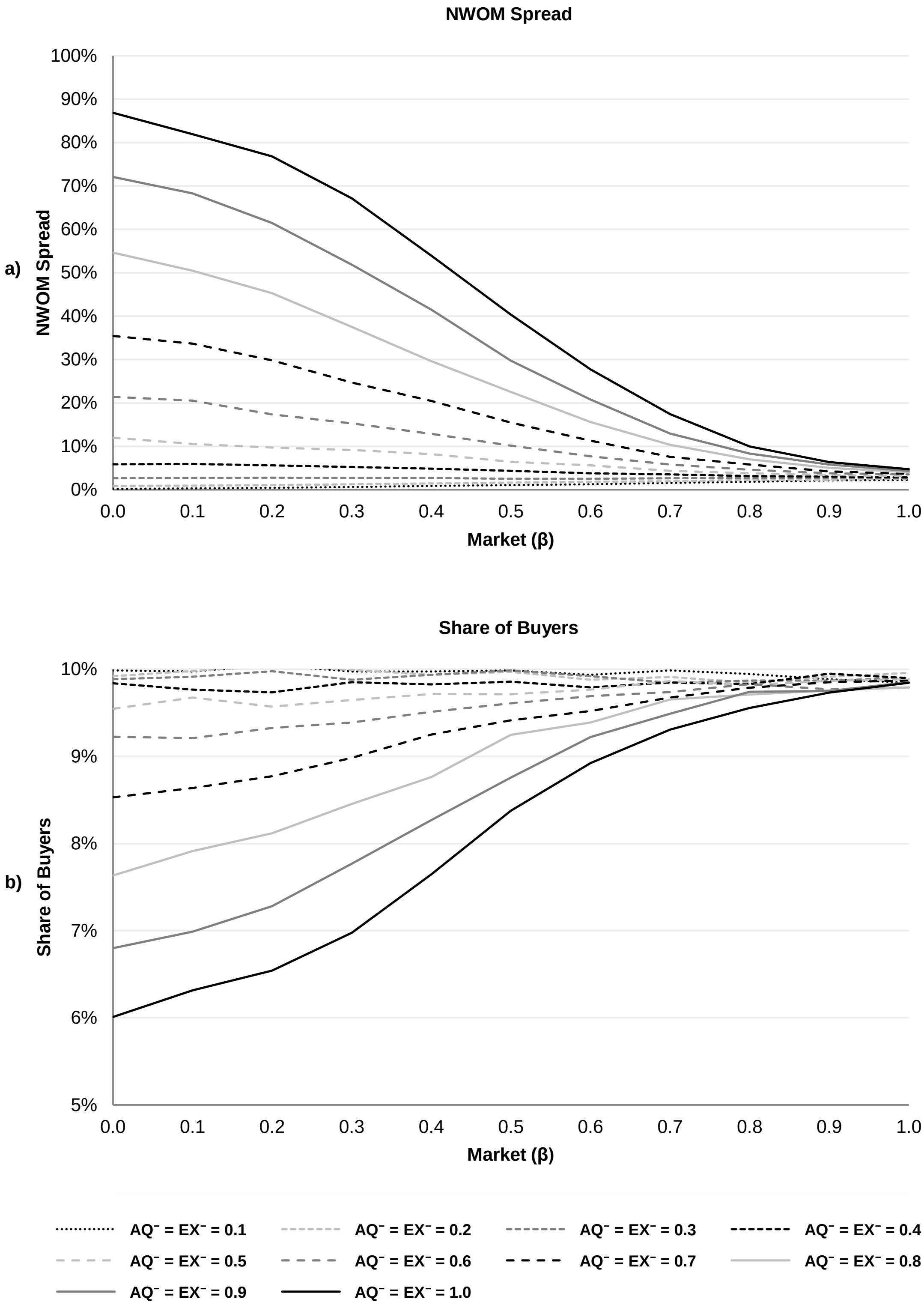

Figure 11. NWOM spread and share of buyers for different values of AQ^{-} and EX^{-}.

As shown in Figure 11a, the NWOM spread is significantly higher in individualistic markets, which particularly applies to stronger NWOM messages. The more collectivistic a market is ($\beta \rightarrow 1$), the lower is the NWOM spread leading to a hardly distinguishable overlapping of the graphs in the most collectivistic markets. As discussed in the base model's numerical analysis in Section 2.4.2, messages spread further in individualistic markets because the content of a message plays a more important role in the credibility evaluation of OSN members, which, in turn, positively influences their forwarding decision. In collectivistic markets, the perceived credibility of a message is for the most part based on the sending behaviour of an OSN member i's contacts. If they do not send the message, member i will most likely not forward the message either, which restricts the propagation of the message in the OSN.

Figure 11b reveals that the NWOM spread is negatively correlated with the share of buyers. The graphs show that the weakest NWOM messages have a very low impact on the share of buyers irrespective of the market. The strongest NWOM message, by contrast, reduces the number of potential buyers in the OSN by approximately 40% in relative terms in the most individualistic market ($\beta = 0$). As β increases, all NWOM messages start to lose their negative effect on the purchase probability of OSN members. For further examinations, we pick a *weak NWOM message* ($AQ^- = EX^- = 0.3$), *medium NWOM message* ($AQ^- = EX^- = 0.6$), and *strong NWOM message* ($AQ^- = EX^- = 1.0$).

2.6.3 Competitive Setting: Quick-Response Countermeasure

Instead of varying the informational value of the PWOM message in different steps like in the base model, the countermeasure effectiveness of three different PWOM messages will be analysed in the following: a *weak PWOM message* ($AQ^+ = EX^+ = 0.3$), *medium PWOM message* ($AQ^+ = EX^+ = 0.6$), and *strong PWOM message* ($AQ^+ = EX^+ = 1.0$). These messages were launched by either one or eight seeds immediately after the emergence of the NWOM message in the OSN. The resulting values of the NWOM spread and share of buyers achieved by the one seed strategy are depicted in Figure 12. The data for the eight seed strategy is given in Figure 13. The graphs in both figures illustrate that in most cases a considerable reduction of the NWOM spread can only be achieved if the counter-message is very persuasive. If a strong PWOM message is launched by one seed against a weak or medium NWOM message, it is not only able to repair the damage of the NWOM message but can also increase the share of buyers in almost all markets above the initial share of 10% as Figure 12b/d reveal. Only in the case of a strong NWOM message, the deployment of one seed is not sufficient for reversing the economic damage caused by NWOM as shown in Figure 12f. If, however, eight seeds are used for disseminating the strong PWOM message, its impact increases, and the initial share of buyers can again be surpassed as Figure 13f demonstrates. In general, using eight seeds instead of one increases the positive impact of the strong PWOM message in all cases and leads to a higher share of buyers. The effects of activating more seeds are, however, lessened for the weak and medium PWOM messages.

An important finding of the base model was that a strong PWOM message is, to a certain extent, able to compensate for a reduced number of seeds in restricting the prevalence of an NWOM message. The effects of the base model in this regard were examined only in two different markets ($\beta = 0.1$ and $\beta = 0.4$). Figure 12 and Figure 13 show that this finding also holds in more markets as a strong PWOM message with one seed usually outperforms a weak or medium message launched by eight seeds. The superior performance is also reflected in the share of buyers and particularly holds in individualistic markets. The greatest difference in the NWOM spread can be observed for the strong NWOM message in the most individualistic market ($\beta = 0$) where the strong PWOM message with one seed in Figure 12e considerably outperforms the medium message with eight seeds in Figure 13e (30.728% versus 88.181%). The differences of the strong PWOM message disseminated by one seed in comparison to the weaker counter-messages launched by eight seeds were tested for statistical significance, for which the results are given in Table 11. The cases where the strong PWOM message launched by one seed does not perform better than its counterparts are shaded grey. The results reveal that although the strong PWOM message shows a better performance in individualistic markets, it is mostly overtaken in collectivistic markets by weaker PWOM messages that are launched by multiple seeds. This market-dependent switch in influence can be explained by the generally reduced spread of messages in collectivistic markets, which has been discussed in the previous subsection. If the diffusion of both the NWOM and PWOM message is restricted, it increases the likelihood that they never or only rarely meet in the OSN. This means that the PWOM message, despite its strength, will probably not be able to directly fight NWOM and alleviate its effects in collectivistic markets. If disseminated by one seed, it will more likely only positively influence the surroundings of the seed by persuading close-by OSN members. This can be seen as a promotional effect that mitigates the NWOM damage not by recovering irritated OSN members but by generating new sales. If the PWOM message is able to convince them, their individual purchase probability will increase resulting in a higher share of buyers in the OSN. If multiple seeds are used who are scattered throughout the OSN, two effects emerge: (1) the likelihood of reaching the NWOM message is increased and (2) the promotional effect is enhanced by having more positively influenced clusters in the OSN. These effects are seemingly able to outweigh the lack of persuasiveness of the weaker PWOM messages in collectivistic markets. The aspect of being able to reach the NWOM message in the OSN and induce a recovering of negatively influenced OSN members is more closely examined in the context of the optimal reaction model in Section 2.8.3.

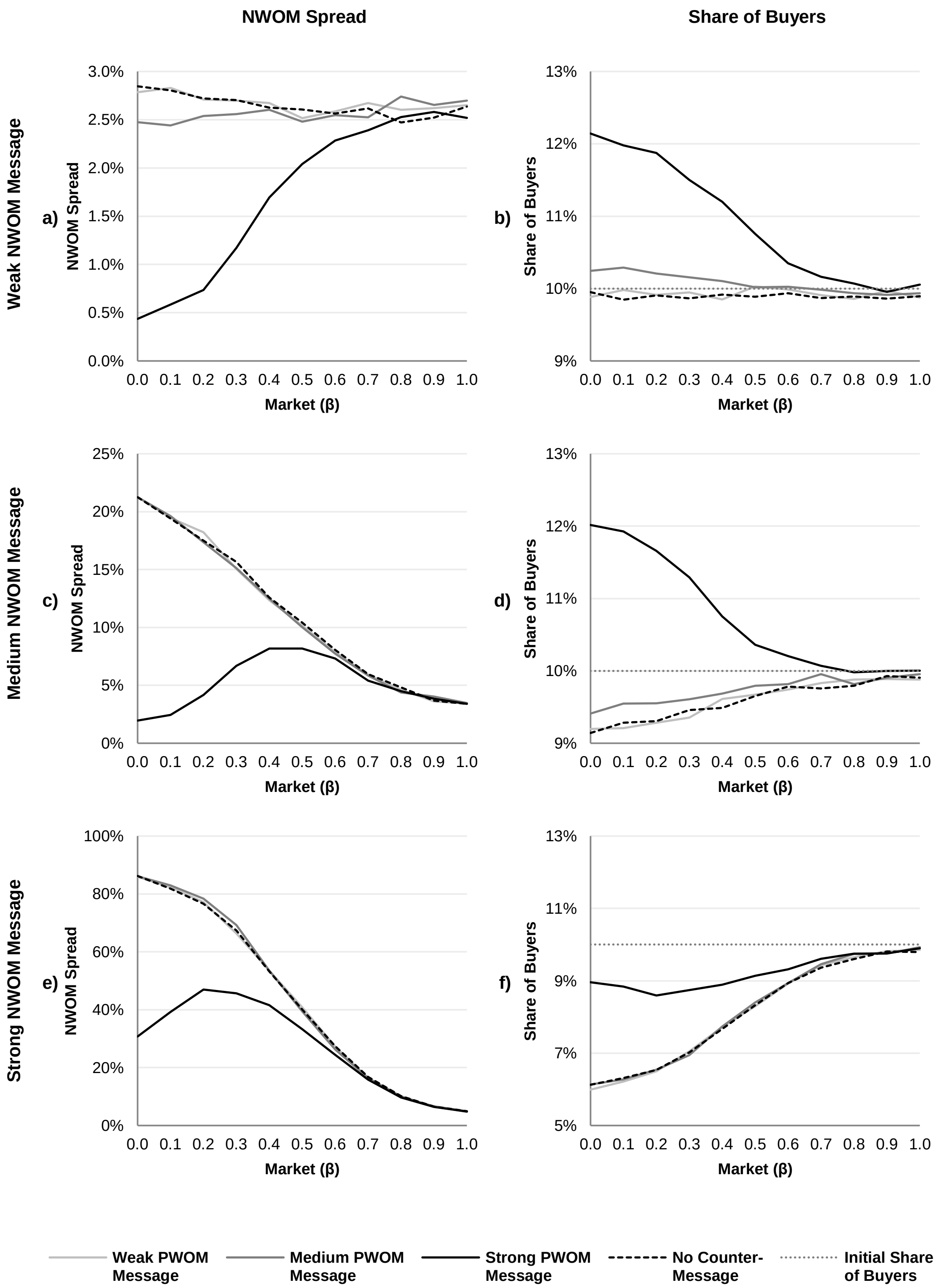

Figure 12. NWOM spread and share of buyers for quick-response countermeasure strategies with one seed.

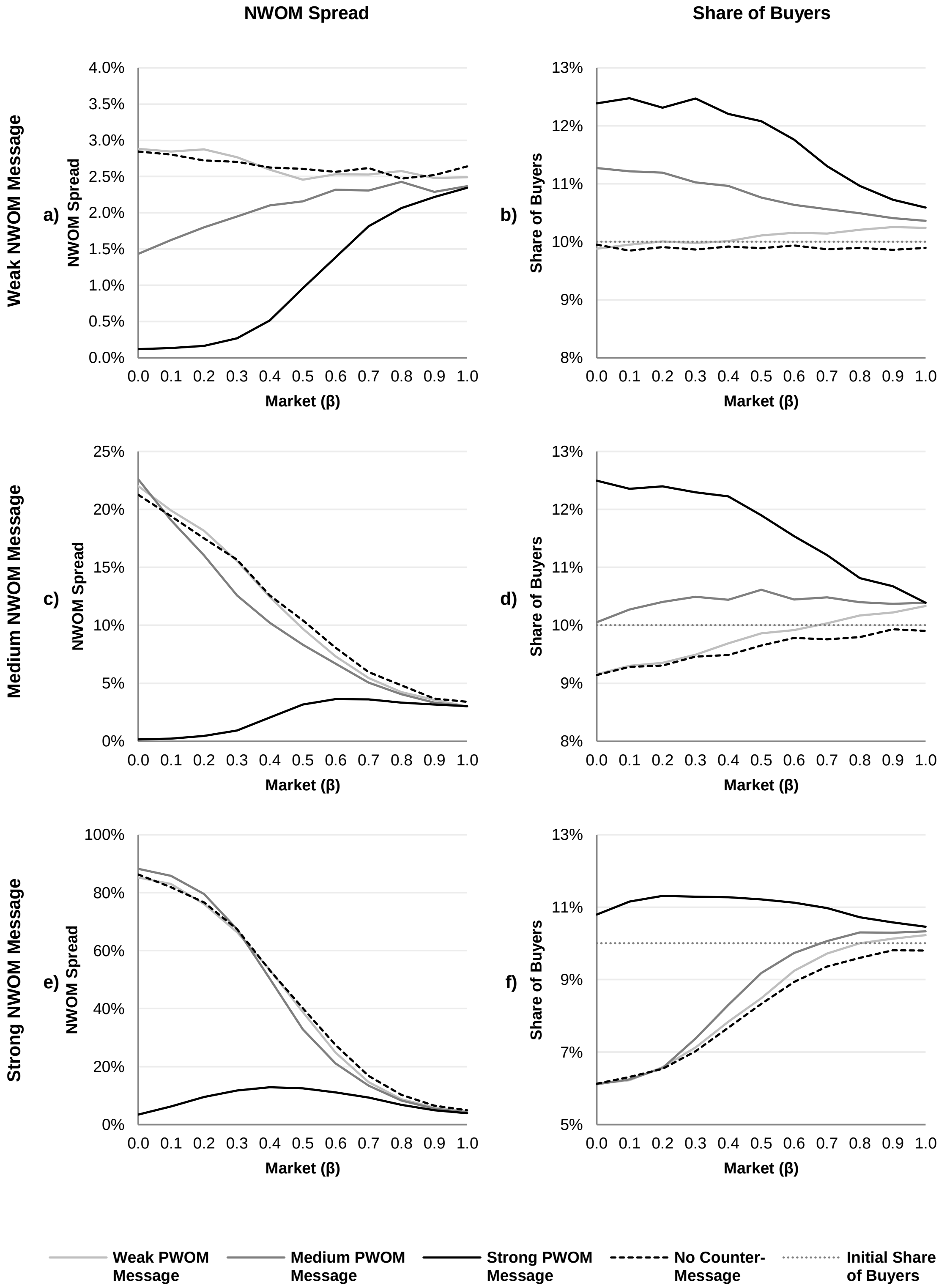

Figure 13. NWOM spread and share of buyers for quick-response countermeasure strategies with eight seeds.

Table 11. Statistical analysis of the immediately launched strong PWOM message's performance as compared to weaker PWOM messages launched immediately by eight seeds.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the strong PWOM message launched by one seed			
		In comparison to the medium PWOM message launched by eight seeds		**In comparison to the weak PWOM message launched by eight seeds**	
NWOM Message	**Market (β)**	**NWOM Spread**	**Share of Buyers**	**NWOM Spread**	**Share of Buyers**
Weak NWOM	**0.0**	-0.998%***	+0.869%***	-2.448%***	+2.263%***
	0.1	-1.037%***	+0.766%***	-2.261%***	+2.028%***
	0.2	-1.066%***	+0.683%***	-2.141%***	+1.868%***
	0.3	-0.778%***	+0.478%***	-1.595%***	+1.523%***
	0.4	-0.407%***	+0.236%***	-0.899%***	+1.190%***
	0.5	-0.115%^{ns}	-0.011%^{ns}	-0.414%***	+0.646%***
	0.6	-0.034%^{ns}	-0.289%***	-0.247%**	+0.192%***
	0.7	+0.084%^{ns}	-0.398%***	-0.136%^{ns}	+0.019%^{ns}
	0.8	+0.099%^{ns}	-0.426%***	-0.049%^{ns}	-0.137%*
	0.9	+0.293%***	-0.455%***	+0.101%^{ns}	-0.302%***
	1.0	+0.152%*	-0.309%***	+0.030%^{ns}	-0.188%***
Medium NWOM	**0.0**	-20.625%***	+1.964%***	-20.041%***	+2.861%***
	0.1	-16.620%***	+1.652%***	-17.470%***	+2.622%***
	0.2	-11.865%***	+1.254%***	-13.989%***	+2.308%***
	0.3	-5.894%***	+0.801%***	-8.871%***	+1.799%***
	0.4	-2.056%***	+0.310%***	-4.265%***	+1.064%***
	0.5	-0.147%^{ns}	-0.253%***	-1.516%***	+0.497%***
	0.6	+0.628%**	-0.240%***	+0.006%^{ns}	+0.286%***
	0.7	+0.345%*	-0.411%***	-0.047%^{ns}	+0.036%^{ns}
	0.8	+0.440%**	-0.416%***	+0.248%^{ns}	-0.190%**
	0.9	+0.529%***	-0.371%***	+0.283%*	-0.218%***
	1.0	+0.399%***	-0.386%***	+0.402%***	-0.331%***
Strong NWOM	**0.0**	-57.453%***	+2.849%***	-54.462%***	+2.829%***
	0.1	-46.526%***	+2.601%***	-43.753%***	+2.619%***
	0.2	-32.503%***	+2.036%***	-29.084%***	+2.015%***
	0.3	-21.706%***	+1.371%***	-20.671%***	+1.621%***
	0.4	-8.701%***	+0.592%***	-11.819%***	+1.056%***
	0.5	+0.448%^{ns}	-0.044%^{ns}	-5.559%***	+0.655%***
	0.6	+3.294%***	-0.418%***	-0.388%^{ns}	+0.077%^{ns}
	0.7	+2.432%***	-0.454%***	+1.204%**	-0.115%*
	0.8	+1.438%***	-0.548%***	+0.938%**	-0.252%***
	0.9	+1.009%***	-0.537%***	+0.603%**	-0.373%***
	1.0	+0.624%***	-0.436%***	+0.300%*	-0.331%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

2.6.4 Competitive Setting: Delayed Countermeasure

For investigating the effects of an increased response delay, the experiments of the previous subsection were reconducted with PWOM messages that were not launched immediately but with a delay of $D = 8t$. The results are depicted in Figure 14 for the one seed and in Figure 15 for the eight seed strategy. A comparison with the quick-response countermeasure figures reveals that the strong PWOM message launched by one seed does not sacrifice much of its superior performance even if it is disseminated with delay. For instance, in Figure 14 the strong PWOM message still leads to a considerable reduction of the NWOM spread. In individualistic markets, it is able to outperform any immediately launched weak or medium PWOM message shown in Figure 12 and Figure 13. The greatest performance difference to the medium PWOM message can be observed for a medium NWOM message in the most individualistic market ($\beta = 0$) where the strong delayed PWOM message in Figure 14c reduces the NWOM spread with one seed significantly more than the medium PWOM message in Figure 12c that is launched immediately by one seed (3.005% versus 21.257%). Even if the medium PWOM message is launched by multiple seeds in Figure 13c, it is still inferior (22.592%). This effect is also present in other scenarios. For instance, Figure 14e shows that in the most individualistic market the delayed strong PWOM message with one seed is able to outperform the medium PWOM message that is disseminated immediately by eight seeds in Figure 13e (68.180% versus 88.181%). Similar results can be observed for the share of buyers. In the cases of a weak and medium NWOM message, the delayed strong PWOM message with one seed in Figure 14b/d outperforms the weaker counter-messages with eight seeds in Figure 13b/d for $\beta < 0.5$. In the case of a strong NWOM message, the delayed PWOM message in Figure 14f still performs better than the weaker counter-messages in Figure 13f for $\beta < 0.3$.

As in the previous subsection, the performance of the strong delayed PWOM message launched by one seed in Figure 14 was tested for statistical significance. Table 12 lists its performance differences to the medium and weak PWOM messages that are disseminated immediately by eight seeds in Figure 13. The statistical analysis confirms that, despite the delay in the reaction, the strong PWOM message is still able to counter NWOM messages more effectively than the weaker counter-messages. In fact, the differences are quite similar for a weak and medium NWOM message when the data across Table 11 and Table 12 is compared. Only in the case of a strong NWOM message, the strong delayed PWOM message loses some ground but still performs better in very individualistic markets.

Table 13 shows the performance differences between the strong delayed PWOM message and the weaker PWOM messages from Figure 12 that are launched immediately by one seed. The strong delayed PWOM message performs in almost all cases as well as or better than the less convincing PWOM messages.

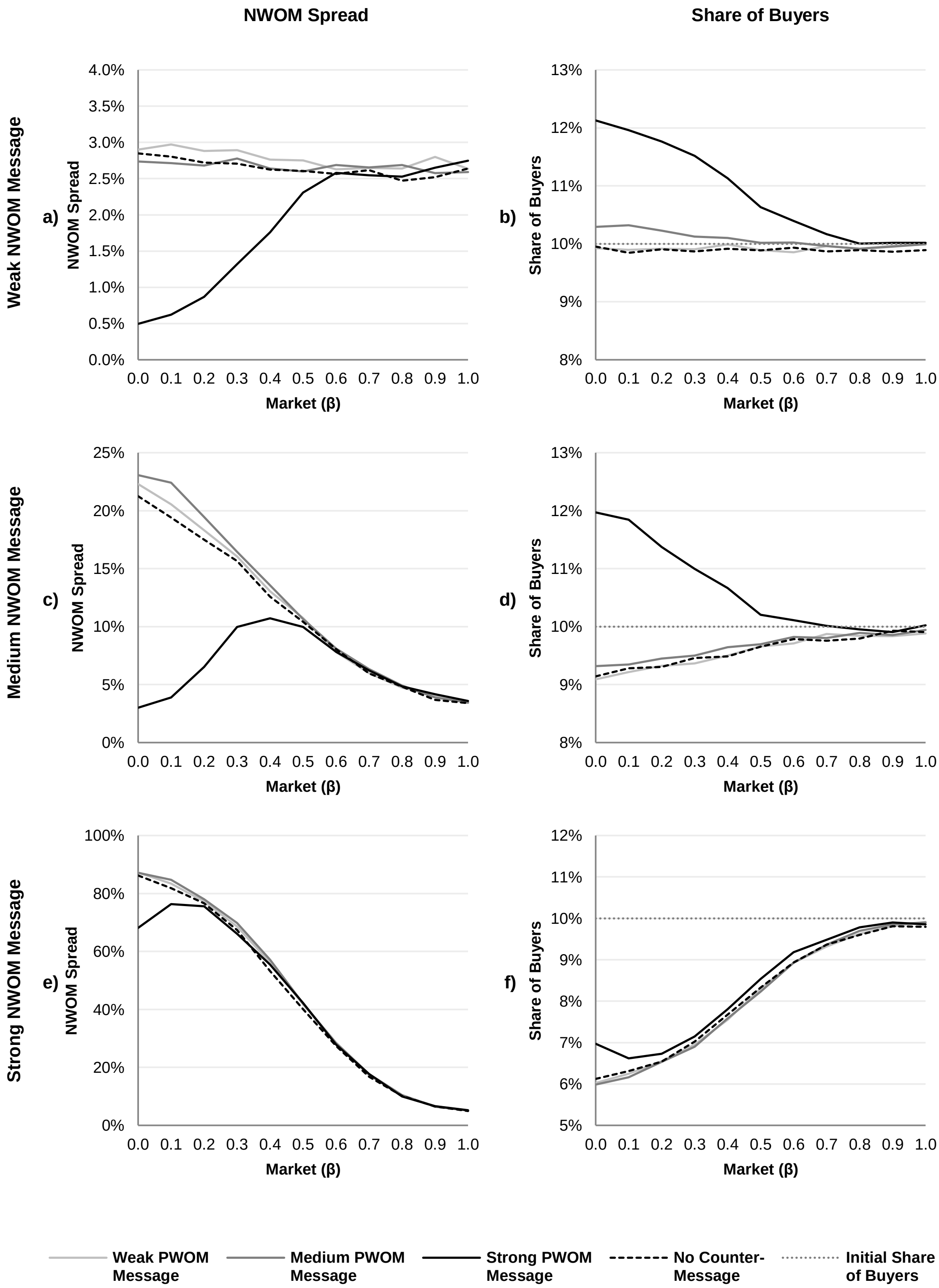

Figure 14. NWOM spread and share of buyers for delayed countermeasure strategies with one seed.

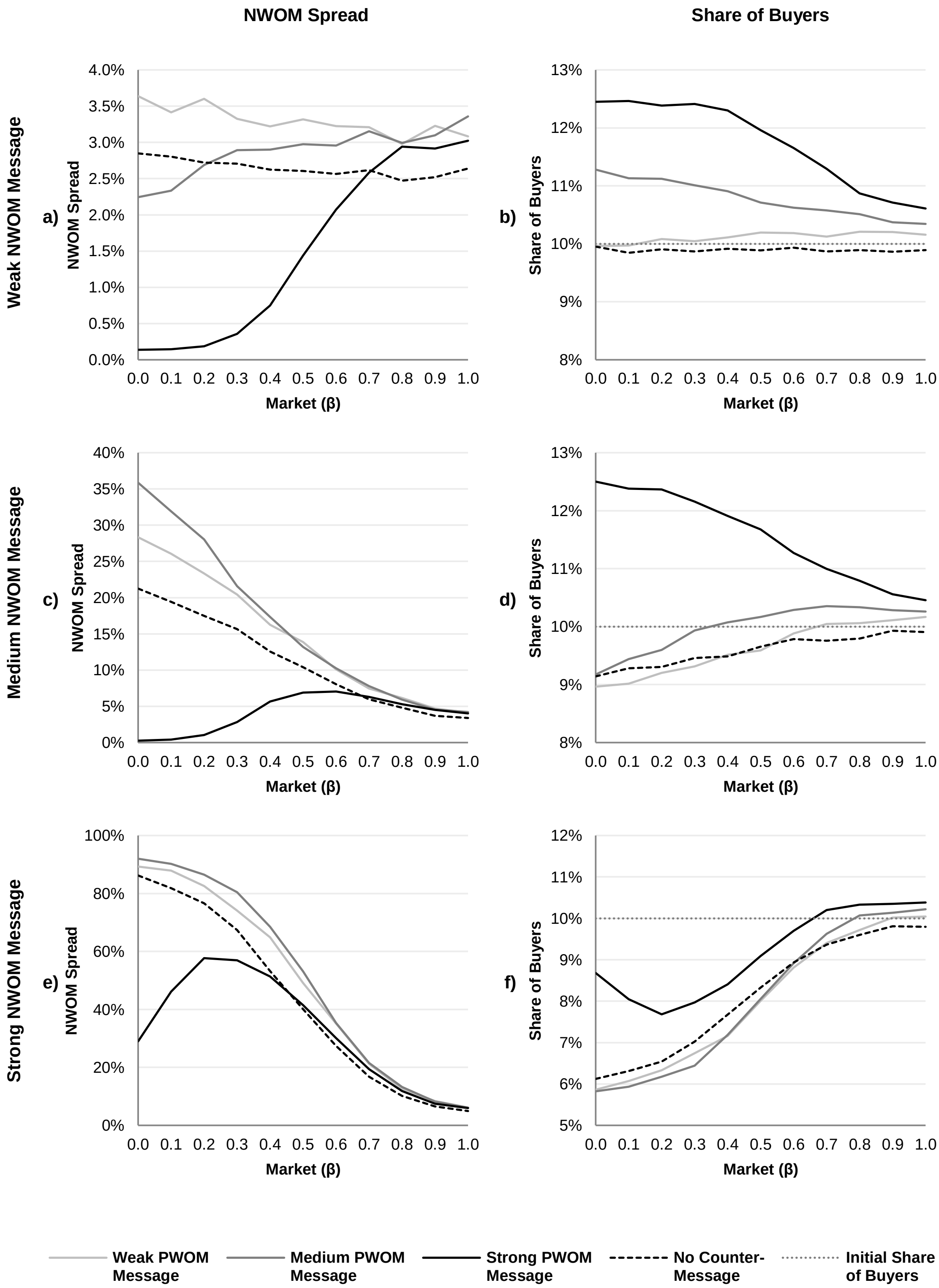

Figure 15. NWOM spread and share of buyers for delayed countermeasure strategies with eight seeds.

Table 12. Statistical analysis of the strong delayed PWOM message's performance as compared to weaker PWOM messages launched immediately by eight seeds.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the strong PWOM message launched by one seed			
		In comparison to the medium PWOM message launched by eight seeds		**In comparison to the weak PWOM message launched by eight seeds**	
NWOM Message	**Market (β)**	**NWOM Spread**	**Share of Buyers**	**NWOM Spread**	**Share of Buyers**
Weak NWOM	**0.0**	-0.936%***	+0.854%***	-2.387%***	+2.249%***
	0.1	-1.001%***	+0.748%***	-2.224%***	+2.009%***
	0.2	-0.933%***	+0.572%***	-2.008%***	+1.757%***
	0.3	-0.629%***	+0.496%***	-1.447%***	+1.541%***
	0.4	-0.342%***	+0.169%**	-0.834%***	+1.123%***
	0.5	+0.150%*	-0.134%*	-0.150%*	+0.522%***
	0.6	+0.262%**	-0.244%***	+0.049%ns	+0.238%***
	0.7	+0.241%**	-0.393%***	+0.021%ns	+0.024%ns
	0.8	+0.101%ns	-0.490%***	-0.047%ns	-0.201%***
	0.9	+0.361%***	-0.389%***	+0.169%*	-0.235%***
	1.0	+0.378%***	-0.345%***	+0.257%**	-0.223%***
Medium NWOM	**0.0**	-19.587%***	+1.919%***	-19.003%***	+2.816%***
	0.1	-15.164%***	+1.572%***	-16.013%***	+2.542%***
	0.2	-9.519%***	+0.969%***	-11.644%***	+2.023%***
	0.3	-2.610%***	+0.506%***	-5.587%***	+1.504%***
	0.4	+0.481%ns	+0.224%***	-1.727%***	+0.977%***
	0.5	+1.653%***	-0.409%***	+0.285%ns	+0.341%***
	0.6	+1.144%***	-0.334%***	+0.522%*	+0.192%***
	0.7	+1.154%***	-0.468%***	+0.761%***	-0.022%ns
	0.8	+0.789%***	-0.446%***	+0.597%***	-0.221%***
	0.9	+0.848%***	-0.464%***	+0.602%***	-0.312%***
	1.0	+0.573%***	-0.368%***	+0.575%***	-0.312%***
Strong NWOM	**0.0**	-20.001%***	+0.864%***	-17.010%***	+0.844%***
	0.1	-9.431%***	+0.377%***	-6.658%***	+0.395%***
	0.2	-3.970%***	+0.170%**	-0.551%ns	+0.149%**
	0.3	-1.303%ns	-0.224%**	-0.269%ns	+0.025%ns
	0.4	+5.177%***	-0.498%***	+2.059%*	-0.034%ns
	0.5	+9.436%***	-0.644%***	+3.430%***	+0.055%ns
	0.6	+6.781%***	-0.553%***	+3.099%***	-0.058%ns
	0.7	+4.338%***	-0.576%***	+3.110%***	-0.238%***
	0.8	+1.689%***	-0.519%***	+1.188%***	-0.222%***
	0.9	+1.140%***	-0.398%***	+0.734%***	-0.234%***
	1.0	+0.985%***	-0.483%***	+0.661%***	-0.377%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ns = not significant

Table 13. Statistical analysis of the strong delayed PWOM message's performance as compared to weaker PWOM messages launched immediately by one seed.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the strong PWOM message launched by one seed			
		In comparison to the medium PWOM message launched by one seed		**In comparison to the weak PWOM message launched by one seed**	
NWOM Message	**Market (β)**	**NWOM Spread**	**Share of Buyers**	**NWOM Spread**	**Share of Buyers**
Weak NWOM	**0.0**	-1.977%***	+1.882%***	-2.287%***	+2.244%***
	0.1	-1.819%***	+1.671%***	-2.207%***	+1.983%***
	0.2	-1.671%***	+1.557%***	-1.841%***	+1.852%***
	0.3	-1.240%***	+1.362%***	-1.381%***	+1.571%***
	0.4	-0.845%***	+1.029%***	-0.914%***	+1.283%***
	0.5	-0.172%*	+0.613%***	-0.210%**	+0.601%***
	0.6	+0.033%^{ns}	+0.368%***	-0.005%^{ns}	+0.409%***
	0.7	+0.022%^{ns}	+0.182%**	-0.125%^{ns}	+0.256%***
	0.8	-0.212%*	+0.067%^{ns}	-0.074%^{ns}	+0.148%**
	0.9	-0.004%^{ns}	+0.105%*	+0.028%^{ns}	+0.052%^{ns}
	1.0	+0.049%^{ns}	+0.083%^{ns}	+0.095%^{ns}	+0.143%**
Medium NWOM	**0.0**	-18.252%***	+2.561%***	-18.267%***	+2.774%***
	0.1	-15.720%***	+2.296%***	-15.570%***	+2.636%***
	0.2	-10.846%***	+1.823%***	-11.695%***	+2.090%***
	0.3	-5.152%***	+1.390%***	-5.082%***	+1.641%***
	0.4	-1.784%***	+0.981%***	-1.644%***	+1.055%***
	0.5	-0.049%^{ns}	+0.409%***	-0.187%^{ns}	+0.532%***
	0.6	+0.109%^{ns}	+0.292%***	-0.029%^{ns}	+0.367%***
	0.7	+0.359%*	+0.059%^{ns}	+0.303%^{ns}	+0.181%**
	0.8	+0.471%**	+0.133%*	+0.201%^{ns}	+0.070%^{ns}
	0.9	+0.150%^{ns}	+0.002%^{ns}	+0.556%***	+0.019%^{ns}
	1.0	+0.122%^{ns}	+0.069%^{ns}	+0.147%^{ns}	+0.142%**
Strong NWOM	**0.0**	-17.929%***	+0.836%***	-17.794%***	+0.978%***
	0.1	-6.602%***	+0.343%***	-5.907%***	+0.400%***
	0.2	-2.797%***	+0.187%**	-1.583%*	+0.228%***
	0.3	-3.142%***	+0.201%**	-0.279%^{ns}	+0.100%^{ns}
	0.4	+1.959%*	+0.065%^{ns}	+1.970%*	+0.080%^{ns}
	0.5	+2.819%***	+0.136%*	+1.407%^{ns}	+0.244%***
	0.6	+1.582%*	+0.243%***	+0.586%^{ns}	+0.255%***
	0.7	+1.388%**	+0.027%^{ns}	+1.355%**	+0.056%^{ns}
	0.8	-0.088%^{ns}	+0.037%^{ns}	+0.226%^{ns}	+0.131%*
	0.9	+0.035%^{ns}	+0.146%**	-0.137%^{ns}	+0.077%^{ns}
	1.0	+0.414%**	-0.077%^{ns}	+0.290%*	-0.003%^{ns}

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

The simulation data further reveals that the reaction to NWOM can be counterproductive. As the graphs in Figure 14 and Figure 15 show, in some situations a delayed reaction with multiple seeds might trigger a new wave of NWOM in the OSN and thereby lead to a further growth in the NWOM spread. When compared to the case where no countermeasure is taken, the delayed reaction can also result in an additionally reduced share of buyers. Table 14 presents a statistical analysis of the tested delayed countermeasure strategies' impact on the NWOM spread and share of buyers in comparison to the no-response strategy. The cases where an undesirable effect occurs (i.e. an additional increase of the NWOM spread or an additional decrease in the share of buyers) are shaded grey. The highlighting in bold indicates that the PWOM message was able to fully reverse the economic damage caused by the NWOM message by reaching a share of buyers of at least 10%.

The data listed in Table 14 demonstrates that countering a weak NWOM message by launching a likewise weak PWOM message with eight seeds increases the NWOM spread in all markets. This also applies if the weak NWOM message is countered by a medium PWOM message except for very individualistic markets. The strong PWOM message, by contrast, is mostly able to decrease the NWOM spread. Only in very collectivistic markets, an additional increase of the NWOM spread can be observed. But as Table 14 further reveals, the triggering of NWOM in these scenarios hardly causes additional damage in the share of buyers when compared to the outcome of the no-response strategy. A similar increase of the NWOM spread can be observed in the cases of medium and strong NWOM messages that are fought against by weak and medium PWOM messages with eight seeds. However, unlike in the case of a weak NWOM message, the triggering of medium and strong NWOM messages may worsen the economic situation of the firm.

The share of buyers data in Table 14 further indicates that if the countermeasure consists of one seed, the PWOM message should be stronger than the NWOM message in order to be able to fully reverse its economic damage. If eight seeds are deployed, an equally strong or even a weaker PWOM message may also be able to reach this goal. However, using multiple seeds gets less effective with increasing NWOM message strength and may result in additional losses as discussed above. For instance, if the PWOM message has a lower strength than the NWOM message and is launched by one seed, it might reduce the share of buyers in a few cases with statistical significance (highlighted in italic). Activating multiple seeds seems to increase the number and intensity of this undesirable effect by triggering more NWOM in the OSN. The risk of causing additional damage is particularly high for strong NWOM messages that are countered by weaker PWOM messages in individualistic markets. Because people attach greater weight to the content of the transmitted messages, using multiple seeds has a counterproductive effect in these scenarios as they mainly initiate new waves of NWOM but can neither exert social pressure on the OSN members nor convince them of the firm's counterstatement due to the overpowering impact of the negativity bias.

Table 15 provides a statistical analysis of the quick-response countermeasure strategies' effectiveness benchmarked against the no-response strategy. When compared to the results of the delayed countermeasure given in Table 14, the question arises why the negative effects of triggering NWOM are more pronounced for delayed reactions but become less of an issue if the counter-message is deployed in a timely manner? An explanation for this is that a delayed PWOM message is confronted with a negatively prepared network and therefore faces greater difficulties in establishing itself in the OSN. Because of this, fewer people forward the PWOM message resulting in a comparatively lower PWOM spread. But at the same time, the PWOM message is responsible for the initiation of new waves of NWOM in the OSN. In the context of a delayed countermeasure, this happens to be more intense if eight seeds are used instead of one. If a firm reacts immediately with eight seeds, the situation is different because the PWOM message has better chances in fighting NWOM since large parts of the OSN have not been influenced by the NWOM message yet. OSN members will forward the PWOM message more often. Consequently, the PWOM spread will be higher leading to fewer people believing in the NWOM message and making purchases more likely. From this, it can be inferred that a PWOM message has two opposing effects on the NWOM spread and share of buyers: (1) it may trigger new waves of NWOM in the OSN and thereby increase the NWOM spread and decrease the number of sales and (2) by reaching a higher spread itself and inducing sales-promotional effects on OSN members, the PWOM message may reduce or even reverse the negative effects caused by the NWOM spread in the OSN.

It must be noted that the degree to which a network is negatively prepared is an important aspect in the context of a delayed reaction. The weaker an NWOM message is, the more likely it is that the delayed PWOM message propagates. To verify this, we analysed the share of OSN members who have received the PWOM message and compared it to the share of members who are convinced of it (i.e. the PWOM spread). These shares are plotted in Figure 16 and Figure 17 for the delayed countermeasure with one and eight seeds respectively. The graphs in Figure 16a/b/c/d and Figure 17a/b/c/d illustrate that the diffusion of a PWOM message regarding both aspects is higher if it faces a weak or medium NWOM message, i.e. more people receive the PWOM message and also believe in it. Note that a large number of PWOM message receptions also indicate more triggering of the NWOM message because of the operationalisation of the OSN members' forwarding decision in Section 2.5.2. Although this leads to an increased NWOM spread as Table 14 and Table 15 revealed, the share of buyers in the cases of a weak and medium NWOM message is hardly affected because PWOM's promotional effect (2) can compensate for its triggering effect (1). This is due to the fact that the NWOM message lacks power in these cases and therefore cannot extensively restrict the PWOM message from spreading in the OSN. The PWOM message gets forwarded more often and is able to reach a relatively high spread, which, in turn, results in more sales. The situation changes if the firm faces a strong NWOM message. Its overwhelming strength, due to the negativity bias, prevents many OSN members from believing in the PWOM message even though they have received it, which is evidenced by the graphs shown in Figure 16e/f and Figure 17e/f. Because this impedes a high PWOM spread, the PWOM message is not able to unfold its promotional effect (2), which therefore cannot outweigh the economic damage caused by its triggering effect (1).

To summarise, the degree of the negative preparation of a network determines which of PWOM's two opposing effects will dominate. The more negatively influenced the network and the weaker the firm's response is, the less likely will the PWOM message be able to make use of its promotional effect and reverse the damages of the NWOM message and vice versa.

Table 14. Statistical analysis of the delayed countermeasure strategies' performance.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by a delayed countermeasure as compared to the no-response strategy											
		NWOM Spread						Share of Buyers					
		1 Seed			8 Seeds			1 Seed			8 Seeds		
NWOM Message	Market (β)	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM
Weak NWOM	0.0	+0.053%^{ns}	-0.109%^{ns}	-2.350%***	+0.792%***	-0.602%***	-2.709%***	-0.028%^{ns}	+0.339%***	+2.175%***	+0.008%^{ns}	+1.331%***	+2.498%***
	0.1	+0.167%*	-0.088%^{ns}	-2.182%***	+0.612%***	-0.469%***	-2.657%***	+0.052%^{ns}	+0.472%***	+2.116%***	+0.123%*	+1.283%***	+2.616%***
	0.2	+0.162%^{ns}	-0.039%^{ns}	-1.853%***	+0.879%***	-0.032%^{ns}	-2.535%***	+0.007%^{ns}	+0.322%***	+1.856%***	+0.176%**	+1.216%***	+2.478%***
	0.3	+0.188%*	+0.072%^{ns}	-1.386%***	+0.621%***	+0.187%*	-2.347%***	+0.039%^{ns}	+0.259%***	+1.652%***	+0.180%**	+1.143%***	+2.545%***
	0.4	+0.135%^{ns}	+0.014%^{ns}	-0.867%***	+0.593%***	+0.276%**	-1.875%***	+0.072%^{ns}	+0.184%***	+1.217%***	+0.197%***	+0.992%***	+2.386%***
	0.5	+0.142%^{ns}	-0.007%^{ns}	-0.301%***	+0.710%***	+0.369%***	-1.167%***	+0.002%^{ns}	+0.130%*	+0.743%***	+0.305%***	+0.824%***	+2.071%***
	0.6	+0.064%^{ns}	+0.124%^{ns}	+0.016%^{ns}	+0.659%***	+0.391%***	-0.493%***	-0.079%^{ns}	+0.088%^{ns}	+0.460%***	+0.250%***	+0.690%***	+1.720%***
	0.7	+0.028%^{ns}	+0.036%^{ns}	-0.071%^{ns}	+0.591%***	+0.537%***	-0.035%^{ns}	+0.092%^{ns}	+0.091%^{ns}	+0.297%***	+0.258%***	+0.709%***	+1.425%***
	0.8	+0.169%*	+0.216%*	+0.057%^{ns}	+0.506%***	+0.523%***	+0.471%***	+0.023%^{ns}	+0.025%^{ns}	+0.112%*	+0.315%***	+0.617%***	+0.976%***
	0.9	+0.277%**	+0.054%^{ns}	+0.128%^{ns}	+0.707%***	+0.576%***	+0.393%***	+0.101%*	+0.091%^{ns}	+0.157%**	+0.340%***	+0.511%***	+0.849%***
	1.0	-0.001%^{ns}	-0.046%^{ns}	+0.108%^{ns}	+0.444%***	+0.721%***	+0.387%***	+0.097%^{ns}	+0.101%*	+0.124%*	+0.262%***	+0.450%***	+0.716%***
Medium NWOM	0.0	+1.031%*	+1.815%**	-18.253%***	+7.090%***	+14.602%***	-21.006%***	-0.051%^{ns}	+0.177%**	+2.828%***	-0.179%**	+0.030%^{ns}	+3.360%***
	0.1	+1.131%*	+2.997%***	-15.518%***	+6.634%***	+12.519%***	-18.989%***	-0.069%^{ns}	+0.064%^{ns}	+2.561%***	-0.266%***	+0.157%**	+3.096%***
	0.2	+0.819%^{ns}	+1.952%***	-10.979%***	+5.853%***	+10.532%***	-16.453%***	+0.019%^{ns}	+0.142%*	+2.066%***	-0.106%^{ns}	+0.289%***	+3.059%***
	0.3	+0.398%^{ns}	+0.789%*	-5.698%***	+4.751%***	+5.940%***	-12.827%***	-0.091%^{ns}	+0.041%^{ns}	+1.538%***	-0.147%**	+0.477%***	+2.698%***
	0.4	+0.461%^{ns}	+0.977%**	-1.871%***	+3.685%***	+4.770%***	-6.917%***	+0.012%^{ns}	+0.157%**	+1.177%***	+0.024%^{ns}	+0.583%***	+2.421%***
	0.5	+0.330%^{ns}	+0.220%^{ns}	-0.437%^{ns}	+3.448%***	+2.794%***	-3.529%***	+0.008%^{ns}	+0.045%^{ns}	+0.551%***	-0.061%^{ns}	+0.514%***	+2.025%***
	0.6	-0.252%^{ns}	+0.052%^{ns}	-0.223%^{ns}	+2.047%***	+2.187%***	-1.015%***	-0.074%^{ns}	+0.040%^{ns}	+0.327%***	+0.098%^{ns}	+0.506%***	+1.487%***
	0.7	+0.012%^{ns}	+0.374%*	+0.249%^{ns}	+1.501%***	+1.819%***	+0.317%^{ns}	+0.114%*	+0.047%^{ns}	+0.255%***	+0.290%***	+0.595%***	+1.241%***
	0.8	-0.088%^{ns}	+0.105%^{ns}	+0.034%^{ns}	+1.319%***	+1.103%***	+0.474%**	+0.047%^{ns}	+0.095%^{ns}	+0.155%**	+0.264%***	+0.538%***	+0.998%***
	0.9	+0.388%**	+0.214%^{ns}	+0.486%***	+1.008%***	+0.863%***	+0.834%***	-0.093%^{ns}	-0.076%^{ns}	-0.022%^{ns}	+0.182%**	+0.356%***	+0.631%***
	1.0	+0.019%^{ns}	+0.036%^{ns}	+0.176%^{ns}	+0.744%***	+0.813%***	+0.613%***	-0.023%^{ns}	+0.036%^{ns}	+0.116%*	+0.263%***	+0.355%***	+0.548%***
Strong NWOM	0.0	+1.011%*	+0.933%*	-18.039%***	+3.118%***	+5.789%***	-57.246%***	-0.098%*	-0.140%**	+0.849%***	-0.265%***	-0.303%***	+2.558%***
	0.1	+1.574%**	+2.861%***	-5.468%***	+6.084%***	+8.375%***	-35.702%***	-0.068%^{ns}	-0.150%**	+0.304%***	-0.244%***	-0.378%***	+1.732%***
	0.2	+0.687%^{ns}	+1.373%*	-1.074%^{ns}	+5.997%***	+9.902%***	-18.944%***	+0.006%^{ns}	-0.004%^{ns}	+0.191%**	-0.206%***	-0.365%***	+1.146%***
	0.3	+1.198%^{ns}	+2.413%**	-1.347%^{ns}	+6.679%***	+12.997%***	-10.452%***	-0.071%^{ns}	-0.126%*	+0.125%*	-0.278%***	-0.581%***	+0.947%***
	0.4	+2.944%***	+3.935%***	+2.269%**	+11.680%***	+15.282%***	-1.855%*	-0.119%*	-0.087%^{ns}	+0.133%*	-0.512%***	-0.486%***	+0.734%***
	0.5	+1.597%*	+1.910%*	+2.115%**	+9.003%***	+12.995%***	+1.380%^{ns}	-0.026%^{ns}	-0.097%^{ns}	+0.212%**	-0.321%***	-0.270%***	+0.763%***
	0.6	+0.870%^{ns}	+1.027%^{ns}	+0.491%^{ns}	+7.724%***	+7.959%***	+2.699%***	-0.007%^{ns}	-0.007%^{ns}	+0.242%***	-0.124%*	-0.019%^{ns}	+0.759%***
	0.7	+0.510%^{ns}	+0.924%*	+1.004%*	+4.488%***	+4.783%***	+2.674%***	-0.043%^{ns}	+0.001%^{ns}	+0.120%*	+0.038%^{ns}	+0.264%***	+0.837%***
	0.8	+0.143%^{ns}	+0.240%^{ns}	-0.255%^{ns}	+2.351%***	+2.998%***	+1.681%***	+0.031%^{ns}	+0.100%*	+0.184%**	+0.123%*	+0.473%***	+0.736%***
	0.9	+0.092%^{ns}	-0.137%^{ns}	+0.062%^{ns}	+1.806%***	+1.704%***	+0.945%***	-0.000%^{ns}	+0.044%^{ns}	+0.088%^{ns}	+0.207%***	+0.329%***	+0.539%***
	1.0	+0.191%^{ns}	+0.165%^{ns}	+0.238%^{ns}	+1.181%***	+1.134%***	+1.054%***	+0.117%*	+0.103%*	+0.053%^{ns}	+0.247%***	+0.419%***	+0.586%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 15. Statistical analysis of the quick-response countermeasure strategies' performance.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by a quick-response countermeasure as compared to the no-response strategy											
		NWOM Spread						Share of Buyers					
		1 Seed			8 Seeds			1 Seed			8 Seeds		
NWOM Message	Market (β)	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM	Weak PWOM	Medium PWOM	Strong PWOM
Weak NWOM	0.0	-0.063%^{ns}	-0.373%***	-2.411%***	+0.037%^{ns}	-1.414%***	-2.729%***	-0.069%^{ns}	+0.294%***	+2.190%***	-0.073%^{ns}	+1.321%***	+2.436%***
	0.1	+0.025%^{ns}	-0.364%***	-2.219%***	+0.042%^{ns}	-1.181%***	-2.672%***	+0.133%*	+0.444%***	+2.134%***	+0.106%*	+1.368%***	+2.630%***
	0.2	-0.012%^{ns}	-0.183%*	-1.986%***	+0.154%^{ns}	-0.920%***	-2.557%***	+0.005%^{ns}	+0.299%***	+1.967%***	+0.099%*	+1.284%***	+2.404%***
	0.3	-0.005%^{ns}	-0.146%^{ns}	-1.534%***	+0.061%^{ns}	-0.757%***	-2.438%***	+0.082%^{ns}	+0.290%***	+1.634%***	+0.111%*	+1.157%***	+2.603%***
	0.4	+0.047%^{ns}	-0.022%^{ns}	-0.932%***	-0.033%^{ns}	-0.525%***	-2.111%***	-0.066%^{ns}	+0.188%***	+1.284%***	+0.093%^{ns}	+1.047%***	+2.288%***
	0.5	-0.091%^{ns}	-0.128%^{ns}	-0.565%***	-0.151%*	-0.450%***	-1.648%***	+0.141%*	+0.129%*	+0.866%***	+0.220%***	+0.877%***	+2.193%***
	0.6	+0.021%^{ns}	-0.017%^{ns}	-0.280%***	-0.033%^{ns}	-0.246%**	-1.179%***	+0.052%^{ns}	+0.092%^{ns}	+0.415%***	+0.223%***	+0.704%***	+1.828%***
	0.7	+0.054%^{ns}	-0.093%^{ns}	-0.228%**	-0.092%^{ns}	-0.312%***	-0.805%***	+0.041%^{ns}	+0.115%*	+0.292%***	+0.273%***	+0.690%***	+1.436%***
	0.8	+0.131%^{ns}	+0.269%**	+0.055%^{ns}	+0.104%^{ns}	-0.043%^{ns}	-0.407%***	-0.036%^{ns}	+0.045%^{ns}	+0.176%**	+0.313%***	+0.602%***	+1.072%***
	0.9	+0.100%^{ns}	+0.132%^{ns}	+0.061%^{ns}	-0.041%^{ns}	-0.233%**	-0.302%***	+0.105%*	+0.052%^{ns}	+0.091%^{ns}	+0.392%***	+0.546%***	+0.864%***
	1.0	+0.013%^{ns}	+0.060%^{ns}	-0.118%^{ns}	-0.148%^{ns}	-0.270%**	-0.293%***	-0.019%^{ns}	+0.040%^{ns}	+0.159%**	+0.347%***	+0.469%***	+0.694%***
Medium NWOM	0.0	+0.014%^{ns}	-0.001%^{ns}	-19.291%***	+0.750%^{ns}	+1.334%*	-21.094%***	+0.054%^{ns}	+0.267%***	+2.873%***	+0.012%^{ns}	+0.909%***	+3.354%***
	0.1	+0.052%^{ns}	+0.202%^{ns}	-16.974%***	+0.495%^{ns}	-0.354%^{ns}	-19.197%***	-0.075%^{ns}	+0.265%***	+2.642%***	+0.020%^{ns}	+0.990%***	+3.072%***
	0.2	+0.716%^{ns}	-0.133%^{ns}	-13.325%***	+0.664%^{ns}	-1.460%**	-17.043%***	-0.023%^{ns}	+0.243%***	+2.352%***	+0.044%^{ns}	+1.098%***	+3.091%***
	0.3	-0.616%^{ns}	-0.546%^{ns}	-8.982%***	-0.111%^{ns}	-3.088%***	-14.736%***	-0.103%*	+0.148%**	+1.833%***	+0.034%^{ns}	+1.032%***	+2.835%***
	0.4	-0.226%^{ns}	-0.087%^{ns}	-4.408%***	-0.144%^{ns}	-2.352%***	-10.529%***	+0.122%*	+0.195%***	+1.263%***	+0.200%***	+0.953%***	+2.734%***
	0.5	-0.250%^{ns}	-0.388%^{ns}	-2.237%***	-0.722%*	-2.090%***	-7.248%***	+0.019%^{ns}	+0.142%**	+0.707%***	+0.209%***	+0.959%***	+2.246%***
	0.6	-0.194%^{ns}	-0.331%^{ns}	-0.739%**	-0.745%**	-1.367%***	-4.417%***	-0.040%^{ns}	+0.035%^{ns}	+0.421%***	+0.134%*	+0.661%***	+1.753%***
	0.7	-0.053%^{ns}	-0.110%^{ns}	-0.559%**	-0.512%**	-0.904%***	-2.356%***	+0.074%^{ns}	+0.197%***	+0.313%***	+0.277%***	+0.724%***	+1.453%***
	0.8	-0.167%^{ns}	-0.437%**	-0.315%*	-0.563%***	-0.756%***	-1.487%***	+0.085%^{ns}	+0.022%^{ns}	+0.186%**	+0.376%***	+0.601%***	+1.020%***
	0.9	-0.071%^{ns}	+0.335%**	+0.167%^{ns}	-0.116%^{ns}	-0.362%**	-0.509%***	-0.041%^{ns}	-0.024%^{ns}	+0.071%^{ns}	+0.290%***	+0.442%***	+0.746%***
	1.0	+0.029%^{ns}	+0.053%^{ns}	+0.002%^{ns}	-0.400%***	-0.397%***	-0.392%***	-0.026%^{ns}	+0.048%^{ns}	+0.098%^{ns}	+0.429%***	+0.484%***	+0.484%***
Strong NWOM	0.0	-0.245%^{ns}	-0.110%^{ns}	-55.491%***	-1.029%*	+1.962%***	-82.774%***	-0.129%**	+0.013%^{ns}	+2.834%***	+0.005%^{ns}	-0.015%^{ns}	+4.671%***
	0.1	+0.439%^{ns}	+1.134%*	-42.563%***	+1.190%*	+3.963%***	-75.557%***	-0.096%^{ns}	-0.039%^{ns}	+2.529%***	-0.090%^{ns}	-0.072%^{ns}	+4.839%***
	0.2	+0.509%^{ns}	+1.723%*	-29.607%***	-0.523%^{ns}	+2.896%***	-67.082%***	-0.037%^{ns}	+0.005%^{ns}	+2.057%***	+0.042%^{ns}	+0.022%^{ns}	+4.776%***
	0.3	-1.068%^{ns}	+1.796%*	-21.749%***	-1.078%^{ns}	-0.043%^{ns}	-55.725%***	+0.025%^{ns}	-0.076%^{ns}	+1.720%***	+0.100%^{ns}	+0.349%***	+4.268%***
	0.4	+0.299%^{ns}	+0.310%^{ns}	-11.610%***	+0.209%^{ns}	-2.908%***	-40.285%***	+0.052%^{ns}	+0.067%^{ns}	+1.222%***	+0.166%**	+0.630%***	+3.601%***
	0.5	+0.708%^{ns}	-0.704%^{ns}	-6.873%***	-1.315%^{ns}	-7.321%***	-27.622%***	-0.033%^{ns}	+0.075%^{ns}	+0.812%***	+0.157%*	+0.856%***	+2.887%***
	0.6	-0.095%^{ns}	-1.091%^{ns}	-2.996%***	-2.608%***	-6.290%***	-16.335%***	-0.013%^{ns}	-0.001%^{ns}	+0.378%***	+0.301%***	+0.795%***	+2.186%***
	0.7	-0.350%^{ns}	-0.383%^{ns}	-0.902%*	-2.106%***	-3.334%***	-7.402%***	+0.064%^{ns}	+0.094%^{ns}	+0.243%***	+0.358%***	+0.697%***	+1.613%***
	0.8	-0.481%^{ns}	-0.168%^{ns}	-0.506%^{ns}	-1.444%***	-1.944%***	-3.461%***	+0.053%^{ns}	+0.147%**	+0.154%**	+0.406%***	+0.703%***	+1.123%***
	0.9	+0.199%^{ns}	+0.027%^{ns}	-0.070%^{ns}	-0.672%**	-1.078%***	-1.588%***	+0.012%^{ns}	-0.058%^{ns}	-0.051%^{ns}	+0.322%***	+0.486%***	+0.771%***
	1.0	-0.053%^{ns}	-0.176%^{ns}	-0.123%^{ns}	-0.423%**	-0.747%***	-1.026%***	+0.056%^{ns}	+0.130%*	+0.100%*	+0.431%***	+0.536%***	+0.659%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

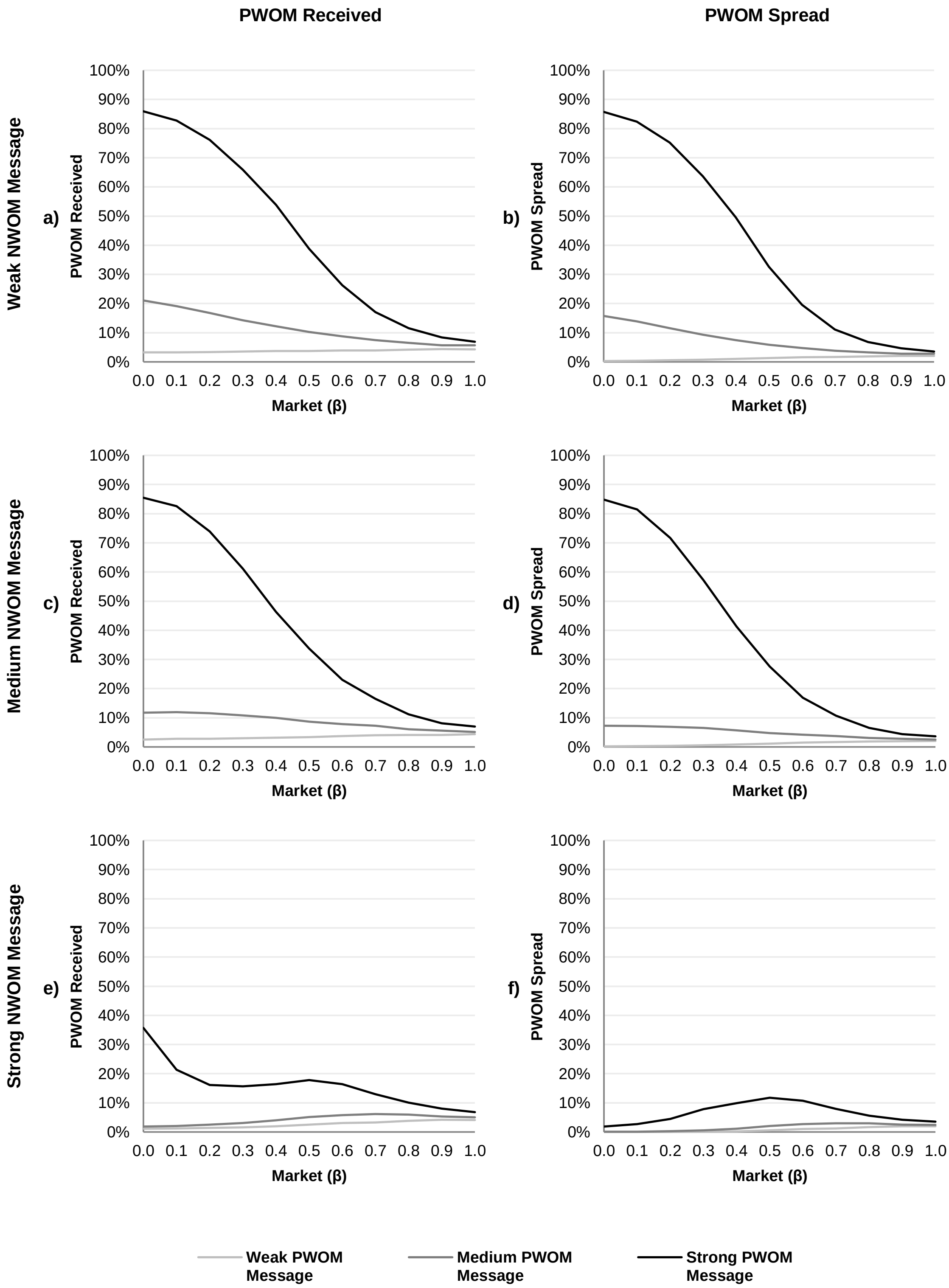

Figure 16. Share of OSN members who have received the PWOM message and are convinced of it for delayed countermeasure strategies with one seed.

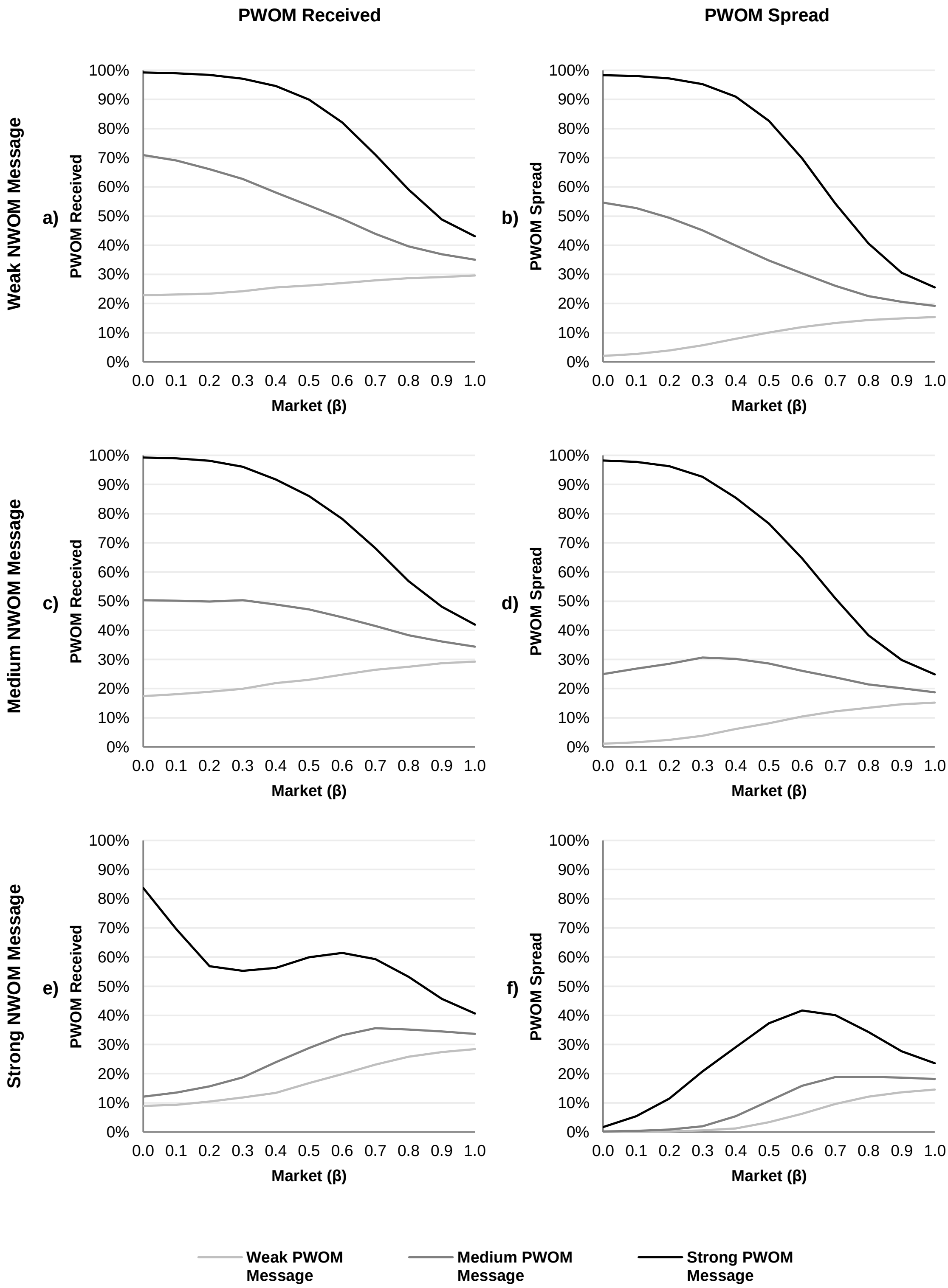

Figure 17. Share of OSN members who have received the PWOM message and are convinced of it for delayed countermeasure strategies with eight seeds.

2.7 Optimal Reaction Model: Extensions

2.7.1 Forwarding of Messages: Public Messaging with Rejuvenation

Due to today's lively usage of OSN, their members are confronted with an overwhelming number of messages and news resulting in an information overload (Canali and Lancellotti 2012, p. 28; Liang and Fu 2017, pp. 1-4). From the perspective of an OSN member, this impedes the filtering and processing of all received information, which can easily get lost in the masses and replaced by new information. This is reinforced by the fact that common ways of sharing information in OSN are public posts presented to all followers, which increases the volume of accessible information. Therefore, unlike in the base and purchase model, where private messaging is used to forward information, the optimal reaction model incorporates public messaging. Because messages are publicly shared, the perceived tie strength to an individual receiver is not considered in the forwarding process. However, an OSN member may still carefully consider whether to forward a received message by evaluating its timeliness and usefulness for his contacts with the aim of avoiding reputational damage. This could be caused by forwarding outdated, unnecessary, or not noteworthy information (Pescher et al. 2014, p. 47; Sohn 2014, pp. 145-146). Thus, a message has to offer a certain level of uniqueness and topicality in order to get forwarded. The perceived credibility C_{it}^{m} of a message may serve as a proxy for this because it is conceivable that a high degree of credibility makes a message more inimitable by drawing more attention. Hence, we define member i's forwarding probability FP_{it}^{m} of message m at time step t to be based on the message's credibility C_{it}^{m} and the individually perceived ageing factor AF_{it}:

$$FP_{it}^{m} = C_{it}^{m} \cdot AF_{it}, \qquad \forall i \in \{1, \dots, I : r_{it}^{m} = 1\} \tag{19}$$

Then, the actual forwarding decision FD_{it}^{m} of member i regarding message m at time step t is given by:

$$FD_{it}^{m} \sim \mathrm{Ber}(FP_{it}^{m}), \qquad \forall i \in V_{t}^{m,senders} \tag{20}$$

Like in the previous models, we still assume and require that a sender does not forward the message multiple times. By incorporating the forwarding decision FD_{it}^{m}, the set of potential senders in the OSN is changed to: $V_{t}^{m,senders} = \{i \in V : \sum_{j \in N_{i}^{following}} r_{ijt-1}^{\{+,-\}} \geq 1 \,\wedge\, CD_{it}^{\bar{m}} = 0 \,\wedge\, \sum_{\tau=1}^{t-1} FD_{i\tau}^{m} = 0\}$ $\forall t \geq 1$. If member i decides to share the message, all of his followers will receive it at the subsequent time step $t+1$ such that $r_{jit+1}^{m} = FD_{it}^{m}$ $\forall j \in N_{i}^{followers}$.

2.7.2 Optimal Reaction Strategy of the Firm

Confronted with an NWOM message that is being spread in an OSN, a firm can react to it in different ways. Based on the developed diffusion model, there are three adjusting levers for developing an appropriate countermeasure strategy:

(1) the persuasiveness of the PWOM message,
(2) the quantity of seeds, and
(3) the quality of seeds.

The persuasiveness of the PWOM message refers to the message's informational value that is represented by its argument quality AQ^+ and expressiveness EX^+. When launching a PWOM message, the firm has to decide on the number of seeds who initially disseminate it in the OSN. These seeds are characterised by a certain quality resulting from different nodal characteristics and positions in the OSN that determine their ability to exert influence on other OSN members (Mochalova and Nanopoulos 2014, pp. 2-3).

By taking a countermeasure against NWOM, the firm aims to increase the share of buyers in the OSN and thereby her profit. However, each countermeasure is tied to the costs for composing the message and the costs for activating the seeds. The former costs depend on the desired persuasiveness of the message and the time required for designing such a message. Let $f(AQ^+, EX^+)$ with $f: [0,1]^2 \rightarrow \{1, \ldots, T\}$ be a function that calculates the time in time steps that is needed to compose a message of argument quality AQ^+ and expressiveness EX^+. To determine the total composing costs, the resulting duration is multiplied by an hourly rate $HR, 0 < HR$, that is specified in monetary units per time step: $f(AQ^+, EX^+) \cdot HR$. The required message composing time also defines the PWOM message's time of emergence T^+ in the OSN.

The seed costs depend on the number of activated seeds $SN^+, 0 < SN^+$, and their quality. As mentioned above, the seed quality is based on nodal characteristics and positions that can be quantified by centrality measures (see Section 2.8.4 for further details). These are used for categorising OSN members into different seed quality classes SQ_k with $k = 1, \ldots, K$ that are associated with seed quality costs $C_{SQ_k}, 0 < C_{SQ_k}$, where $C_{SQ_1} < C_{SQ_2} < \cdots < C_{SQ_K}$. In this context, let $SQ^+ \in \{SQ_k: k = 1, \ldots, K\}$ be the selected PWOM seed quality class for the countermeasure and let $C_{SQ^+}, 0 < C_{SQ^+}$, describe its cost in monetary units. To limit the complexity of the firm's decision model, we restrict countermeasures to include only one PWOM seed quality class. Consequently, the seed costs of the countermeasure are given by $C_{SQ^+} \cdot SN^+$.

If a firm decides to react to NWOM, a change in the share of buyers ΔB_T occurs in comparison to the potentially reduced share of buyers that would have persisted if no countermeasures had been taken against NWOM. The impact of PWOM depends on the NWOM scenario that is depicted by the NWOM message and the quality of the NWOM seed: (AQ^-, EX^-, SQ^-) with $SQ^- \in \{SQ_k : k = 1, \ldots, K\}$. Let $P, 0 < P$, be the product contribution margin and recall that $|V|$ is the size of the OSN. Then, the revenue of the firm generated by the countermeasure strategy in a given NWOM scenario is calculated by: $\Delta B_T(AQ^+, EX^+, SQ^+, SN^+)_{AQ^-, EX^-, SQ^-} \cdot |V| \cdot P$. Based on this, the firm's overall goal is to maximise her profit Π resulting from the deployment of the countermeasure strategy in a given NWOM scenario:

$$\begin{aligned} &\text{Maximise } \Pi(AQ^+, EX^+, SQ^+, SN^+) = \\ &\quad \Delta B_T(AQ^+, EX^+, SQ^+, SN^+)_{AQ^-, EX^-, SQ^-} \cdot |V| \cdot P \\ &\quad -\big(f(AQ^+, EX^+) \cdot HR + C_{SQ^+} \cdot SN^+\big) \end{aligned} \tag{21}$$

2.8 Optimal Reaction Model: Numerical Analysis

2.8.1 Parameterisation

Because the seed quality and number of seeds are discrete variables, a differentiation of Equation (21) with respect to the firm's decision variables is not possible. Even though each one of all the possible SQ^+ and SN^+ combinations considered by itself would be differentiable, an analytical solution would still not be feasible since the change in the share of buyers ΔB_T is a stochastic function. Because of this, we analysed the propagation of different messages in a graph by simulation in order to numerically assess the resulting change in the share of buyers.

Instead of using artificially generated networks, as it was the case in the numerical analysis of the base and purchase model, a sub-graph of Facebook consisting of 63731 vertices and 817035 undirected edges (Viswanath et al. 2009) was used for obtaining more realistic results. In its original form, several isolated small islands existed in the used sub-graph that could not be reached from the rest of the network. In order to get a connected graph, we removed these islands from the dataset leading to 63392 vertices and 816886 edges that remained. For the cleansed Facebook dataset, the average path length and global clustering coefficient were $APL = 4.322$ and $GCC = 0.222$ respectively. These indicate that information travel fast in the network, and that social relationships are diversified due to the little overlapping of clusters. As a means of comparison, we also tested a much greater sub-graph of Facebook that consisted of 3097165 vertices and 23667394 undirected edges (Rossi and Ahmed 2015). The global clustering coefficient was smaller with $GCC = 0.097$ indicating a lower social cohesion in the network. However, the size of the network impeded the calculation of the average path length with the available resources. The bigger size also extended the computing time considerably by approximately 55 times. We therefore restricted the use of the larger sub-graph to NWOM scenarios without countermeasure.

Investigations regarding the sharing of links on Facebook have shown that the number of shares is halved every 3.2 hours (Krum 2013, p. 151). Thus, unlike in the parameterisation of the previous models, we set the half-life of both messages to $T^m_{1/2} = 3.2$ time steps, which can henceforth be interpreted as hours. The parameterisation of the remaining variables is consistent with the purchase model's parameterisation provided in Section 2.6.1. For all the following experiments, we conducted the simulation 500 times.

2.8.2 Non-Competitive Setting: NWOM Spread and Take-Offs in Different Markets

In order to compare different countermeasure strategies in terms of effectiveness, the impact of NWOM in the absence of PWOM needs to be determined. Like in the numerical analysis of the purchase model, we varied the informational value of an NWOM message $AQ^- = EX^- \in \{0.1, 0.2, \dots, 1.0\}$ for examining its propagation in different markets $\beta \in \{0.0, 0.1, \dots, 1.0\}$. The mean of the resulting NWOM spread and share of buyers for the small and large sub-graph of Facebook are depicted in Figure 18 and Figure 19 respectively. The corresponding numerical data with the standard deviation is listed in Table 16 and Table 17.

The results show that the more individualistic (collectivistic) a market is, the higher (lower) is the NWOM spread for a given message strength. While weak NWOM messages hardly propagate in collectivistic markets, they can still reach a substantial level of dissemination in individualistic markets. As discussed before, this is because in collectivistic markets people tend to closely observe the behaviour of their peers and are oriented towards their decisions. If a message is weak, it is perceived as credible only by a small share of OSN members and is therefore not able to build up sufficient peer pressure that is required for reaching a high credibility and wide diffusion. In individualistic markets, peer pressure plays a less important role, because of which even a rather weak message can get forwarded by a notable number of OSN members resulting in a comparatively higher spread. Figure 18 reveals for the smaller sub-graph that the effects of the message strength on the NWOM spread are non-linear in a given market. There are large marginal increases for $AQ^- = EX^- \leq 0.4$ that are gradually lessened for $0.4 < AQ^- = EX^-$. This cannot be observed for the larger sub-graph in Figure 19, where the distances are evenly distributed.

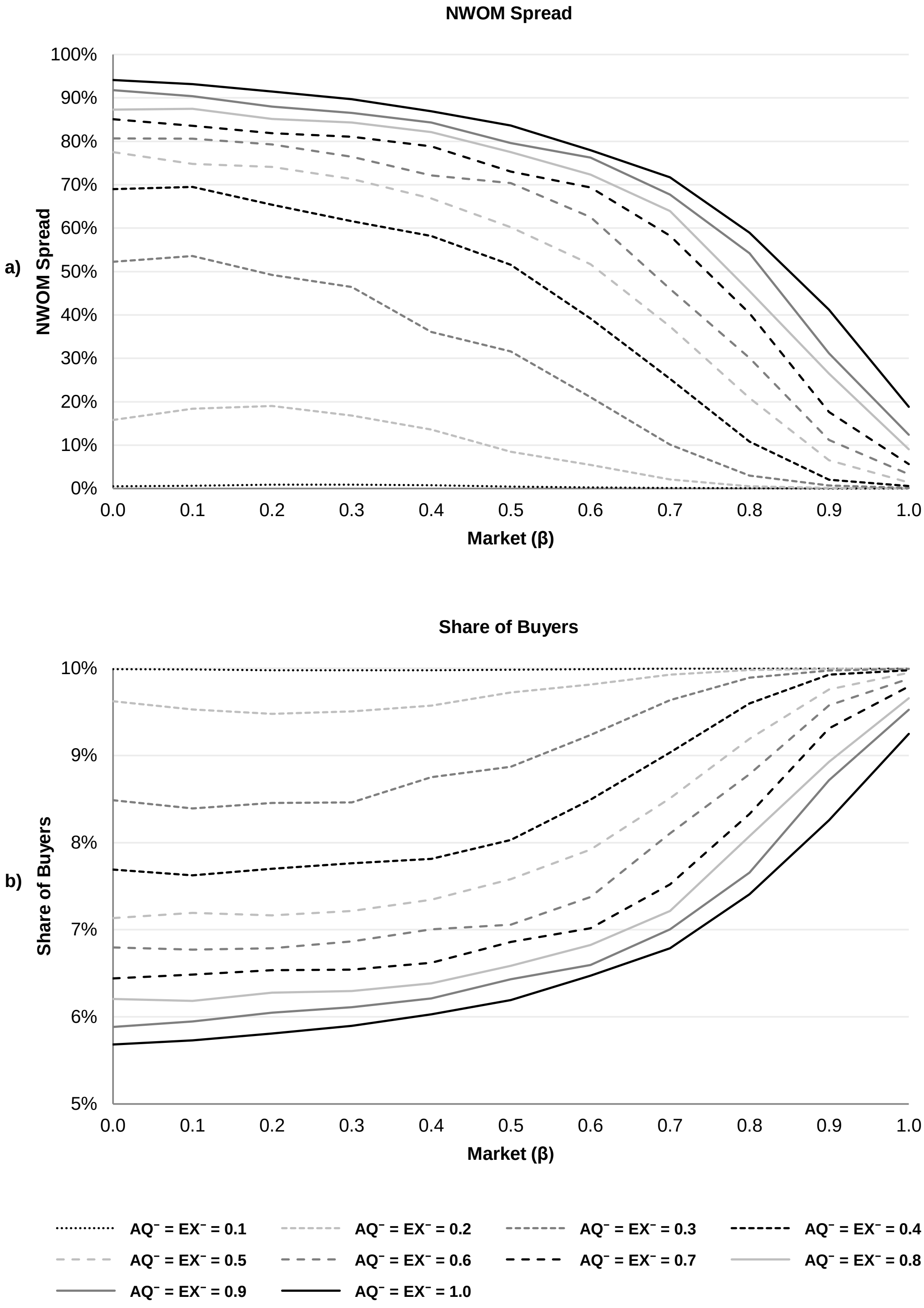

Figure 18. NWOM spread and share of buyers in the Facebook sub-graph with 63992 vertices.

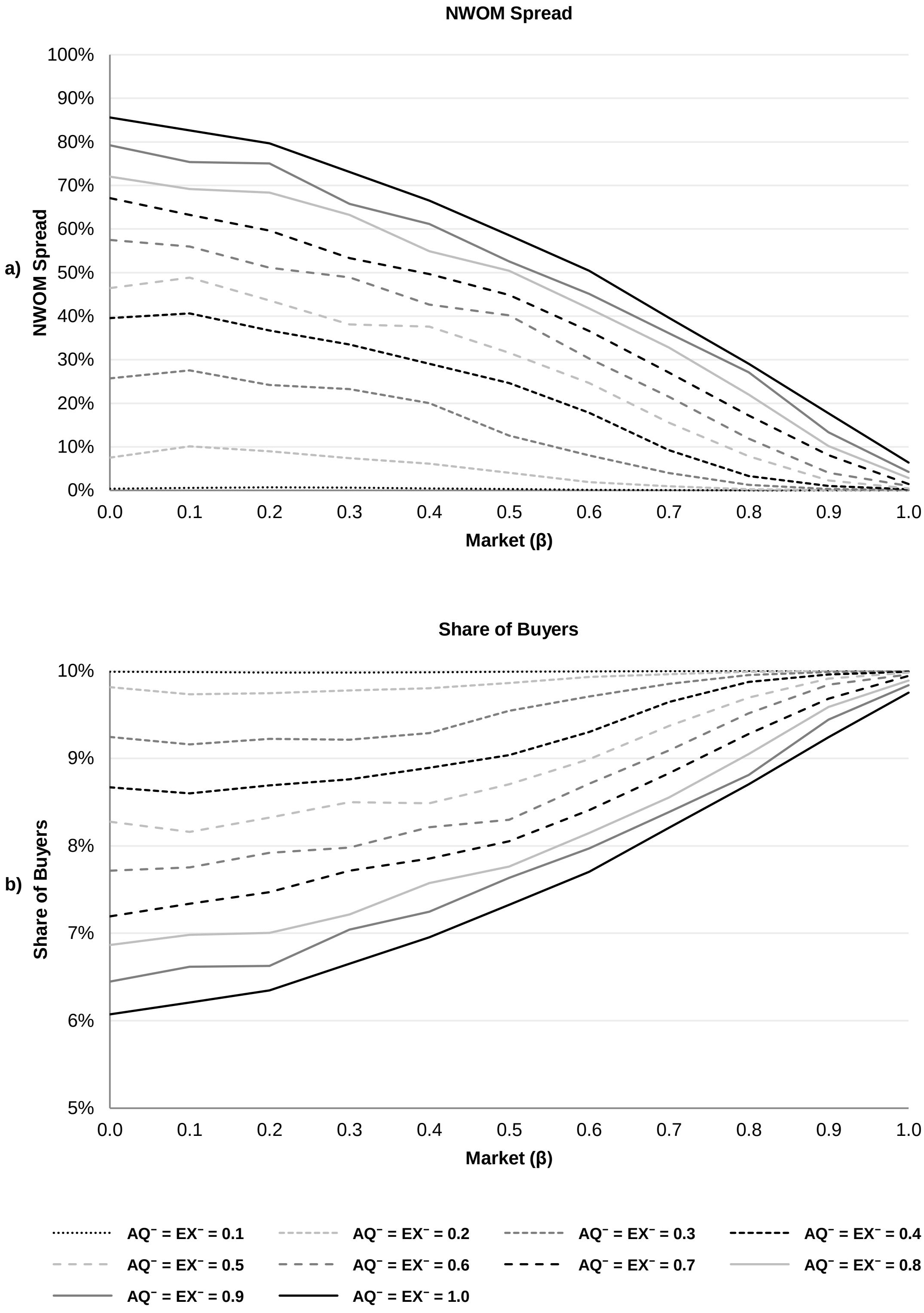

Figure 19. NWOM spread and share of buyers in the Facebook sub-graph with 3097165 vertices.

Table 16. Mean (standard deviation) of the NWOM spread and share of buyers in the Facebook sub-graph with 63992 vertices.

		NWOM spread and share of buyers for different NWOM messages and markets (β)										
		Highly Individualistic Markets										**Highly Collectivistic Markets**
	Message Strength	**β = 0.0**	**β = 0.1**	**β = 0.2**	**β = 0.3**	**β = 0.4**	**β = 0.5**	**β = 0.6**	**β = 0.7**	**β = 0.8**	**β = 0.9**	**β = 1.0**
NWOM Spread	**0.1**	0.504% (0.643%)	0.646% (0.967%)	0.917% (1.289%)	0.879% (1.432%)	0.774% (1.411%)	0.478% (0.968%)	0.291% (0.607%)	0.119% (0.282%)	0.059% (0.144%)	0.020% (0.051%)	0.015% (0.037%)
	0.2	15.803% (13.103%)	18.414% (15.205%)	19.020% (16.874%)	16.821% (16.764%)	13.599% (15.797%)	8.470% (11.791%)	5.440% (8.192%)	2.111% (4.003%)	0.521% (1.084%)	0.167% (0.412%)	0.049% (0.130%)
	0.3	52.228% (28.883%)	53.545% (28.514%)	49.226% (29.529%)	46.457% (29.466%)	36.053% (29.890%)	31.609% (26.341%)	21.067% (21.545%)	10.143% (13.369%)	2.985% (5.606%)	0.736% (1.472%)	0.154% (0.394%)
	0.4	69.003% (31.653%)	69.481% (30.382%)	65.356% (32.519%)	61.561% (33.187%)	58.198% (32.767%)	51.576% (30.903%)	39.184% (29.659%)	25.272% (24.227%)	10.794% (13.819%)	2.006% (4.045%)	0.586% (1.214%)
	0.5	77.516% (27.946%)	74.822% (30.355%)	74.120% (30.838%)	71.315% (32.060%)	66.823% (33.493%)	60.202% (34.358%)	51.663% (33.021%)	37.350% (30.227%)	20.843% (21.841%)	6.540% (10.035%)	1.427% (2.848%)
	0.6	80.652% (27.865%)	80.610% (27.558%)	79.287% (28.333%)	76.408% (30.538%)	72.131% (33.473%)	70.390% (31.940%)	62.515% (34.100%)	46.013% (33.375%)	30.091% (28.133%)	11.184% (15.536%)	3.281% (5.826%)
	0.7	85.101% (23.832%)	83.600% (26.056%)	81.851% (27.979%)	81.071% (28.321%)	78.829% (29.098%)	73.031% (32.886%)	69.358% (32.692%)	58.265% (33.845%)	40.342% (31.289%)	17.621% (20.750%)	5.613% (9.108%)
	0.8	87.279% (22.895%)	87.507% (22.194%)	85.133% (25.558%)	84.317% (25.965%)	82.121% (27.827%)	77.510% (31.208%)	72.338% (33.092%)	63.942% (34.442%)	45.462% (34.139%)	26.445% (26.190%)	9.034% (13.216%)
	0.9	91.798% (15.677%)	90.369% (18.517%)	88.011% (22.713%)	86.571% (24.214%)	84.315% (26.304%)	79.623% (30.402%)	76.246% (31.703%)	67.745% (34.254%)	54.228% (34.338%)	31.146% (29.112%)	12.418% (15.924%)
	1.0	94.125% (10.481%)	93.143% (13.398%)	91.457% (17.244%)	89.677% (20.638%)	86.934% (23.939%)	83.627% (27.351%)	77.923% (31.394%)	71.688% (33.454%)	58.967% (35.171%)	41.218% (31.544%)	18.854% (21.865%)
Share of Buyers	**0.1**	9.990% (0.013%)	9.986% (0.022%)	9.977% (0.032%)	9.976% (0.039%)	9.977% (0.042%)	9.985% (0.030%)	9.990% (0.020%)	9.996% (0.010%)	9.998% (0.005%)	9.999% (0.002%)	9.999% (0.001%)
	0.2	9.622% (0.320%)	9.529% (0.399%)	9.477% (0.478%)	9.506% (0.510%)	9.573% (0.514%)	9.723% (0.399%)	9.815% (0.289%)	9.927% (0.143%)	9.982% (0.038%)	9.994% (0.015%)	9.998% (0.005%)
	0.3	8.487% (0.842%)	8.391% (0.866%)	8.456% (0.944%)	8.462% (1.000%)	8.750% (1.066%)	8.870% (0.981%)	9.236% (0.815%)	9.635% (0.503%)	9.893% (0.208%)	9.974% (0.053%)	9.994% (0.014%)
	0.4	7.690% (1.062%)	7.623% (1.044%)	7.698% (1.153%)	7.762% (1.223%)	7.814% (1.252%)	8.031% (1.215%)	8.491% (1.190%)	9.033% (0.967%)	9.598% (0.539%)	9.928% (0.151%)	9.979% (0.044%)
	0.5	7.133% (1.035%)	7.194% (1.140%)	7.165% (1.183%)	7.216% (1.257%)	7.345% (1.344%)	7.580% (1.406%)	7.919% (1.369%)	8.508% (1.255%)	9.192% (0.892%)	9.756% (0.395%)	9.949% (0.106%)
	0.6	6.798% (1.107%)	6.771% (1.104%)	6.788% (1.150%)	6.865% (1.257%)	7.005% (1.397%)	7.059% (1.349%)	7.376% (1.455%)	8.106% (1.423%)	8.785% (1.182%)	9.574% (0.621%)	9.879% (0.225%)
	0.7	6.442% (0.997%)	6.486% (1.096%)	6.536% (1.185%)	6.542% (1.209%)	6.621% (1.253%)	6.859% (1.422%)	7.017% (1.423%)	7.522% (1.482%)	8.329% (1.351%)	9.310% (0.856%)	9.792% (0.358%)
	0.8	6.204% (0.996%)	6.185% (0.968%)	6.276% (1.119%)	6.298% (1.141%)	6.385% (1.227%)	6.587% (1.378%)	6.825% (1.467%)	7.216% (1.523%)	8.075% (1.496%)	8.928% (1.111%)	9.656% (0.530%)
	0.9	5.886% (0.703%)	5.947% (0.831%)	6.049% (1.020%)	6.111% (1.088%)	6.213% (1.183%)	6.431% (1.366%)	6.595% (1.425%)	7.004% (1.530%)	7.656% (1.526%)	8.715% (1.255%)	9.525% (0.648%)
	1.0	5.683% (0.481%)	5.729% (0.615%)	5.810% (0.790%)	5.896% (0.945%)	6.029% (1.094%)	6.193% (1.246%)	6.474% (1.425%)	6.788% (1.516%)	7.407% (1.579%)	8.256% (1.386%)	9.248% (0.918%)

Table 17. Mean (standard deviation) of the NWOM spread and share of buyers in the Facebook sub-graph with 3097165 vertices.

		NWOM spread and share of buyers for different NWOM messages and markets (β)										
		Highly Individualistic Markets										**Highly Collectivistic Markets**
	Message Strength	**β = 0.0**	**β = 0.1**	**β = 0.2**	**β = 0.3**	**β = 0.4**	**β = 0.5**	**β = 0.6**	**β = 0.7**	**β = 0.8**	**β = 0.9**	**β = 1.0**
NWOM Spread	**0.1**	0.406% (0.685%)	0.577% (0.999%)	0.695% (1.242%)	0.652% (1.261%)	0.461% (1.036%)	0.315% (0.706%)	0.152% (0.412%)	0.051% (0.181%)	0.013% (0.053%)	0.005% (0.023%)	0.002% (0.010%)
	0.2	7.530% (9.534%)	10.129% (11.363%)	8.982% (11.974%)	7.412% (10.727%)	6.124% (9.370%)	4.048% (6.189%)	1.892% (3.661%)	0.980% (1.856%)	0.272% (0.634%)	0.051% (0.184%)	0.019% (0.070%)
	0.3	25.741% (26.054%)	27.546% (25.920%)	24.181% (25.855%)	23.248% (24.611%)	20.061% (22.456%)	12.587% (17.483%)	8.045% (11.839%)	3.976% (6.590%)	1.254% (2.437%)	0.307% (0.717%)	0.070% (0.207%)
	0.4	39.537% (32.942%)	40.611% (31.978%)	36.700% (32.080%)	33.491% (30.981%)	29.044% (29.027%)	24.643% (26.587%)	17.793% (21.665%)	9.262% (13.650%)	3.313% (6.299%)	1.034% (2.000%)	0.257% (0.586%)
	0.5	46.445% (35.934%)	48.823% (34.786%)	43.564% (34.947%)	38.096% (34.734%)	37.579% (33.253%)	31.614% (31.318%)	24.650% (27.041%)	15.538% (20.958%)	7.854% (12.175%)	2.282% (3.989%)	0.443% (1.083%)
	0.6	57.474% (35.510%)	55.979% (35.607%)	51.087% (36.697%)	48.901% (35.943%)	42.661% (35.786%)	40.194% (34.173%)	30.270% (31.829%)	21.512% (26.422%)	11.908% (17.558%)	4.070% (7.244%)	1.031% (2.051%)
	0.7	67.061% (33.075%)	63.230% (35.106%)	59.661% (36.092%)	53.347% (37.287%)	49.680% (36.974%)	44.877% (35.881%)	36.557% (34.067%)	27.032% (29.626%)	17.184% (21.981%)	8.077% (11.833%)	1.487% (3.187%)
	0.8	71.996% (32.497%)	69.149% (34.080%)	68.330% (33.491%)	63.235% (35.304%)	54.897% (37.511%)	50.441% (36.907%)	41.779% (35.864%)	32.780% (32.639%)	21.980% (26.014%)	10.169% (15.294%)	2.842% (5.187%)
	0.9	79.207% (28.269%)	75.361% (31.292%)	75.015% (30.637%)	65.745% (36.075%)	61.131% (36.788%)	52.549% (38.078%)	45.116% (37.370%)	36.105% (34.459%)	27.084% (28.990%)	13.320% (19.070%)	4.250% (7.577%)
	1.0	85.603% (21.768%)	82.635% (25.472%)	79.666% (28.128%)	73.075% (32.973%)	66.548% (35.712%)	58.575% (37.475%)	50.431% (37.732%)	39.619% (36.036%)	29.084% (30.633%)	17.688% (22.491%)	6.367% (9.945%)
Share of Buyers	**0.1**	9.991% (0.015%)	9.986% (0.025%)	9.981% (0.034%)	9.981% (0.037%)	9.985% (0.034%)	9.989% (0.025%)	9.994% (0.015%)	9.998% (0.007%)	9.999% (0.002%)	10.000% (0.001%)	10.000% (0.000%)
	0.2	9.815% (0.236%)	9.733% (0.302%)	9.745% (0.342%)	9.775% (0.329%)	9.801% (0.307%)	9.861% (0.212%)	9.931% (0.132%)	9.963% (0.071%)	9.989% (0.025%)	9.998% (0.008%)	9.999% (0.003%)
	0.3	9.244% (0.766%)	9.160% (0.793%)	9.223% (0.836%)	9.212% (0.842%)	9.287% (0.807%)	9.543% (0.645%)	9.706% (0.441%)	9.852% (0.247%)	9.951% (0.094%)	9.988% (0.029%)	9.997% (0.009%)
	0.4	8.668% (1.111%)	8.598% (1.106%)	8.690% (1.148%)	8.761% (1.151%)	8.891% (1.114%)	9.036% (1.050%)	9.302% (0.866%)	9.645% (0.539%)	9.873% (0.245%)	9.959% (0.079%)	9.989% (0.024%)
	0.5	8.276% (1.334%)	8.159% (1.312%)	8.323% (1.346%)	8.498% (1.371%)	8.486% (1.343%)	8.705% (1.289%)	8.989% (1.122%)	9.369% (0.866%)	9.693% (0.486%)	9.912% (0.154%)	9.982% (0.044%)
	0.6	7.714% (1.412%)	7.752% (1.430%)	7.921% (1.494%)	7.980% (1.486%)	8.212% (1.501%)	8.297% (1.451%)	8.709% (1.363%)	9.090% (1.129%)	9.516% (0.732%)	9.843% (0.286%)	9.959% (0.081%)
	0.7	7.193% (1.385%)	7.338% (1.478%)	7.469% (1.532%)	7.717% (1.597%)	7.855% (1.597%)	8.051% (1.560%)	8.408% (1.488%)	8.831% (1.291%)	9.280% (0.941%)	9.681% (0.480%)	9.942% (0.124%)
	0.8	6.867% (1.414%)	6.982% (1.488%)	7.006% (1.468%)	7.217% (1.554%)	7.574% (1.658%)	7.764% (1.637%)	8.147% (1.593%)	8.553% (1.448%)	9.051% (1.138%)	9.587% (0.639%)	9.890% (0.202%)
	0.9	6.449% (1.268%)	6.618% (1.404%)	6.629% (1.377%)	7.041% (1.624%)	7.246% (1.658%)	7.632% (1.716%)	7.969% (1.683%)	8.384% (1.546%)	8.810% (1.290%)	9.442% (0.818%)	9.835% (0.301%)
	1.0	6.072% (0.999%)	6.209% (1.169%)	6.347% (1.290%)	6.651% (1.511%)	6.954% (1.635%)	7.324% (1.712%)	7.703% (1.719%)	8.206% (1.634%)	8.705% (1.374%)	9.243% (0.984%)	9.750% (0.397%)

Usually, the cumulative diffusion process in social networks follows an S-shaped curve where the rate of diffusion changes over time (Bass 1969, p. 219; Delre et al. 2007a, pp. 827-830; Leskovec et al. 2007, p. 6). In the phase of the greatest growth, a critical mass is reached that induces a *take-off* after which large parts of the network are impacted by the diffusion (Delre et al. 2007a, p. 827). In our experiments, the likelihood of a take-off increases with the message strength. When the informational value of a message surpasses a certain threshold, the critical mass is frequently reached in the conducted simulations leading to a higher average spread in the OSN. If the strength of an NWOM message is below this threshold, a take-off hardly occurs, which limits its spread. For the analysis of the non-competitive setting, we define take-offs as diffusions where at least 75% of the OSN members are convinced of the message. Table 18 and Table 19 show for each tested Facebook sub-graph the likelihood of take-offs, which is represented by the relative frequency of take-off occurrences across all simulation repetitions. In highly individualistic markets, the message strength threshold for triggering take-offs in the smaller sub-graph seems to be in the range of $0.3 \leq AQ^{-} = EX^{-} \leq 0.4$. The range is slightly increased in the larger sub-graph with $0.4 \leq AQ^{-} = EX^{-} \leq 0.5$. For highly collectivistic markets, the threshold range shifts towards the maximum message strength of 1.0 making take-offs less likely. For the subsequent examinations, we pick an *individualistic market* ($\beta = 0.3$) and a *collectivistic market* ($\beta = 0.7$), where we investigate the effects of a *weak NWOM message* ($AQ^{-} = EX^{-} = 0.2$), *medium NWOM message* ($AQ^{-} = EX^{-} = 0.6$), and *strong NWOM message* ($AQ^{-} = EX^{-} = 1.0$). Unlike in the experiments of the previous models, an informational value of 0.2 instead of 0.3 was chosen for the weak NWOM message in order to examine the impact of a message that does not cause take-offs.

Figure 20 and Figure 21 depict for the defined NWOM messages the time-dependent cumulative share of OSN members who have received the message as well as the cumulative share of members who are convinced of it (i.e. the NWOM spread). In the individualistic market, a significant share of members is reluctant to believe in the weak NWOM message upon reception. This is also reflected in the share of buyers, which is only slightly reduced. In the cases of a medium and strong NWOM message, almost all receivers are persuaded by the respective message leading to a greater reduction of the share of buyers. In the collectivistic market, there is a greater discrepancy between the reception of the messages and their ability to persuade OSN members, who are more sceptical of the received information. Even if the NWOM message is strong, a small share of members still remains unconvinced.

In sum, the results of this subsection indicate that the spread of not countered NWOM messages and their damaging effects on the share of buyers are considerably smaller in collectivistic markets.

Table 18. Likelihood of take-offs in the Facebook sub-graph with 63992 vertices.

	Frequency of diffusions across all 500 simulation repetitions in different markets (β) where an NWOM spread equal to or greater than 75% was reached										
	Highly Individualistic Markets										Highly Collectivistic Markets
Message Strength	**β = 0.0**	**β = 0.1**	**β = 0.2**	**β = 0.3**	**β = 0.4**	**β = 0.5**	**β = 0.6**	**β = 0.7**	**β = 0.8**	**β = 0.9**	**β = 1.0**
0.1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.3	1.80%	6.80%	9.40%	6.20%	1.40%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.4	81.00%	74.80%	74.00%	65.60%	44.60%	27.80%	4.60%	0.20%	0.00%	0.00%	0.00%
0.5	86.00%	86.60%	82.60%	76.40%	72.40%	64.40%	36.60%	5.60%	0.00%	0.00%	0.00%
0.6	89.80%	90.00%	87.00%	86.60%	82.40%	75.00%	63.40%	26.60%	1.80%	0.00%	0.00%
0.7	90.80%	93.00%	89.80%	87.80%	84.60%	82.80%	72.60%	48.80%	12.20%	0.00%	0.00%
0.8	94.00%	91.80%	93.00%	89.00%	89.40%	86.40%	81.00%	64.00%	26.00%	0.20%	0.00%
0.9	95.20%	96.40%	95.40%	93.00%	92.40%	88.60%	86.00%	70.20%	50.80%	5.00%	0.00%
1.0	98.00%	98.00%	97.00%	95.20%	91.80%	91.20%	87.60%	75.60%	60.60%	13.20%	0.00%

Table 19. Likelihood of take-offs in the Facebook sub-graph with 3097165 vertices.

	Frequency of diffusions across all 500 simulation repetitions in different markets (β) where an NWOM spread equal to or greater than 75% was reached										
	Highly Individualistic Markets										Highly Collectivistic Markets
Message Strength	**β = 0.0**	**β = 0.1**	**β = 0.2**	**β = 0.3**	**β = 0.4**	**β = 0.5**	**β = 0.6**	**β = 0.7**	**β = 0.8**	**β = 0.9**	**β = 1.0**
0.1	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.2	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.3	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.4	0.60%	0.20%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.5	27.40%	25.80%	16.20%	7.40%	3.60%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.6	61.40%	59.40%	47.80%	35.80%	19.00%	7.00%	0.20%	0.00%	0.00%	0.00%	0.00%
0.7	79.40%	74.80%	69.00%	57.20%	46.00%	26.00%	5.40%	0.20%	0.00%	0.00%	0.00%
0.8	82.80%	80.20%	79.40%	74.60%	61.80%	45.60%	20.40%	2.60%	0.00%	0.00%	0.00%
0.9	88.80%	85.40%	85.80%	76.60%	71.40%	58.00%	35.80%	7.60%	0.20%	0.00%	0.00%
1.0	94.00%	91.40%	89.00%	83.20%	77.00%	66.40%	51.60%	18.20%	0.20%	0.00%	0.00%

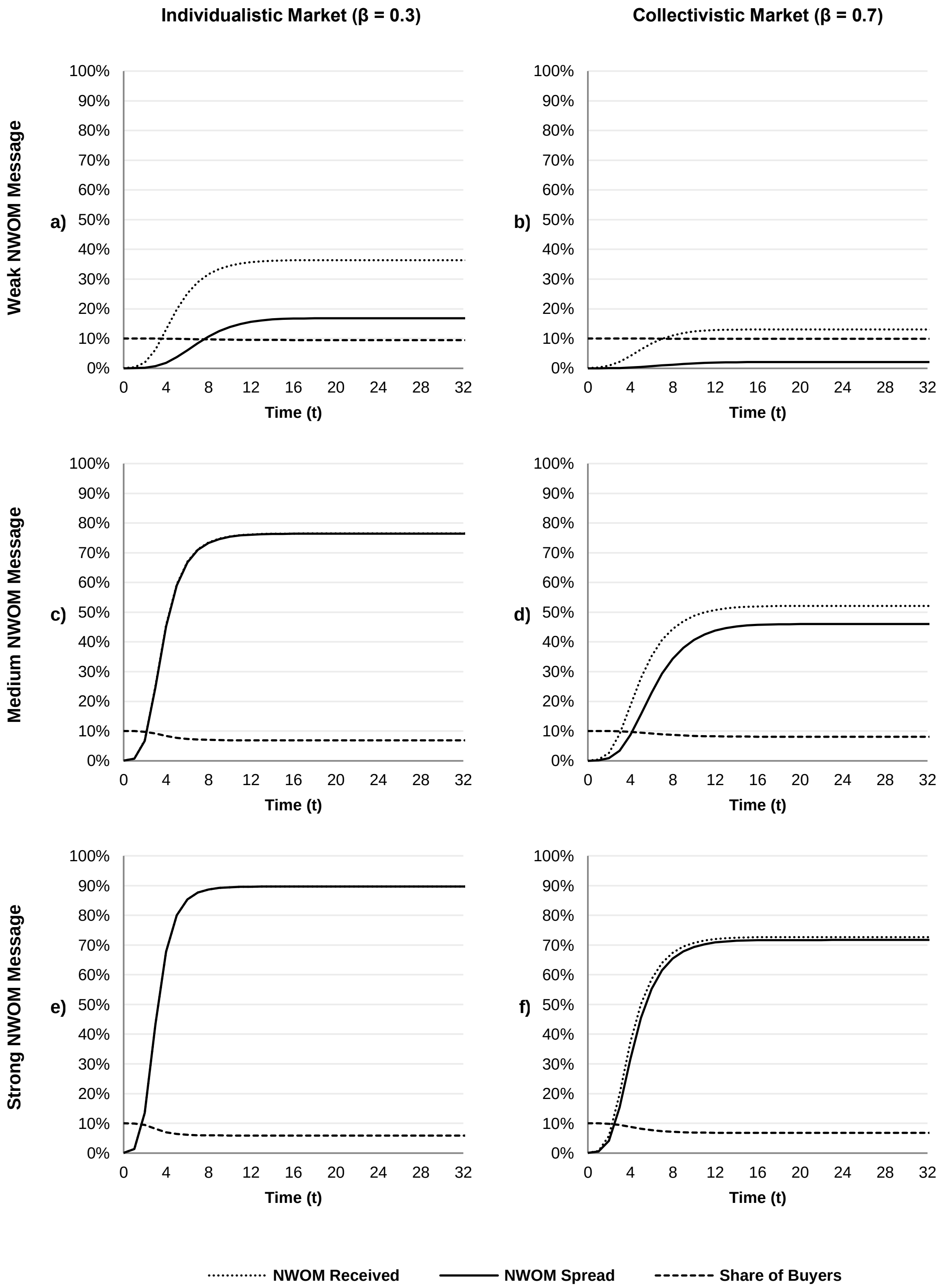

Figure 20. NWOM spread and share of buyers development over time for an individualistic and collectivistic market in the Facebook sub-graph with 63992 vertices.

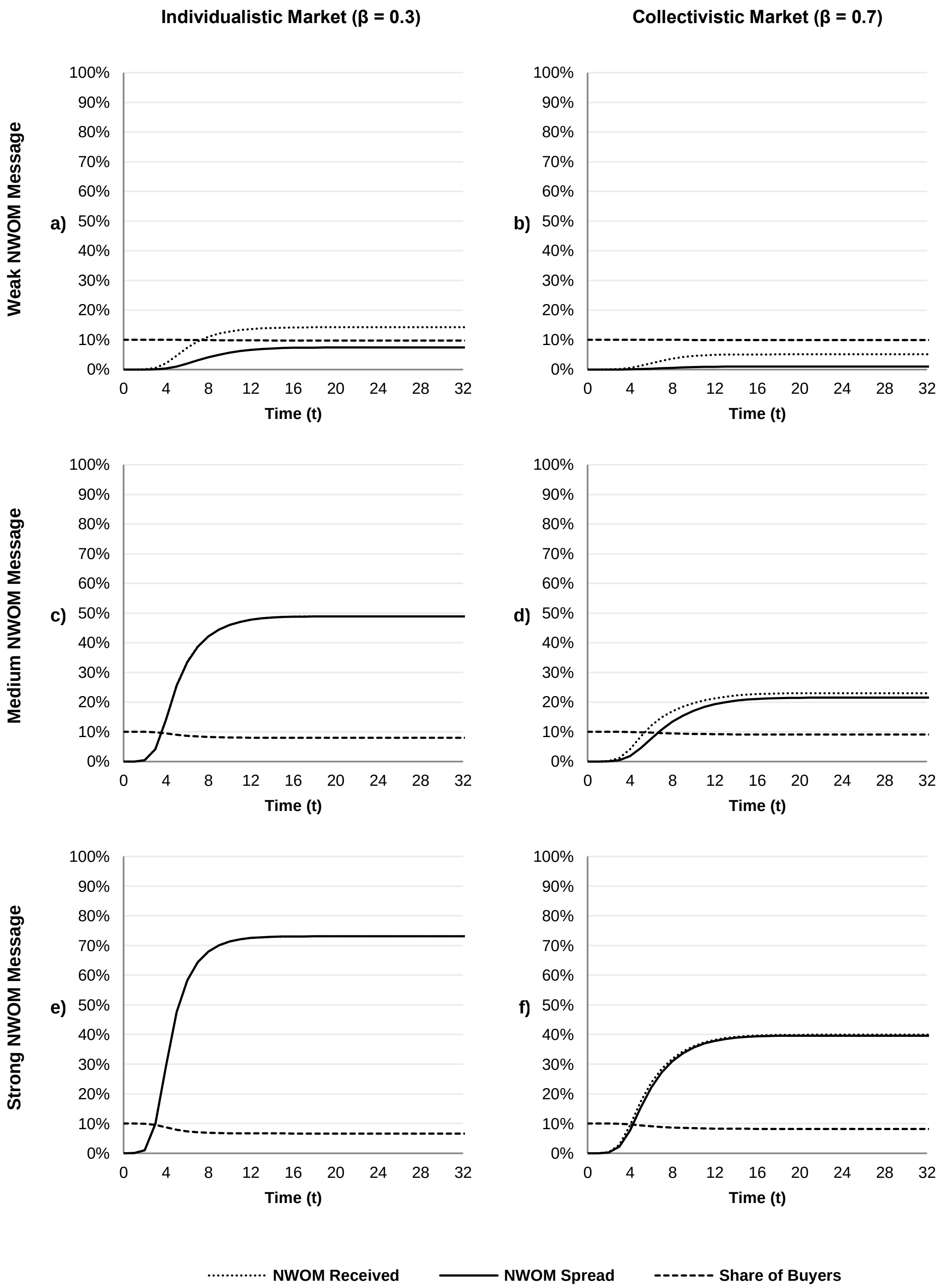

Figure 21. NWOM spread and share of buyers development over time for an individualistic and collectivistic market in the Facebook sub-graph with 3097165 vertices.

2.8.3 Competitive Setting: Influence of Message Strength, Delay, and Seed Quantity

A firm may react to an NWOM message by composing a PWOM message and spreading it in the OSN. As the experiments of the previous models have shown, firms are usually better advised not to react immediately to an identified NWOM message but to take time to design a well-developed and persuasive PWOM message. For maximising the response's spread, a firm may also activate multiple seeds. In the following, we will concentrate on the smaller Facebook sub-graph with 63392 vertices, where we tested the effectiveness of different countermeasure strategies that were varied in terms of message strength, response delay, and seed quantity. For this, we defined a *weak PWOM message* ($AQ^{+} = EX^{+} = 0.2$), *medium PWOM message* ($AQ^{+} = EX^{+} = 0.6$), and *strong PWOM message* ($AQ^{+} = EX^{+} = 1.0$). These were used by the firm to react to NWOM with one or ten seeds and a delay of two or 24 time steps (hours). The resulting NWOM spread and share of buyers are depicted with their standard deviation in Figure 22 and Figure 23 respectively. The changes of the NWOM spread and share of buyers caused by the countermeasures in comparison to the no-response strategy were tested for statistical significance. The results for the individualistic and collectivistic market are listed in Table 20 and Table 21 respectively. Unintended and counterproductive effects (i.e. an additional increase of the NWOM spread or an additional decrease in the share of buyers) are shaded grey in the tables. Even though the results of the previous subsection indicated that NWOM is less damaging in the collectivistic market, the share of buyers data provided in the above-mentioned tables reveals that the tested countermeasure strategies are also less effective. In the collectivistic market, the share of buyers was, on average, increased by +0.572%, which is in relative terms 46.988% less than the average increase of +1.079% in the individualistic market.

The share of buyers results depicted in Figure 23 indicate that in some cases a delayed response yields the same outcome as a quickly launched message. For instance, if the firm is able to counter a weak NWOM message with a strong PWOM response, she does not need to be concerned about a delay because it hardly affects the share of buyers as shown in Figure 23a/b. With increasing NWOM message strength, the response speed becomes more important. Particularly in the cases of a strong NWOM message depicted in Figure 23e/f, a delay eliminates most of the effects of a strong response in both markets and should therefore be avoided. The changes evoked by the increased response delay of the countermeasure were also tested for statistical significance and are listed in Table 22. The average reduction of the share of buyers caused by the delay was -0.234% in the individualistic market. The results suggest that a delay is more harmful in the collectivistic market, where the average reduction was in relative terms 27.350% greater with -0.298%. This is because the delayed message is confronted with a solidified social agglomerate where the negative message has already gained the upper hand leaving no room for opposing opinions.

For investigating the effects of an increased number of seeds, Table 23 provides a statistical analysis of the differences that occur when ten seeds instead of one are deployed in the defined countermeasure strategies. In both markets, multiple seeds mostly have a statistically significant impact on the share of buyers if the PWOM message is stronger than the NWOM message. This also applies if both messages are strong, but only if the firm reacts quickly. If there is a high discrepancy between the strengths of the two messages like in the case of a weak NWOM message that is countered by a strong PWOM message (highlighted in bold), multiple seeds lead to a rather small additional increase in the share of buyers irrespective of the delay. It can be argued that one seed already suffices to utilise most of the strong response's potential in such cases.

Table 23 also reveals that the response delay has a moderating effect on the effectiveness of activating multiple seeds, which is more pronounced in the collectivistic market. For instance, if the firm reacts to a medium NWOM message with a strong PWOM message, a prolonged reaction time can make the activation of multiple seeds lose its significant effect in the collectivistic but not in the individualistic market (highlighted in italic). In fact, in the individualistic market an increased delay appears to positively influence the usage of multiple seeds as long as the counter-message is stronger than the NWOM message. Note that this does not mean that the firm should favour a delay over a quick reaction in order to make the usage of multiple seeds more effective. Instead, it implies that in the individualistic market multiple seeds are, despite the delay, able to increase the share of buyers and thereby make up for the longer reaction time. This can hardly be observed in the collectivistic market, where the reaction speed seems to be of pivotal importance. Although the normative social influence is higher valued in this market, multiple seeds cannot compensate for an increased response delay (see Figure 23d for a visualisation of this matter). Aside from this finding, the activation of multiple seeds is more worthwhile in the collectivistic market, where, on average, the share of buyers was increased by +6.225%, which is in relative terms 67.339% more than the increase in the individualistic market with +3.720%.

The remaining results listed in Table 23 as well as Table 20 and Table 21 further show that the activation of multiple seeds can have counterproductive effects. Using a weak PWOM message mostly yields unintended results by triggering new waves of NWOM in the OSN even if the firm reacts quickly. These results confirm that the findings of the purchase model also hold in larger graphs with real-world OSN structure. As Table 20 and Table 21 reveal, the triggering effect and its negative consequences on the NWOM spread and share of buyers are reinforced in most of the shaded cases if the counter-message is disseminated by multiple seeds. This is also reflected in the message reception statistics provided in the tables that demonstrate the perils of premature and unsubstantial responses to NWOM. Suppose, for example, that the firm reacts to a weak NWOM message with a likewise weak PWOM message in the individualistic market (first data row in Table 20). The NWOM spread is not only increased from formerly 16.821% to 25.002%, but the share of OSN members who have received at least one message is more than twice as high with 58.284%. Despite the fact that a majority of these members only received the PWOM message, they nevertheless got informed of the topic and made aware that "something went wrong" to the extent that the firm was required to issue a statement. Even though it was not explicitly modelled in this study, the long-term behaviour of potential customers could be affected by such information. A firm should therefore carefully consider whether to react to NWOM with weak counter-messages.

Table 20 and Table 21 also include statistics for the tested scenarios that concern the recovery of formerly negatively influenced OSN members who are saved by the countermeasure. For determining the recovery effect of PWOM, at first a conceptualisation of NWOM's potential damage is needed. If no countermeasures are taken, the NWOM spread is progressive, i.e. an OSN member who has been convinced of the NWOM message will not revise his opinion. We therefore define the potential damage as the share of OSN members who have believed in the NWOM message at least once during the examined time horizon. A negatively influenced OSN member is regarded as recovered if his purchase probability is equal to or greater than his initial purchase probability at the end of the time horizon. This is the case if he changes his mind upon receiving PWOM and either remains indifferent or believes in the counter-message. If the recovered (absolute) share of OSN members is subtracted from the potential damage, it equals the actual NWOM spread. Small deviations in the tables stem from rounding the statistics to three decimal places. The cases where in relative terms at least 30% of the potential damage could be reversed are highlighted in bold and prove that the recovery is more difficult in collectivistic markets. The listed statistics further indicate that a high rate of recovery can in most cases only be achieved if the counter-message is stronger than the NWOM message, which underlines the importance of the informational value of the response. The damage can hardly be undone if a weak PWOM message is used. If a strong NWOM message is to be countered, the firm is compelled to react with a likewise strong response. Even though the recovery rates are negligibly low in such cases, the response still increases the share of buyers by acquiring new customers and thereby helps to mitigate the economic damage of a strong NWOM message. For best results, the firm should therefore opt for a PWOM response that is, as far as possible, stronger than the NWOM message.

However, designing a strong PWOM message that adequately addresses and deals with the complaints included in the NWOM message will conceivably take more time than issuing a statement with a weak counter-message. Thus, firms typically face the dilemma of choosing between reacting to NWOM as soon as possible (Mochalova and Nanopoulos 2014, pp. 10-11; van Laer and de Ruyter 2010, p. 164; van Noort and Willemsen 2012, p. 131) and a high-quality response that resolves the issue and limits the risk of provoking more NWOM (Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92). In this context, the black dotted lines in Figure 22 and Figure 23 mark the level of a strong delayed PWOM message (i.e. $AQ^{+} = EX^{+} = 1.0$ and $D = 24t$) that is emitted by one seed. In most of the shown cases, it outperforms weaker PWOM messages that are sent out almost immediately (i.e. $D = 2t$). The differences of these messages to the strong delayed PWOM message were tested for statistical significance, for which the results are given in Table 24. In regard to the share of buyers, the strong delayed PWOM message yields equivalent or better results than the weaker PWOM messages in the individualistic market even if the number of involved seeds is increased to ten, which holds irrespective of the delay. This also applies to the collectivistic market but unreservedly only holds for the comparison with the weak PWOM message. If a medium PWOM message is deployed by ten seeds in the collectivistic market, it might outperform the strong delayed PWOM message launched by one seed.

To summarise, the performance examinations of different countermeasure strategies in this subsection indicate that in the individualistic market the message strength is more important than a quick reaction or using multiple seeds. These latter points have higher relevance in the collectivistic market, where a quick and possibly weaker reaction with multiple seeds is sometimes superior to a delayed strong PWOM message launched by one seed.

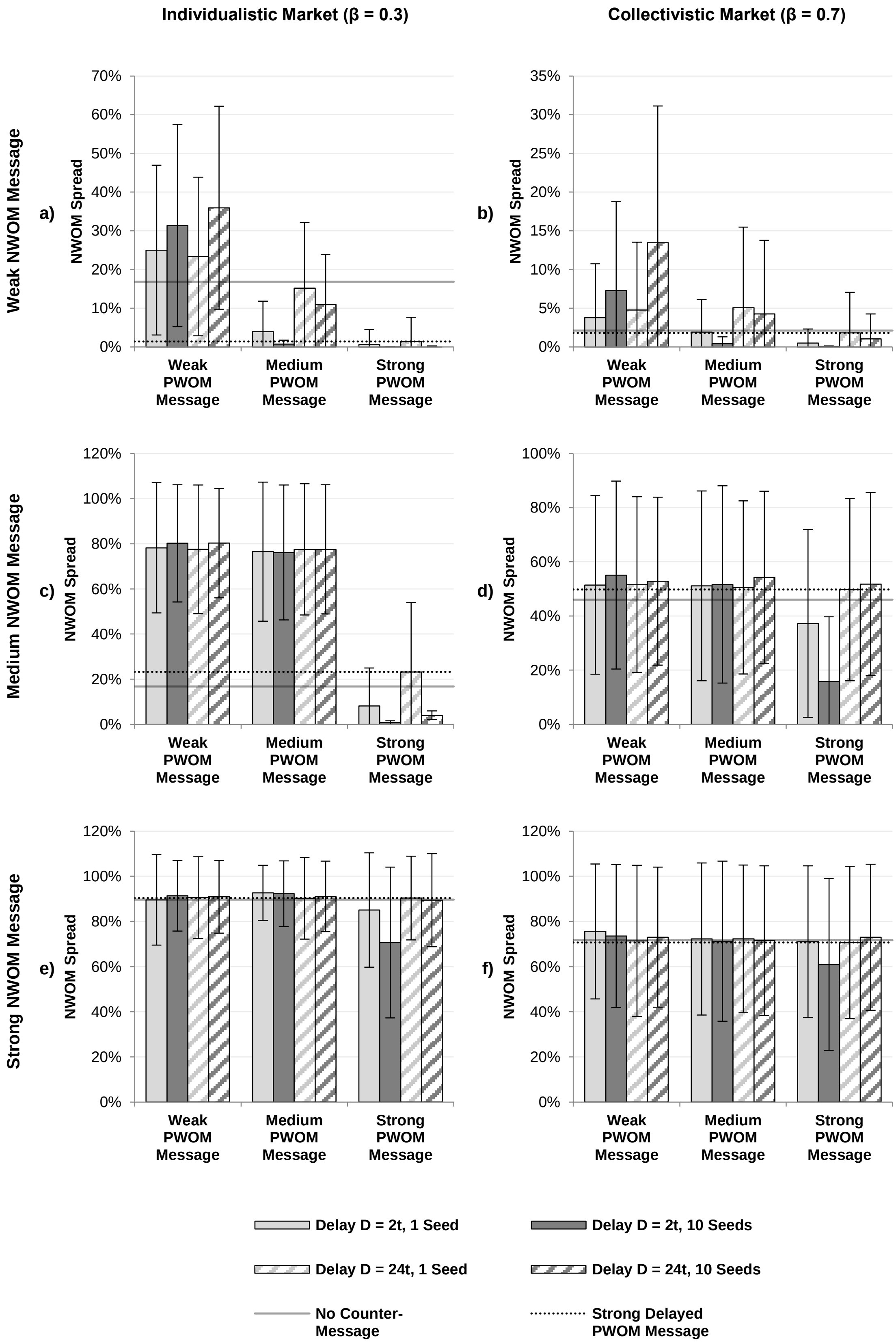

Figure 22. Effects of varied response delay and seed quantity on the NWOM spread.

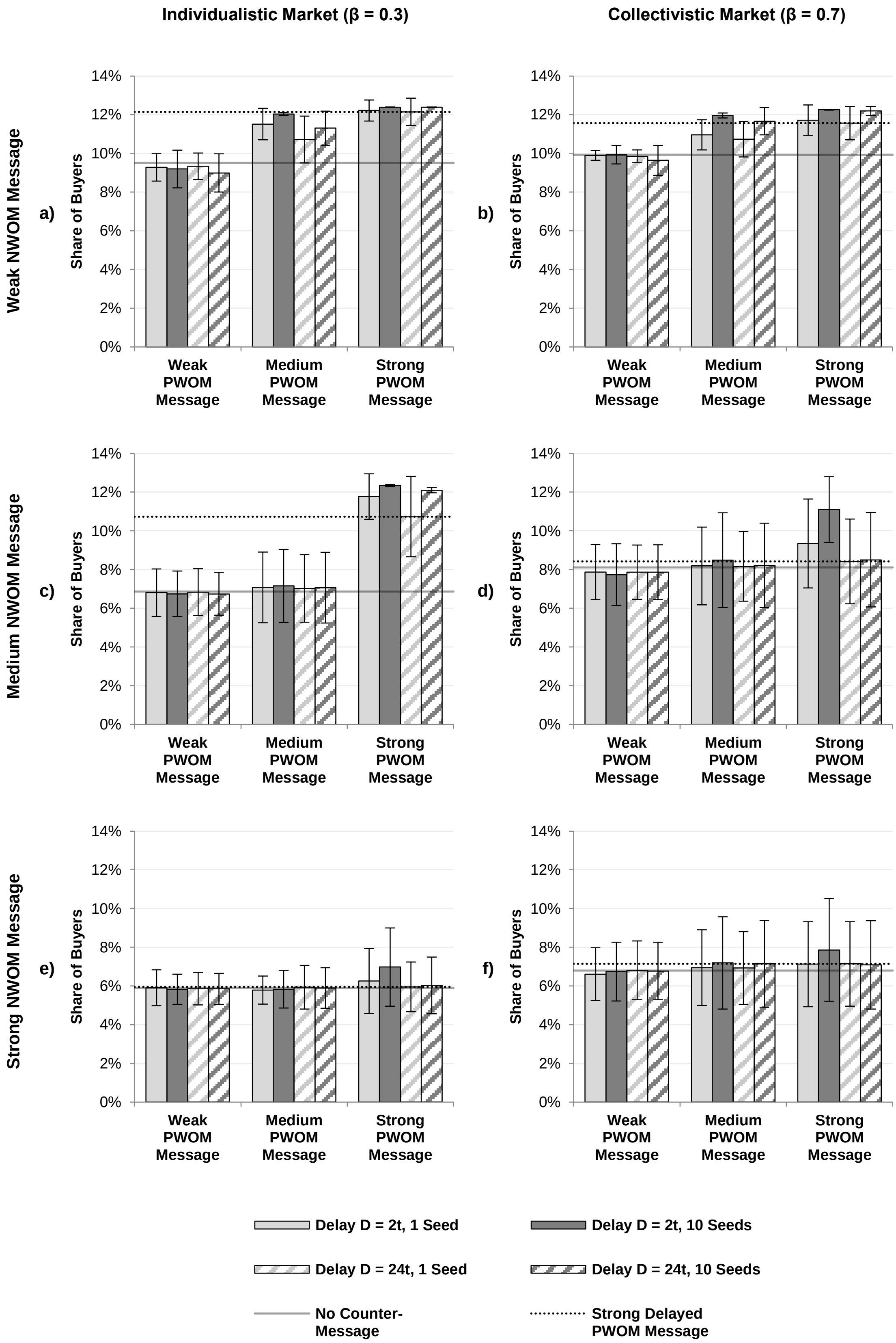

Figure 23. Effects of varied response delay and seed quantity on the share of buyers.

Table 20. Statistical analysis of the defined countermeasure strategies' performance in the individualistic market.

				Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the defined countermeasure strategies									
				Countermeasure (Difference to No-Response Strategy)			Message Reception Statistics				Recovery Statistics		
NWOM Message	**PWOM Message**	**Delay (t)**	**Seeds**	**NWOM Spread**	**Share of Buyers**	**PWOM Spread**	**Received NWOM**	**Received PWOM**	**Received Both**	**Received at Least One**	**Potential Damage**	**Recovered (Absolute)**	**Recovered (Relative)**
Weak NWOM	**Weak PWOM**	**2**	**1**	25.002% (+8.181%***)	9.283% (-0.223%***)	2.128%	43.848%	36.002%	21.566%	58.284%	25.099%	0.098%	0.389%
			10	31.357% (+14.536%***)	9.195% (-0.311%***)	8.066%	48.920%	69.586%	40.232%	78.274%	31.659%	0.302%	0.954%
		24	**1**	23.348% (+6.527%***)	9.332% (-0.173%***)	1.867%	42.085%	24.541%	9.983%	56.643%	23.377%	0.029%	0.125%
			10	35.951% (+19.129%***)	8.991% (-0.515%***)	5.800%	51.568%	50.921%	26.795%	75.694%	36.056%	0.105%	0.292%
	Medium PWOM	**2**	**1**	3.935% (-12.887%***)	11.511% (+2.006%***)	67.275%	32.383%	77.562%	28.001%	81.945%	8.294%	4.359%	**52.560%**
			10	0.742% (-16.080%***)	12.036% (+2.531%***)	84.801%	26.096%	92.544%	25.889%	92.751%	3.286%	2.544%	**77.431%**
		24	**1**	15.172% (-1.649%^{ns})	10.721% (+1.215%***)	49.867%	43.436%	67.912%	31.420%	79.928%	23.920%	8.747%	**36.569%**
			10	10.939% (-5.882%***)	11.303% (+1.797%***)	68.661%	49.539%	88.559%	46.104%	91.995%	28.274%	17.335%	**61.312%**
	Strong PWOM	**2**	**1**	0.594% (-16.227%***)	12.219% (+2.713%***)	90.117%	21.729%	90.339%	20.396%	91.671%	3.535%	2.940%	**83.190%**
			10	0.015% (-16.806%***)	12.388% (+2.882%***)	96.222%	12.436%	96.342%	12.421%	96.356%	0.999%	0.983%	**98.452%**
		24	**1**	1.429% (-15.393%***)	12.146% (+2.641%***)	88.224%	39.505%	88.462%	36.793%	91.175%	18.992%	17.563%	**92.478%**
			10	0.107% (-16.714%***)	12.383% (+2.878%***)	96.168%	37.487%	96.303%	37.380%	96.410%	17.393%	17.286%	**99.385%**
Medium NWOM	**Weak PWOM**	**2**	**1**	78.214% (+1.806%^{ns})	6.801% (-0.063%^{ns})	0.576%	78.312%	7.065%	1.903%	83.474%	78.214%	0.000%	0.001%
			10	80.210% (+3.802%*)	6.745% (-0.120%^{ns})	1.542%	80.454%	18.390%	11.144%	87.700%	80.214%	0.004%	0.005%
		24	**1**	77.567% (+1.160%^{ns})	6.834% (-0.031%^{ns})	0.413%	77.716%	5.272%	1.596%	81.392%	77.569%	0.002%	0.002%
			10	80.297% (+3.889%*)	6.747% (-0.118%^{ns})	1.342%	80.610%	9.619%	3.244%	86.984%	80.302%	0.006%	0.007%
	Medium PWOM	**2**	**1**	76.511% (+0.103%^{ns})	7.078% (+0.213%*)	9.316%	78.017%	19.861%	10.305%	87.572%	76.625%	0.115%	0.150%
			10	76.142% (-0.266%^{ns})	7.151% (+0.286%**)	12.071%	80.748%	42.819%	31.578%	91.990%	76.569%	0.427%	0.558%
		24	**1**	77.514% (+1.106%^{ns})	7.024% (+0.159%*)	8.418%	78.695%	10.095%	1.537%	87.253%	77.564%	0.051%	0.065%
			10	77.514% (+1.106%^{ns})	7.069% (+0.204%*)	10.287%	79.273%	12.830%	2.846%	89.257%	77.551%	0.037%	0.047%
	Strong PWOM	**2**	**1**	8.150% (-68.258%***)	11.775% (+4.910%***)	84.988%	69.069%	88.193%	62.788%	94.475%	60.185%	52.035%	**86.458%**
			10	0.800% (-75.607%***)	12.340% (+5.475%***)	95.601%	54.228%	96.046%	53.631%	96.643%	34.950%	34.150%	**97.710%**
		24	**1**	23.267% (-53.141%***)	10.734% (+3.869%***)	68.109%	79.112%	73.256%	58.907%	93.462%	78.600%	55.333%	**70.399%**
			10	4.037% (-72.371%***)	12.105% (+5.240%***)	91.488%	79.142%	93.478%	76.226%	96.395%	78.320%	74.283%	**94.846%**
Strong NWOM	**Weak PWOM**	**2**	**1**	89.541% (-0.136%^{ns})	5.906% (+0.011%^{ns})	0.113%	89.545%	2.986%	1.716%	90.815%	89.541%	0.000%	0.000%
			10	91.377% (+1.700%^{ns})	5.831% (-0.065%^{ns})	0.487%	91.403%	9.401%	7.173%	93.632%	91.377%	0.000%	0.000%
		24	**1**	90.586% (+0.909%^{ns})	5.856% (-0.039%^{ns})	0.078%	90.589%	1.124%	0.379%	91.333%	90.586%	0.000%	0.000%
			10	90.949% (+1.272%^{ns})	5.851% (-0.045%^{ns})	0.499%	90.970%	4.117%	1.804%	93.283%	90.949%	0.000%	0.000%
	Medium PWOM	**2**	**1**	92.658% (+2.980%**)	5.784% (-0.112%*)	0.999%	92.728%	5.688%	4.598%	93.818%	92.659%	0.002%	0.002%
			10	92.278% (+2.600%*)	5.833% (-0.063%^{ns})	2.374%	92.446%	20.017%	17.517%	94.946%	92.280%	0.002%	0.002%
		24	**1**	90.242% (+0.565%^{ns})	5.935% (+0.039%^{ns})	2.622%	90.413%	4.803%	1.955%	93.261%	90.244%	0.002%	0.002%
			10	91.089% (+1.412%^{ns})	5.897% (+0.001%^{ns})	2.648%	91.253%	5.151%	2.359%	94.046%	91.090%	0.001%	0.001%
	Strong PWOM	**2**	**1**	85.062% (-4.615%***)	6.259% (+0.363%***)	6.178%	89.518%	20.782%	15.362%	94.938%	87.147%	2.085%	2.393%
			10	70.684% (-18.993%***)	6.980% (+1.085%***)	8.778%	89.411%	49.035%	42.271%	96.174%	80.408%	9.724%	12.093%
		24	**1**	90.351% (+0.674%^{ns})	5.954% (+0.058%^{ns})	3.568%	90.361%	3.787%	0.214%	93.935%	90.358%	0.007%	0.007%
			10	89.419% (-0.259%^{ns})	6.027% (+0.132%*)	4.827%	89.562%	6.636%	1.887%	94.310%	89.474%	0.055%	0.061%

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 21. Statistical analysis of the defined countermeasure strategies' performance in the collectivistic market.

				Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the defined countermeasure strategies									
				Countermeasure (Difference to No-Response Strategy)			**Message Reception Statistics**				**Recovery Statistics**		
NWOM Message	**PWOM Message**	**Delay (t)**	**Seeds**	**NWOM Spread**	**Share of Buyers**	**PWOM Spread**	**Received NWOM**	**Received PWOM**	**Received Both**	**Received at Least One**	**Potential Damage**	**Recovered (Absolute)**	**Recovered (Relative)**
Weak NWOM	**Weak PWOM**	**2**	**1**	3.772% (+1.661%***)	9.894% (-0.033%**)	1.184%	16.644%	15.252%	5.956%	25.940%	3.800%	0.028%	0.738%
			10	7.284% (+5.172%***)	9.931% (+0.004%^{ns})	8.368%	22.380%	48.405%	17.697%	53.088%	7.490%	0.206%	2.752%
		24	**1**	4.756% (+2.644%***)	9.847% (-0.080%***)	0.833%	17.416%	13.593%	5.924%	25.085%	4.775%	0.020%	0.411%
			10	13.472% (+11.361%***)	9.637% (-0.290%***)	6.544%	26.793%	45.801%	18.476%	54.118%	13.588%	0.116%	0.853%
	Medium PWOM	**2**	**1**	1.907% (-0.205%^{ns})	10.964% (+1.037%***)	42.253%	17.105%	57.027%	13.087%	61.045%	2.935%	1.028%	**35.032%**
			10	0.425% (-1.686%***)	11.959% (+2.032%***)	80.236%	15.662%	87.764%	15.458%	87.967%	1.696%	1.271%	**74.939%**
		24	**1**	5.067% (+2.955%***)	10.733% (+0.806%***)	37.982%	21.507%	53.975%	16.258%	59.224%	6.829%	1.762%	**25.805%**
			10	4.246% (+2.135%***)	11.661% (+1.734%***)	74.559%	24.960%	86.561%	23.519%	88.001%	8.426%	4.180%	**49.605%**
	Strong PWOM	**2**	**1**	0.513% (-1.598%***)	11.713% (+1.786%***)	69.946%	13.423%	74.670%	11.641%	76.452%	1.382%	0.869%	**62.859%**
			10	0.046% (-2.065%***)	12.259% (+2.332%***)	91.162%	9.716%	93.314%	9.688%	93.343%	0.539%	0.493%	**91.422%**
		24	**1**	1.814% (-0.297%^{ns})	11.565% (+1.638%***)	66.158%	18.919%	71.461%	16.372%	74.009%	4.180%	2.366%	**56.598%**
			10	1.028% (-1.084%***)	12.189% (+2.262%***)	89.995%	20.342%	92.959%	19.968%	93.334%	4.461%	3.433%	**76.967%**
Medium NWOM	**Weak PWOM**	**2**	**1**	51.435% (+5.422%**)	7.867% (-0.240%**)	0.350%	57.104%	6.932%	3.243%	60.793%	51.438%	0.003%	0.006%
			10	55.083% (+9.070%***)	7.733% (-0.373%***)	2.865%	59.857%	29.141%	16.468%	72.530%	55.126%	0.043%	0.077%
		24	**1**	51.629% (+5.616%**)	7.864% (-0.242%**)	0.297%	57.545%	3.825%	0.550%	60.821%	51.634%	0.004%	0.008%
			10	52.872% (+6.859%***)	7.864% (-0.242%**)	2.201%	59.484%	12.858%	2.454%	69.888%	52.904%	0.032%	0.061%
	Medium PWOM	**2**	**1**	51.136% (+5.123%**)	8.186% (+0.079%^{ns})	14.379%	57.491%	31.827%	15.100%	74.219%	51.746%	0.610%	1.179%
			10	51.631% (+5.617%**)	8.485% (+0.378%**)	29.515%	63.389%	65.169%	39.804%	88.754%	54.249%	2.619%	4.827%
		24	**1**	50.574% (+4.560%*)	8.161% (+0.054%^{ns})	10.245%	57.162%	14.892%	1.956%	70.098%	50.658%	0.084%	0.166%
			10	54.316% (+8.303%***)	8.218% (+0.112%^{ns})	19.791%	60.446%	24.385%	3.790%	81.041%	54.479%	0.163%	0.300%
	Strong PWOM	**2**	**1**	37.215% (-8.798%***)	9.342% (+1.235%***)	37.663%	53.356%	54.545%	27.191%	80.710%	43.137%	5.922%	13.728%
			10	15.840% (-30.173%***)	11.101% (+2.994%***)	72.265%	50.001%	87.065%	43.877%	93.189%	30.604%	14.764%	**48.241%**
		24	**1**	49.732% (+3.719%*)	8.419% (+0.313%**)	19.986%	55.306%	23.031%	2.330%	76.006%	50.030%	0.297%	0.594%
			10	51.768% (+5.755%**)	8.502% (+0.395%***)	27.584%	58.025%	32.739%	6.313%	84.450%	52.823%	1.055%	1.997%
Strong NWOM	**Weak PWOM**	**2**	**1**	75.587% (+3.899%*)	6.613% (-0.175%*)	0.131%	76.610%	2.749%	1.137%	78.221%	75.587%	0.000%	0.000%
			10	73.517% (+1.829%^{ns})	6.741% (-0.047%^{ns})	1.461%	74.733%	15.830%	8.684%	81.879%	73.534%	0.017%	0.023%
		24	**1**	71.362% (-0.326%^{ns})	6.808% (+0.020%^{ns})	0.163%	72.391%	1.992%	0.146%	74.237%	71.362%	0.000%	0.000%
			10	73.002% (+1.315%^{ns})	6.772% (-0.016%^{ns})	1.256%	74.358%	8.623%	2.056%	80.924%	73.012%	0.009%	0.013%
	Medium PWOM	**2**	**1**	72.262% (+0.574%^{ns})	6.944% (+0.157%^{ns})	7.936%	73.454%	15.093%	5.241%	83.305%	72.326%	0.064%	0.089%
			10	71.279% (-0.409%^{ns})	7.192% (+0.404%***)	16.912%	74.183%	37.610%	21.289%	90.504%	71.722%	0.443%	0.618%
		24	**1**	72.307% (+0.619%^{ns})	6.931% (+0.143%^{ns})	6.934%	73.494%	9.294%	0.357%	82.430%	72.337%	0.030%	0.041%
			10	71.494% (-0.194%^{ns})	7.146% (+0.358%**)	14.170%	73.426%	16.009%	1.533%	87.903%	71.705%	0.211%	0.294%
	Strong PWOM	**2**	**1**	71.045% (-0.643%^{ns})	7.126% (+0.338%**)	13.301%	74.256%	24.867%	11.782%	87.342%	72.055%	1.010%	1.401%
			10	60.943% (-10.745%***)	7.859% (+1.071%***)	25.141%	70.471%	52.632%	30.243%	92.860%	64.829%	3.886%	5.994%
		24	**1**	70.668% (-1.020%^{ns})	7.138% (+0.350%**)	12.103%	71.864%	13.027%	0.249%	84.643%	70.690%	0.022%	0.032%
			10	72.969% (+1.281%^{ns})	7.091% (+0.303%**)	14.618%	74.110%	15.428%	0.614%	88.924%	72.996%	0.027%	0.036%

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 22. Statistical analysis of an increased response delay's effect on the NWOM spread and share of buyers.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by increasing the response delay from two to 24 time steps (t) in the defined countermeasure strategies											
		NWOM Spread						**Share of Buyers**					
		Individualistic Market (β=0.3)			**Collectivistic Market (β=0.7)**			**Individualistic Market (β=0.3)**			**Collectivistic Market (β=0.7)**		
NWOM Message	**Seeds**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**
Weak NWOM	**1**	-1.654%^{ns}	+11.238%***	+0.834%**	+0.984%*	+3.160%***	+1.301%***	+0.049%^{ns}	-0.790%***	-0.072%*	-0.047%**	-0.232%***	-0.147%**
	10	+4.594%**	+10.197%***	+0.091%***	+6.188%***	+3.821%***	+0.981%***	-0.204%***	-0.734%***	-0.004%***	-0.294%***	-0.298%***	-0.070%***
Medium NWOM	**1**	-0.646%^{ns}	+1.003%^{ns}	+15.117%***	+0.194%^{ns}	-0.562%^{ns}	+12.517%***	+0.033%^{ns}	-0.054%^{ns}	-1.042%***	-0.002%^{ns}	-0.025%^{ns}	-0.923%***
	10	+0.087%^{ns}	+1.372%^{ns}	+3.237%***	-2.211%^{ns}	+2.685%^{ns}	+35.928%***	+0.002%^{ns}	-0.082%^{ns}	-0.235%***	+0.131%^{ns}	-0.267%*	-2.599%***
Strong NWOM	**1**	+1.045%^{ns}	-2.416%**	+5.289%***	-4.225%*	+0.046%^{ns}	-0.377%^{ns}	-0.050%^{ns}	+0.151%**	-0.305%***	+0.195%*	-0.013%^{ns}	+0.012%^{ns}
	10	-0.428%^{ns}	-1.189%^{ns}	+18.734%***	-0.514%^{ns}	+0.215%^{ns}	+12.026%***	+0.020%^{ns}	+0.064%^{ns}	-0.953%***	+0.031%^{ns}	-0.046%^{ns}	-0.768%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 23. Statistical analysis of an increased seed quantity's effect on the NWOM spread and share of buyers.

		Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by increasing the number of PWOM seeds from one to ten in the defined countermeasure strategies											
		NWOM Spread						**Share of Buyers**					
		Individualistic Market (β=0.3)			**Collectivistic Market (β=0.7)**			**Individualistic Market (β=0.3)**			**Collectivistic Market (β=0.7)**		
NWOM Message	**Delay (t)**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**
Weak NWOM	**2**	+6.355%***	-3.193%***	-0.579%***	+3.512%***	-1.482%***	-0.467%***	-0.088%^{ns}	+0.525%***	**+0.169%*** **	+0.037%^{ns}	+0.994%***	**+0.546%*** **
	24	+12.603%***	-4.233%***	-1.322%***	+8.716%***	-0.820%^{ns}	-0.786%**	-0.341%***	+0.582%***	**+0.237%*** **	-0.210%***	+0.928%***	**+0.624%*** **
Medium NWOM	**2**	+1.996%^{ns}	-0.369%^{ns}	-7.350%***	+3.648%*	+0.495%^{ns}	-21.375%***	-0.056%^{ns}	+0.073%^{ns}	*+0.565%****	-0.133%^{ns}	+0.299%*	*+1.759%****
	24	+2.730%^{ns}	+0.000%^{ns}	-19.230%***	+1.243%^{ns}	+3.742%*	+2.036%^{ns}	-0.087%^{ns}	+0.045%^{ns}	*+1.372%****	-0.000%^{ns}	+0.057%^{ns}	*+0.083%*^{ns}
Strong NWOM	**2**	+1.836%^{ns}	-0.380%^{ns}	-14.378%***	-2.070%^{ns}	-0.983%^{ns}	-10.102%***	-0.076%^{ns}	+0.049%^{ns}	+0.721%***	+0.128%^{ns}	+0.248%*	+0.733%***
	24	+0.363%^{ns}	+0.847%^{ns}	-0.933%^{ns}	+1.641%^{ns}	-0.813%^{ns}	+2.301%^{ns}	-0.005%^{ns}	-0.038%^{ns}	+0.073%^{ns}	-0.036%^{ns}	+0.215%^{ns}	-0.047%^{ns}

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

Table 24. Statistical analysis of the strong delayed PWOM message's performance as compared to the other defined countermeasure strategies.

			Changes in the NWOM spread (the less, the better) and share of buyers (the more, the better) evoked by the strong delayed PWOM message as compared to the other defined countermeasure strategies											
			NWOM Spread						**Share of Buyers**					
			Individualistic Market (β=0.3)			**Collectivistic Market (β=0.7)**			**Individualistic Market (β=0.3)**			**Collectivistic Market (β=0.7)**		
NWOM Message	**Delay (t)**	**Seeds**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**	**Weak PWOM Message**	**Medium PWOM Message**	**Strong PWOM Message**
Weak NWOM	**2**	**1**	-23.573%***	-2.506%***	+0.834%**	-1.958%***	-0.093%^{ns}	+1.301%***	+2.864%***	+0.635%***	-0.072%*	+1.672%***	+0.601%***	-0.147%**
		10	-29.928%***	+0.687%**	+1.413%***	-5.470%***	+1.389%***	+1.768%***	+2.952%***	+0.110%***	-0.241%***	+1.634%***	-0.394%***	-0.694%***
	24	**1**	-21.919%***	-13.744%***	-	-2.942%***	-3.252%***	-	+2.814%***	+1.426%***	-	+1.718%***	+0.833%***	-
		10	-34.522%***	-9.510%***	+1.322%***	-11.658%***	-2.432%***	+0.786%**	+3.156%***	+0.844%***	-0.237%***	+1.928%***	-0.096%*	-0.624%***
Medium NWOM	**2**	**1**	-54.947%***	-53.244%***	+15.117%***	-1.703%^{ns}	-1.404%^{ns}	+12.517%***	+3.932%***	+3.655%***	-1.042%***	+0.552%***	+0.233%*	-0.923%***
		10	-56.943%***	-52.875%***	+22.466%***	-5.351%**	-1.898%^{ns}	+33.892%***	+3.989%***	+3.582%***	-1.607%***	+0.686%***	-0.066%^{ns}	-2.682%***
	24	**1**	-54.301%***	-54.247%***	-	-1.897%^{ns}	-0.841%^{ns}	-	+3.900%***	+3.710%***	-	+0.555%***	+0.258%*	-
		10	-57.030%***	-54.248%***	+19.230%***	-3.140%^{ns}	-4.584%*	-2.036%^{ns}	+3.987%***	+3.665%***	-1.372%***	+0.555%***	+0.201%^{ns}	-0.083%^{ns}
Strong NWOM	**2**	**1**	+0.810%^{ns}	-2.306%*	+5.289%***	-4.919%**	-1.594%^{ns}	-0.377%^{ns}	+0.048%^{ns}	+0.170%**	-0.305%***	+0.525%***	+0.194%^{ns}	+0.012%^{ns}
		10	-1.026%^{ns}	-1.926%*	+19.667%***	-2.849%^{ns}	-0.611%^{ns}	+9.725%***	+0.123%*	+0.121%*	-1.026%***	+0.397%***	-0.054%^{ns}	-0.721%***
	24	**1**	-0.235%^{ns}	+0.109%^{ns}	-	-0.694%^{ns}	-1.639%^{ns}	-	+0.098%^{ns}	+0.019%^{ns}	-	+0.330%**	+0.207%^{ns}	-
		10	-0.598%^{ns}	-0.738%^{ns}	+0.933%^{ns}	-2.335%^{ns}	-0.826%^{ns}	-2.301%^{ns}	+0.103%^{ns}	+0.057%^{ns}	-0.073%^{ns}	+0.366%***	-0.008%^{ns}	+0.047%^{ns}

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

2.8.4 Competitive Setting: Influence of Seed Quality and Message Strategies

An important aspect of the propagation of NWOM in OSN concerns the originator of the negative message. Depending on his position in the network, the number of OSN members who are influenced by NWOM can vary widely (Mochalova and Nanopoulos 2014, p. 5). For instance, if an OSN member has many contacts in the network, the expected damage of his actions is assumedly greater. To test the impact of nodal characteristics in the defined markets, we selected three node centrality measures that are regarded as the most important and essential key figures for depicting centrality aspects and are commonly applied in the social network analysis literature: degree centrality, closeness centrality, and betweenness centrality (Abbasi et al. 2012, p. 404; Brandes et al. 2016, p. 153; Freeman 1978, pp. 218-226; Opsahl et al. 2010, p. 245). The degree centrality DC_i of member i measures the number of his contacts (Freeman 1978, pp. 220-221; Kundu et al. 2011, p. 244):

$$DC_i = |\{j \in V: (i,j) \in E\}| = |N_i| \tag{22}$$

Although the degree centrality can be used for determining the social status or popularity of a member (Daly and Haahr 2007, p. 34; Hinz et al. 2010, p. 6), it neglects the position within the whole network (Opsahl et al. 2010, p. 245). Members with numerous edges who are located in unimportant positions in the network are only influential in their direct neighbourhood and could therefore be considered as “local heroes” (Opsahl et al. 2010, p. 245). The closeness centrality remedies this problem by incorporating the geodesic distance to all other network members (Opsahl et al. 2010, pp. 245-247). It determines how “close” a member is to others (Abbasi et al. 2012, p. 406; Badar et al. 2013, p. 759) and is a measure of how quickly a member is able to disseminate information in the network (Lu et al. 2014, p. 1934; Newman 2005, p. 40; Opsahl et al. 2010, p. 245). To calculate the closeness centrality of member i, at first the geodesic distances to the remaining members are summed up (Freeman 1978, p. 225). The reciprocal value of the sum is then used as the measure so that member i’s closeness centrality increases when the total distance to the other members decreases (Freeman 1978, p. 225). In the normalised form, the closeness centrality CC_i of member i can be written in the following way where d_{ij} describes the geodesic distance between two distinct members i and j (Badar et al. 2013, p. 759; Cohen et al. 2014, p. 37; Freeman 1978, p. 226; Olsen et al. 2014, p. 197):

$$CC_i = \frac{|V| - 1}{\sum_{j \in V} d_{ij}} \tag{23}$$

A value of $CC_i = 1$ would indicate that member i is directly connected to all other OSN members (Badar et al. 2013, p. 759; Freeman 1978, p. 226).

The betweenness centrality measures the capability of an OSN member to control the sharing of information between other network participants (Brandes et al. 2016, p. 154; Freeman 1978, p. 222). The underpinning idea is that the diffusion of information follows the path of least resistance and therefore utilises the shortest paths between network members (Brandes et al. 2016, p. 154; Opsahl et al. 2010, p. 247). A member has more control over the information flow if he is placed on many shortest paths (Abbasi et al. 2012, p. 407). For calculating the betweenness centrality of member i, let sp_{hj} denote the number of all shortest paths between two other distinct members h and j, and let $sp_{hj}(i)$ describe the number of these shortest paths that include member i (Abbasi et al. 2012, p. 407; Badar et al. 2013, p. 759; Freeman 1978, p. 223; Olsen et al. 2014, p. 205). The fraction $sp_{hj}(i)/sp_{hj}$ represents the probability that member i is indirectly involved in the information sharing between members h and j (Brandes et al. 2016, p. 154). The maximum value the betweenness centrality can attain in an undirected network is $(|V|-1)\cdot(|V|-2)/2$ (Freeman 1977, p. 38). Based on this, the normalised betweenness centrality BC_i of member i is defined as (Badar et al. 2013, pp. 759-760; Freeman 1977, p. 38, 1978, p. 223):

$$BC_i = \frac{1}{(|V|-1)\cdot(|V|-2)/2} \cdot \sum_{h \in V} \sum_{j \in V} \frac{sp_{hj}(i)}{sp_{hj}} \tag{24}$$

A value of $BC_i = 1$ would imply that member i is part of all shortest paths in the network (Badar et al. 2013, p. 760), which would make him a central hub who controls all connections in a star-shaped network (Freeman 1977, p. 38, 1978, p. 224). Consequently, all remaining members would be characterised by $BC_i = 0$ (Freeman 1977, p. 38, 1978, p. 224).

The distributions of the selected node centrality measures for the smaller sub-graph of Facebook are depicted in Figure 24. In order to differentiate between different levels of seed quality, for each measure we identified low, medium, and high performers among the OSN members. A member was classified as a low (high) performer regarding a measure if his value was part of the bottom (top) 5% percentile of the distribution. If he belonged to neither share, he was classified as a medium performer. This separation leads to 3^3 possible combinations that may occur in the assessment of a member's centrality measure performance. The set sizes of all non-empty combinations are listed in Table 25 and indicate that a correlation exists between the measures, e.g. members who are characterised by a low degree centrality cannot be high performers in the other two measures.

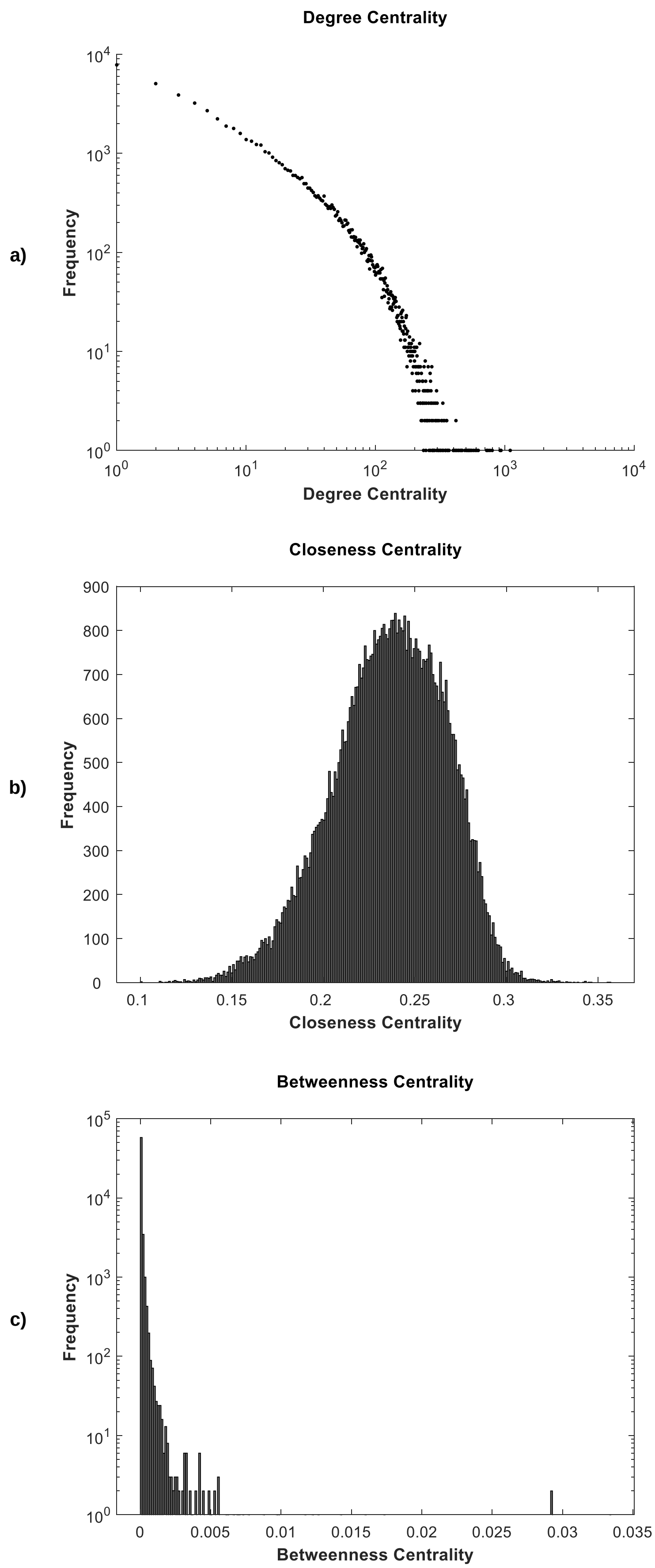

Figure 24. Distribution of the degree, closeness, and betweenness centrality in the used Facebook sub-graph.

Table 25. Occurrences of node centrality measure combinations in the used Facebook sub-graph.

	Classification of the OSN members according to their performance in regard to the used node centrality measures			
	Degree Centrality	**Closeness Centrality**	**Betweenness Centrality**	**Set Size (∑ 63992)**
Combinations	**Low**	**Low**	**Low**	**2287**
	Low	Medium	Low	5535
	Medium	Low	Low	251
	Medium	Low	Medium	633
	Medium	Medium	Low	2172
	Medium	**Medium**	**Medium**	**46894**
	Medium	Medium	High	1118
	Medium	High	Medium	846
	Medium	High	High	544
	High	Medium	Medium	1093
	High	Medium	High	239
	High	High	Medium	511
	High	**High**	**High**	**1269**

The measures are similar regarding their magnitude within a combination because the closeness and betweenness centrality are inherently based on the degree centrality, i.e. a member can only exhibit a high value in the former measures if he is connected to enough other network members. For the used Facebook sub-graph, we plotted the centrality measures against each other in Figure 25 and determined the Pearson correlation coefficient between them. The correlation coefficients suggest that, to some degree, a positive linear relationship exists between the degree and closeness centrality ($\rho = 0.657,\ p < 0.001$) as well as the degree and betweenness centrality ($\rho = 0.523,\ p < 0.001$). A smaller correlation was found between the closeness and betweenness centrality ($\rho = 0.232,\ p < 0.001$).

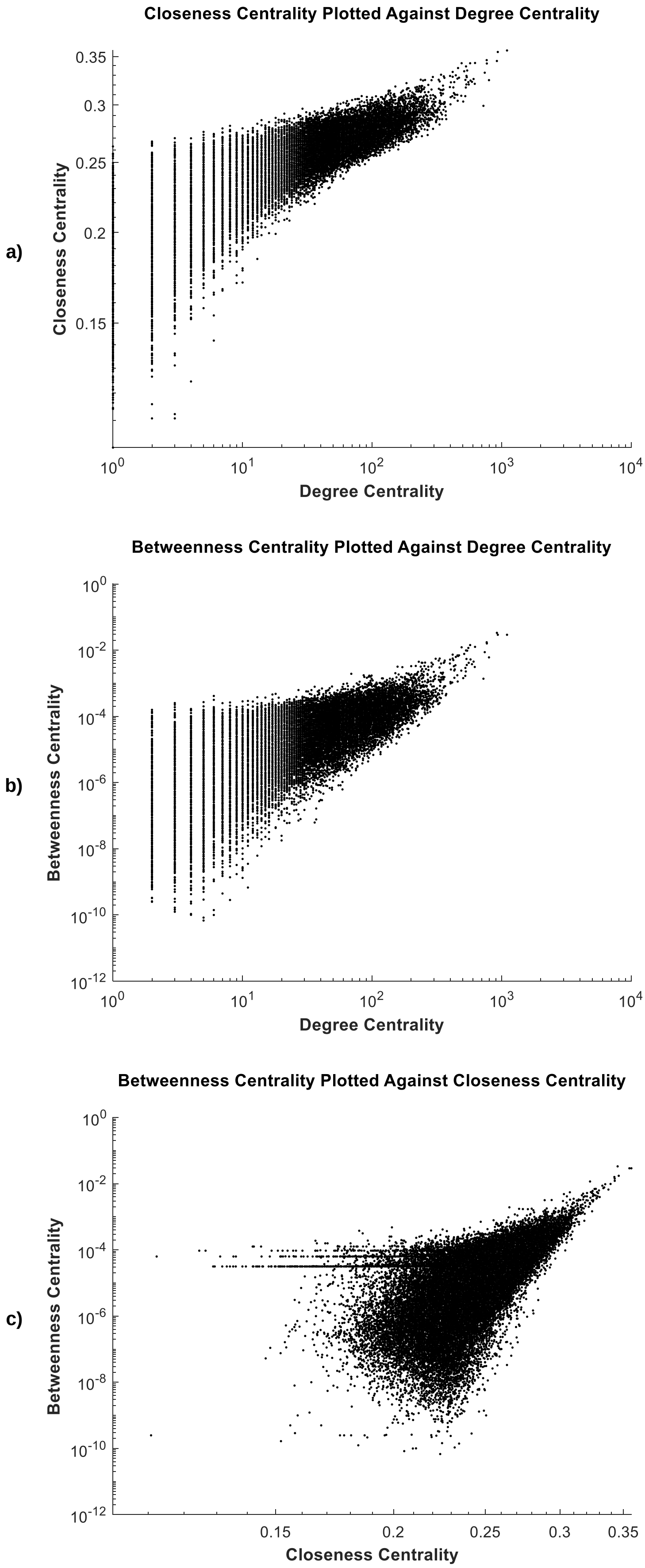

Figure 25. Plotting of the degree, closeness, and betweenness centrality against each other for visualising the frequency of combinations in the used Facebook sub-graph.

For the following examinations, we picked three combinations that exclusively consist of low, medium, and high performers (highlighted in bold in Table 25) and defined the members belonging to these sets as *weak*, *medium*, and *strong seeds* respectively. For these seed quality classes, we first determined the NWOM propagation without any countermeasure. The reached NWOM spreads are given in Table 26, and the changes in the share of buyers, which were tested for statistical significance with a one-sample t-test, are listed in Table 27. The evoked changes in the share of buyers suggest for the individualistic market that a firm should always react to NWOM even if the message is weak unless it is disseminated by a weak NWOM seed. The impact of the weak NWOM seed is negligibly small (highlighted in bold), which could justify the deployment of a no-response strategy. In the collectivistic market, a response to weak NWOM messages is only required if the disseminator is a strong seed. Otherwise, the impact on the share of buyers is similarly small.

Table 26. NWOM spread for different message strengths and seed quality classes.

	NWOM spread of different messages launched by one seed who was selected according to his nodal characteristics in the OSN					
	Individualistic Market (β=0.3)			**Collectivistic Market (β=0.7)**		
	NWOM Message			**NWOM Message**		
NWOM Seed	**Weak NWOM**	**Medium NWOM**	**Strong NWOM**	**Weak NWOM**	**Medium NWOM**	**Strong NWOM**
Random	16.821%	76.408%	89.677%	2.111%	46.013%	71.688%
Weak	0.281%	22.303%	56.118%	0.008%	4.011%	16.837%
Medium	18.719%	83.937%	92.978%	2.003%	56.167%	78.925%
Strong	49.576%	92.209%	96.140%	13.098%	84.161%	92.476%

Table 27. Share of buyers reduction for different message strengths and seed quality classes.

	Reduction of the share of buyers from its initial value of 10% evoked by different NWOM messages launched by one seed who was selected according to his nodal characteristics in the OSN					
	Individualistic Market (β=0.3)			**Collectivistic Market (β=0.7)**		
	NWOM Message			**NWOM Message**		
NWOM Seed	**Weak NWOM**	**Medium NWOM**	**Strong NWOM**	**Weak NWOM**	**Medium NWOM**	**Strong NWOM**
Random	-0.494%***	-3.135%***	-4.104%***	**-0.073%*** **	-1.894%***	-3.212%***
Weak	**-0.007%*** **	-0.886%***	-2.556%***	**-0.0002%** **	-0.139%***	-0.697%***
Medium	-0.548%***	-3.447%***	-4.256%***	**-0.069%*** **	-2.316%***	-3.542%***
Strong	-1.549%***	-3.812%***	-4.405%***	-0.468%***	-3.648%***	-4.203%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, [ns] = not significant

As pointed out in the model Section 2.7.2, a strategy consists of the selected message strength, the number of seeds, and their seed quality. Depending on the findings of the previous subsection, we define two diverging strategies that are varied in terms of strength and delay: (1) a medium message ($AQ^+ = EX^+ = 0.6$) that is launched quickly ($D = 2t$) and (2) a strong message ($AQ^+ = EX^+ = 1.0$) that is disseminated after a significantly longer delay ($D = 24t$) because the strength of a message can be assumed to be degressively proportional to the required composing time. Hereafter, these message strategies will be called *medium quick* (MQ) and *strong delayed* (SD) respectively.

The total costs of a countermeasure strategy include the costs for composing the PWOM message and the seed costs. As an exemplary monetary unit, Dollar ($) is used. With a fixed hourly rate of $300 per time step, the composing of MQ and SD would cost $600 and $7200 respectively. The seed costs depend on the number of seeds and the selected seed quality. The number of followers of an OSN member can be used as an approximate measure to determine his seed activation value, i.e. the costs for publishing sponsored posts on behalf of the firm. Currently, the costs for sponsored posts on Facebook are $25 per 1000 followers (WebFX 2020). As of the first quarter of 2020, Facebook had 2.603 billion monthly active users (Statista 2020e). Because social media sites continuously gain in popularity causing an inflation in the number of followers (i.e. more people have a multitude of followers), it is conceivable that costs for sponsored posts will decrease in future. Based on the mean degree of members, we therefore varied the costs per 1000 followers in the used Facebook sub-graph for determining reasonable seed prices that are presented in Table 28:

Table 28. Seed activation costs depending on the quality of seeds.

		Seed Quality Classes		
		Weak Seeds	**Medium Seeds**	**Strong Seeds**
Mean Degree		1	20.68	187.22
Share in the Used Facebook Sub-Graph		0.0016%	0.0326%	0.2953%
Corresponding Number of Followers on Facebook		41062	849161	7687621
Seed Costs	**$25 per 1000 Followers**	$1026.55	$21229.04	$192190.52
	$10 per 1000 Followers	$410.62	$8491.61	$76876.21
	$1 per 1000 Followers	$41.06	$849.16	$7687.62
	$0.1 per 1000 Followers	$4.11	$84.92	$768.76

For calculating the total seed costs, the prices were multiplied by the number of the activated seeds SN^+, which was varied in different step sizes: $SN^+ \in \{1, 2, \dots, 10, 15, \dots, 50, 60, \dots, 250, 300, \dots, 500, 1000, 1500, 2000\}$. Because of the smaller set size and the high costs of strong seeds, their number was only varied until 50. For the defined message strategies SD and MQ, we separately increased the number of seeds in all selected NWOM scenarios and numerically determined the resulting change in the share of buyers ΔB_T. For each seed number variation, the profit was calculated according to Equation (21) where we set the product contribution margin to $P = 100$. The number of seeds that generated the highest profit was suggested as the recommended action for the firm if the change was statistically significant ($p < 0.01$) as compared to the no-response strategy. If the changes were insignificant or the costs outweighed the revenue, the no-response strategy was recommended instead. The results obtained in this way were then compared between SD and MQ for each scenario, and the better performing message strategy was suggested under specification of the number and quality of seeds. The overall recommendations are provided in the decision matrices shown in Table 29. The intermediate comparisons between SD and MQ for each of the four above-defined seed costs scenarios are given in Table 30, Table 31, Table 32, and Table 33.

The results listed in Table 29 give an overview of the cases where it is advisable to react to NWOM. In the individualistic market, it is always financially worthwhile to respond if the NWOM message is weak or medium. Only if the firm faces a strong NWOM message, it might be better in some cases to refrain from taking any of the examined countermeasures. This is due to PWOM being a double-sided sword: although it can be used for fighting NWOM, it may also unintentionally serve as a catalyst for initiating new waves of NWOM. The likelihood of reactivating NWOM and causing additional financial damage increases with the spread that NWOM has already reached in the OSN. This risk particularly applies to the strong NWOM message if it is launched by an at least medium NWOM seed. In these cases, the share of buyers gets reduced by more than 40% in relative terms. This prevents the tested countermeasure strategies from recouping their costs, because of which their deployment is not suggested. Even though a reaction is recommended in this context for a weak NWOM seed, the loss in sales caused by the strong NWOM message cannot be reversed (i.e. the resulting share of buyers is less than the initial share of buyers of 10% that persisted prior to NWOM) and should therefore be seen as a means of damage limitation.

The results for the collectivistic market show that the economic damage can always be reversed if either the NWOM message or the NWOM seed is weak. None of the analysed countermeasures should be taken, however, for a strong NWOM seed who authors a message that is at least medium.

These results demonstrate and stress the differences between both markets in the recommended handling of NWOM. In the individualistic market, a firm should be cautious in the presence of a strong NWOM message because the message strength, due to its higher valuation in the credibility evaluation, is the crucial factor that determines the degree of dissemination in the OSN. In the collectivistic market, the seed quality plays a pivotal role in this regard because it correlates with a greater potential to exert social pressure, which predominately determines the credibility and thereby the spread of a message. Hence, firms should pay more attention to strong NWOM messages in individualistic markets and closely monitor the activity of strong NWOM seeds in collectivistic markets.

For each tested NWOM message and seed scenario, Table 29 makes recommendations regarding the choice of an appropriate PWOM message strategy. In the individualistic market, the SD message strategy should be used preferably. In none of its cases, MQ is recommended because in individualistic markets people attach more weight to the informational value of a PWOM message, which can easily outweigh a quicker publishing of the response. In the collectivistic market, the MQ message strategy is recommended more often because of the greater importance of the reaction time. If the firm does not respond to NWOM in a timely manner, the risk of the NWOM message reaching a high spread in the OSN and consolidating its impact on OSN members increases. This could aggravate the diffusion of the PWOM message and thereby hamper the recovery of the OSN. Because in collectivistic markets members are more influenced by the actions of their peers rather than the message itself, the effectiveness of a delayed PWOM message, even if it is convincing, is reduced, which could potentially cause the firm's reaction to remain futile. Therefore, in the MQ cases shown in Table 29, it is better to trade in message strength for response speed.

Table 29 also provides insights into which seed strategy should preferably be applied by the firm. In the individualistic market, the suggested number of seeds generally increases with the quality of the NWOM seed, with a few exceptions. Two of them are exemplarily highlighted in bold in Table 29: while 15 weak seeds are suggested in the collectivistic market for countering a medium NWOM message disseminated by a weak NWOM seed, the recommended number of weak seeds is reduced to three for a medium NWOM seed. At first sight, this seems counterintuitive because one would assume that with increasing NWOM seed quality, the number of activated seeds should not be decreased but increased. The reason why a decrease is suggested lies in the relatively high persuasiveness of the medium NWOM message that is enhanced by the medium NWOM seed and makes the countermeasure less efficient. Thus, the point of non-profitability of the countermeasure is reached sooner rendering the activation of a large number of seeds, even if weak, financially unreasonable as they are not able to recover their investment.

A comparison between the two markets in regard to the seed quantity can be drawn for those scenarios where the same message strategy and seed quality is recommended. These cases reveal that the number of seeds is higher in the collectivistic market. This is substantiated by the fact that in the collectivistic market the firm’s response has a better ability to exert social pressure by using multiple seeds in countering NWOM. Another difference is that in the individualistic market the same or roughly the same strategies are recommended to be applied to cases with medium or strong NWOM seeds. This cannot be observed in the collectivistic market, where the results for these seed quality classes show that the lower the seed costs are, the more often is MQ and a higher number of seeds suggested. Hence, the more affordable seeds are, the better is the firm off by valuing quantity over quality. With decreasing costs, the message strength loses more of its already lessened importance because multiple seeds are cheaply available whose deployment can efficiently compensate for the lower message quality. Only after a break-even point is reached, the number of seeds is not increased, but, instead, the next seed quality class is suggested with a potentially smaller number of seeds. Interestingly, activating strong PWOM seeds is hardly recommended. Only when the activation costs are very low ($0.1 per 1000 followers), the firm may benefit from strong seeds in the collectivistic market.

Table 29. Optimal countermeasure strategies for varied seed costs.

		Recommended countermeasure strategies in terms of message strategy, seed quantity, and seed quality																	
		Individualistic Market (β=0.3)									**Collectivistic Market (β=0.7)**								
		Weak NWOM Message			**Medium NWOM Message**			**Strong NWOM Message**			**Weak NWOM Message**			**Medium NWOM Message**			**Strong NWOM Message**		
Seed Costs ($)	**NWOM Seed Quality**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**	**Message Strategy (Optimum Seeds)**	**Share of Buyers**	**Profit ($)**
$25 per 1000 Followers	**Weak**	SD (5x Weak)	12.249%	130690	SD (9x Weak)	11.945%	163009	SD (4x Weak)	8.270%	41058	SD (15x Weak)	11.773%	89797	**SD (15x Weak)**	11.395%	74635	SD (25x Weak)	10.721%	57012
	Medium	SD (6x Weak)	12.232%	162887	SD (2x Medium)	11.759%	280376	--	5.744%	0	SD (1x Medium)	11.785%	89066	**SD (3x Weak)**	8.006%	10137	SD (8x Weak)	6.785%	5333
	Strong	SD (7x Weak)	12.184%	222229	SD (2x Medium)	11.579%	292090	--	5.595%	0	SD (1x Medium)	10.910%	58904	--	6.352%	0	--	5.797%	0
$10 per 1000 Followers	**Weak**	SD (7x Weak)	12.266%	134031	SD (2x Medium)	12.236%	173700	SD (4x Weak)	8.270%	43522	SD (2x Medium)	12.108%	109477	SD (2x Medium)	11.691%	91808	SD (25x Weak)	10.721%	72410
	Medium	SD (9x Weak)	12.255%	166802	SD (3x Medium)	11.898%	306155	--	5.744%	0	SD (2x Medium)	12.075%	111682	SD (10x Weak)	8.073%	13304	SD (8x Weak)	6.785%	10261
	Strong	SD (9x Weak)	12.204%	226957	SD (3x Medium)	11.782%	321938	--	5.595%	0	MQ (4x Medium)	11.304%	77735	--	6.352%	0	--	5.797%	0
$1 per 1000 Followers	**Weak**	SD (2x Medium)	12.359%	141097	SD (5x Medium)	12.306%	190857	SD (3x Medium)	8.385%	49915	SD (5x Medium)	12.221%	129340	MQ (10x Medium)	11.886%	119298	MQ (15x Medium)	11.080%	99323
	Medium	SD (2x Medium)	12.349%	174742	SD (9x Medium)	12.073%	335083	--	5.744%	0	SD (5x Medium)	12.163%	130005	MQ (70x Medium)	9.346%	45261	SD (8x Weak)	6.785%	13217
	Strong	SD (2x Medium)	12.327%	236803	SD (10x Medium)	11.993%	352305	--	5.595%	0	MQ (15x Medium)	11.832%	132444	--	6.352%	0	--	5.797%	0
$0.1 per 1000 Followers	**Weak**	SD (9x Medium)	12.386%	143713	SD (15x Medium)	12.342%	196147	SD (230x Weak)	8.468%	56809	SD (25x Medium)	12.290%	135879	MQ (50x Medium)	12.111%	137790	MQ (20x Strong)	11.839%	144761
	Medium	SD (10x Medium)	12.381%	177614	SD (40x Medium)	12.190%	346741	--	5.744%	0	SD (30x Medium)	12.263%	138038	MQ (45x Strong)	10.636%	151890	MQ (5x Strong)	6.792%	16722
	Strong	SD (15x Medium)	12.373%	240135	SD (50x Medium)	12.147%	366344	--	5.595%	0	MQ (8x Strong)	12.054%	153092	--	6.352%	0	--	5.797%	0

SD = strong delayed PWOM message, MQ = medium quick PWOM message, -- = no reaction

Table 30. Optimal countermeasure strategy decisions for seed costs of $25 per 1000 followers.

			Recommended countermeasure strategies in terms of message strategy, seed quantity, and seed quality, where the optimal decision for a constellation across PWOM seed quality classes is marked with ^{OPT}																	
			Individualistic Market (β=0.3)									**Collectivistic Market (β=0.7)**								
			Weak NWOM Message			**Medium NWOM Message**			**Strong NWOM Message**			**Weak NWOM Message**			**Medium NWOM Message**			**Strong NWOM Message**		
	NWOM Seed Quality	**PWOM Seed Quality**	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***
Strong Delayed (SD) PWOM Message	**Weak**	**Weak**	SD (5)^{OPT}	12.249%	130690	SD (9)^{OPT}	11.945%	163009	SD (4)^{OPT}	8.270%	41058	SD (15)^{OPT}	11.773%	89797	SD (15)^{OPT}	11.395%	74635	SD (25)^{OPT}	10.721%	57012
		Medium	SD (1)	*+0.060%****	*-12273*	SD (1)	*+0.043%^{ns}*	*-9249*	SD (1)	*-0.178%^{ns}*	*-28434*	SD (1)	*+0.060%**	*-2059*	SD (1)	*+0.063%^{ns}*	*-1861*	SD (1)	*-0.108%^{ns}*	*-2384*
		Strong	--	*-2.256%****	*-130690*	SD (1)	*+0.369%****	*-159545*	--	*-0.826%****	*-41058*	--	*-1.773%****	*-89797*	--	*-1.534%****	*-74635*	--	*-1.418%****	*-57012*
	Medium	**Weak**	SD (6)^{OPT}	12.232%	162887	SD (25)	*-0.642%****	*-23900*	--	5.744%	0	SD (20)	*-0.038%^{ns}*	*-1742*	SD (3)^{OPT}	8.006%	10137	SD (8)^{OPT}	6.785%	5333
		Medium	SD (1)	*+0.072%****	*-10521*	SD (2)^{OPT}	11.759%	280376	--	5.744%	0	SD (1)^{OPT}	11.785%	89066	--	*-0.322%****	*-10137*	--	*-0.327%****	*-5333*
		Strong	--	*-2.780%****	*-162887*	SD (1)	*+0.295%****	*-131049*	--	5.744%	0	--	*-1.853%****	*-89066*	--	*-0.322%****	*-10137*	--	*-0.327%****	*-5333*
	Strong	**Weak**	SD (7)^{OPT}	12.184%	222229	SD (30)	*-0.641%****	*-28945*	--	5.595%	0	SD (30)	*-0.210%****	*-22875*	--	6.352%	0	--	5.797%	0
		Medium	SD (1)	*+0.075%****	*-9267*	SD (2)^{OPT}	11.579%	292090	--	5.595%	0	SD (1)^{OPT}	10.910%	58904	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	*+0.178%****	*-173742*	SD (1)	*+0.399%****	*-124460*	--	5.595%	0	--	*-1.378%****	*-58904*	--	6.352%	0	--	5.797%	0
Medium Quick (MQ) PWOM Message	**Weak**	**Weak**	MQ (15)^{OPT}	11.779%	97218	MQ (20)^{OPT}	10.432%	62378	MQ (6)^{OPT}	7.848%	18887	MQ (20)	*-0.976%****	*-39922*	MQ (30)	*-0.814%****	*-39931*	MQ (8)	*-0.542%****	*-21361*
		Medium	MQ (1)	*+0.083%****	*-550*	MQ (1)	*-0.089%^{ns}*	*-6348*	--	*-0.405%***	*-18887*	MQ (2)^{OPT}	11.539%	54489	MQ (2)^{OPT}	11.319%	49343	MQ (1)^{OPT}	10.064%	26410
		Strong	--	*-1.786%****	*-97218*	--	*-1.317%****	*-62378*	--	*-0.405%***	*-18887*	--	*-1.539%****	*-54489*	--	*-1.458%****	*-49343*	--	*-0.761%****	*-26410*
	Medium	**Weak**	MQ (15)	*-0.211%****	*-7550*	MQ (5)^{OPT}	6.829%	11737	--	5.744%	0	MQ (25)	*-0.925%****	*-41814*	--	7.684%	0	--	6.458%	0
		Medium	MQ (1)^{OPT}	11.682%	119535	--	*-0.276%****	*-11737*	--	5.744%	0	MQ (2)^{OPT}	11.466%	54220	--	7.684%	0	--	6.458%	0
		Strong	--	*-2.230%****	*-119535*	--	*-0.276%****	*-11737*	--	5.744%	0	--	*-1.535%****	*-54220*	--	7.684%	0	--	6.458%	0
	Strong	**Weak**	MQ (35)	*-0.983%****	*-55811*	--	6.188%	0	--	5.595%	0	--	*-1.389%****	*-45004*	--	6.352%	0	--	5.797%	0
		Medium	MQ (2)^{OPT}	11.457%	147498	--	6.188%	0	--	5.595%	0	MQ (2)^{OPT}	10.922%	45004	--	6.352%	0	--	5.797%	0
		Strong	MQ (1)	*+0.337%****	*-128364*	--	6.188%	0	--	5.595%	0	--	*-1.389%****	*-45004*	--	6.352%	0	--	5.797%	0
SD versus MQ PWOM Message	**Weak**	**Weak**	SD (5)^{OPT}	12.249%	130690	SD (9)^{OPT}	11.945%	163009	SD (4)^{OPT}	8.270%	41058	SD (15)^{OPT}	11.773%	89797	SD (15)^{OPT}	11.395%	74635	SD (25)^{OPT}	10.721%	57012
		Medium	SD (1)	*+0.060%****	*-12273*	SD (1)	*+0.043%^{ns}*	*-9249*	SD (1)	*-0.178%^{ns}*	*-28434*	SD (1)	*+0.060%**	*-2059*	SD (1)	*+0.063%^{ns}*	*-1861*	SD (1)	*-0.108%^{ns}*	*-2384*
		Strong	--	*-2.256%****	*-130690*	SD (1)	*+0.369%****	*-159545*	--	*-0.826%****	*-41058*	--	*-1.773%****	*-89797*	--	*-1.534%****	*-74635*	--	*-1.418%****	*-57012*
	Medium	**Weak**	SD (6)^{OPT}	12.232%	162887	SD (25)	*-0.642%****	*-23900*	--	5.744%	0	SD (20)	*-0.038%^{ns}*	*-1742*	SD (3)^{OPT}	8.006%	10137	SD (8)^{OPT}	6.785%	5333
		Medium	SD (1)	*+0.072%****	*-10521*	SD (2)^{OPT}	11.759%	280376	--	5.744%	0	SD (1)^{OPT}	11.785%	89066	--	*-0.322%****	*-10137*	--	*-0.327%****	*-5333*
		Strong	--	*-2.780%****	*-162887*	SD (1)	*+0.295%****	*-131049*	--	5.744%	0	--	*-1.853%****	*-89066*	--	*-0.322%****	*-10137*	--	*-0.327%****	*-5333*
	Strong	**Weak**	SD (7)^{OPT}	12.184%	222229	SD (30)	*-0.641%****	*-28945*	--	5.595%	0	SD (30)	*-0.210%****	*-22875*	--	6.352%	0	--	5.797%	0
		Medium	SD (1)	*+0.075%****	*-9267*	SD (2)^{OPT}	11.579%	292090	--	5.595%	0	SD (1)^{OPT}	10.910%	58904	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	*+0.178%****	*-173742*	SD (1)	*+0.399%****	*-124460*	--	5.595%	0	--	*-1.378%****	*-58904*	--	6.352%	0	--	5.797%	0

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant, SD = strong delayed PWOM message, MQ = medium quick PWOM message, -- = no reaction

Table 31. Optimal countermeasure strategies decisions for seed costs of $10 per 1000 followers.

			Recommended countermeasure strategies in terms of message strategy, seed quantity, and seed quality, where the optimal decision for a constellation across PWOM seed quality classes is marked with ^{OPT}																	
			Individualistic Market (β=0.3)									**Collectivistic Market (β=0.7)**								
			Weak NWOM Message			**Medium NWOM Message**			**Strong NWOM Message**			**Weak NWOM Message**			**Medium NWOM Message**			**Strong NWOM Message**		
	NWOM Seed Quality	**PWOM Seed Quality**	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***
Strong Delayed (SD) PWOM Message	**Weak**	**Weak**	SD (7)^{OPT}	12.266%	134031	SD (20)	*-0.152%****	*-851*	SD (4)^{OPT}	8.270%	43522	SD (25)	*-0.232%****	*-7976*	SD (15)	*-0.296%****	*-7934*	SD (25)^{OPT}	10.721%	72410
		Medium	SD (1)	*+0.043%****	*-2877*	SD (2)^{OPT}	12.236%	173700	SD (3)	*+0.115%^{ns}*	*-16534*	SD (2)^{OPT}	12.108%	109477	SD (2)^{OPT}	11.691%	91808	SD (3)	*+0.186%^{ns}*	*-3391*
		Strong	SD (1)	*+0.118%****	*-66537*	SD (1)	*+0.078%****	*-54922*	--	*-0.826%****	*-43522*	SD (1)	*+0.142%****	*-50919*	SD (1)	*+0.112%^{ns}*	*-52774*	SD (1)	*+0.173%^{ns}*	*-55647*
	Medium	**Weak**	SD (9)^{OPT}	12.255%	166802	SD (50)	*-0.505%****	*-27055*	--	5.744%	0	SD (25)	*-0.287%****	*-11471*	SD (10)^{OPT}	8.073%	13304	SD (8)^{OPT}	6.785%	10261
		Medium	SD (1)	*+0.049%****	*-1698*	SD (3)^{OPT}	11.898%	306155	--	5.744%	0	SD (2)^{OPT}	12.075%	111682	SD (2)	*+0.095%^{ns}*	*-6847*	--	*-0.327%****	*-10261*
		Strong	SD (1)	*+0.122%****	*-65429*	SD (1)	*+0.156%****	*-41513*	--	5.744%	0	SD (1)	*+0.124%****	*-52052*	--	*-0.388%****	*-13304*	--	*-0.327%****	*-10261*
	Strong	**Weak**	SD (9)^{OPT}	12.204%	226957	SD (60)	*-0.556%****	*-34427*	--	5.595%	0	SD (40)	*-0.500%****	*-22620*	--	6.352%	0	--	5.797%	0
		Medium	SD (1)	*+0.056%****	*-1256*	SD (3)^{OPT}	11.782%	321938	--	5.595%	0	SD (3)^{OPT}	11.270%	77495	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	*+0.158%****	*-63155*	SD (1)	*+0.196%****	*-38993*	--	5.595%	0	SD (1)	*+0.078%^{ns}*	*-46471*	--	6.352%	0	--	5.797%	0
Medium Quick (MQ) PWOM Message	**Weak**	**Weak**	MQ (15)	*-0.220%****	*-3146*	MQ (20)	*-0.194%^{ns}*	*-3498*	MQ (20)^{OPT}	7.970%	24531	MQ (60)	*-0.700%****	*-43538*	MQ (70)	*-0.637%****	*-43662*	MQ (50)	*-0.573%****	*-31405*
		Medium	MQ (2)^{OPT}	11.999%	109603	MQ (2)^{OPT}	10.625%	78195	--	*-0.526%****	*-24531*	MQ (3)^{OPT}	11.728%	83488	MQ (3)^{OPT}	11.496%	77567	MQ (3)^{OPT}	10.495%	49472
		Strong	MQ (1)	*+0.076%****	*-55060*	MQ (1)	*+0.051%^{ns}*	*-56686*	--	*-0.526%****	*-24531*	MQ (1)	*+0.240%****	*-36161*	MQ (1)	*+0.336%****	*-30099*	MQ (1)	*+0.383%***	*-27121*
	Medium	**Weak**	MQ (40)	*-0.244%****	*-14924*	MQ (5)^{OPT}	6.829%	14817	--	5.744%	0	MQ (50)	*-0.843%****	*-48491*	--	7.684%	0	--	6.458%	0
		Medium	MQ (2)^{OPT}	11.902%	137708	MQ (1)	*-0.085%^{ns}*	*-11808*	--	5.744%	0	MQ (3)^{OPT}	11.667%	83967	--	7.684%	0	--	6.458%	0
		Strong	MQ (1)	*+0.120%****	*-52294*	--	*-0.276%****	*-14817*	--	5.744%	0	MQ (1)	*+0.266%****	*-34530*	--	7.684%	0	--	6.458%	0
	Strong	**Weak**	MQ (50)	*-0.788%****	*-53474*	--	6.188%	0	--	5.595%	0	--	*-1.772%****	*-77735*	--	6.352%	0	--	5.797%	0
		Medium	MQ (2)^{OPT}	11.457%	172973	--	6.188%	0	--	5.595%	0	MQ (4)^{OPT}	11.304%	77735	--	6.352%	0	--	5.797%	0
		Strong	MQ (1)	*+0.337%****	*-38525*	--	6.188%	0	--	5.595%	0	MQ (1)	*+0.386%****	*-18447*	--	6.352%	0	--	5.797%	0
SD versus MQ PWOM Message	**Weak**	**Weak**	SD (7)^{OPT}	12.266%	134031	SD (20)	*-0.152%****	*-851*	SD (4)^{OPT}	8.270%	43522	SD (25)	*-0.232%****	*-7976*	SD (15)	*-0.296%****	*-7934*	SD (25)^{OPT}	10.721%	72410
		Medium	SD (1)	*+0.043%****	*-2877*	SD (2)^{OPT}	12.236%	173700	SD (3)	*+0.115%^{ns}*	*-16534*	SD (2)^{OPT}	12.108%	109477	SD (2)^{OPT}	11.691%	91808	SD (3)	*+0.186%^{ns}*	*-3391*
		Strong	SD (1)	*+0.118%****	*-66537*	SD (1)	*+0.078%****	*-54922*	--	*-0.826%****	*-43522*	SD (1)	*+0.142%****	*-50919*	MQ (1)	*+0.141%**	*-44340*	MQ (1)	*+0.157%^{ns}*	*-50059*
	Medium	**Weak**	SD (9)^{OPT}	12.255%	166802	SD (50)	*-0.505%****	*-27055*	--	5.744%	0	SD (25)	*-0.287%****	*-11471*	SD (10)^{OPT}	8.073%	13304	SD (8)^{OPT}	6.785%	10261
		Medium	SD (1)	*+0.049%****	*-1698*	SD (3)^{OPT}	11.898%	306155	--	5.744%	0	SD (2)^{OPT}	12.075%	111682	SD (2)	*+0.095%^{ns}*	*-6847*	--	*-0.327%****	*-10261*
		Strong	SD (1)	*+0.122%****	*-65429*	SD (1)	*+0.156%****	*-41513*	--	5.744%	0	SD (1)	*+0.124%****	*-52052*	--	*-0.388%****	*-13304*	--	*-0.327%****	*-10261*
	Strong	**Weak**	SD (9)^{OPT}	12.204%	226957	SD (60)	*-0.556%****	*-34427*	--	5.595%	0	SD (40)	*-0.533%****	*-22860*	--	6.352%	0	--	5.797%	0
		Medium	SD (1)	*+0.056%****	*-1256*	SD (3)^{OPT}	11.782%	321938	--	5.595%	0	MQ (4)^{OPT}	11.304%	77735	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	*+0.158%****	*-63155*	SD (1)	*+0.196%****	*-38993*	--	5.595%	0	MQ (1)	*+0.386%****	*-18447*	--	6.352%	0	--	5.797%	0

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant, SD = strong delayed PWOM message, MQ = medium quick PWOM message, -- = no reaction

Table 32. Optimal countermeasure strategy decisions for seed costs of $1 per 1000 followers.

			Recommended countermeasure strategies in terms of message strategy, seed quantity, and seed quality, where the optimal decision for a constellation across PWOM seed quality classes is marked with ^{OPT}																	
			Individualistic Market (β=0.3)									**Collectivistic Market (β=0.7)**								
			Weak NWOM Message			**Medium NWOM Message**			**Strong NWOM Message**			**Weak NWOM Message**			**Medium NWOM Message**			**Strong NWOM Message**		
	NWOM Seed Quality	**PWOM Seed Quality**	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***
Strong Delayed (SD) PWOM Message	**Weak**	**Weak**	SD (40)	-0.043%***	-2673	SD (130)	-0.071%***	-5573	SD (230)	+0.083%^{ns}	-1606	SD (140)	-0.128%***	-9606	SD (100)	-0.105%^{ns}	-8227	SD (100)	-0.149%^{ns}	-5882
		Medium	SD (2)^{OPT}	12.359%	141097	SD (5)^{OPT}	12.306%	190857	SD (3)^{OPT}	8.385%	49915	SD (5)^{OPT}	12.221%	129340	SD (3)^{OPT}	11.785%	112223	SD (9)^{OPT}	11.047%	95707
		Strong	SD (1)	+0.025%***	-4414	SD (1)	+0.009%^{ns}	-2890	SD (1)	-0.234%^{ns}	-19959	SD (1)	+0.029%***	-1593	SD (1)	+0.018%^{ns}	-4001	SD (1)	-0.153%^{ns}	-9755
	Medium	**Weak**	SD (40)	-0.047%***	-2911	SD (220)	-0.290%***	-19792	--	5.744%	0	SD (150)	-0.136%***	-10520	SD (60)^{OPT}	8.225%	24598	SD (8)^{OPT}	6.785%	13217
		Medium	SD (2)^{OPT}	12.349%	174742	SD (9)^{OPT}	12.073%	335083	--	5.744%	0	SD (5)^{OPT}	12.163%	130005	SD (3)	+0.001%^{ns}	-34	--	-0.327%***	-13217
		Strong	SD (1)	+0.029%***	-4181	SD (1)	-0.019%**	-1253	--	5.744%	0	SD (1)	+0.036%***	-1187	SD (2)	-0.166%^{ns}	-23415	--	-0.327%***	-13217
	Strong	**Weak**	SD (40)	-0.060%***	-3722	SD (240)	-0.335%***	-22612	--	5.595%	0	SD (190)	-0.312%***	-21633	--	6.352%	0	--	5.797%	0
		Medium	SD (2)^{OPT}	12.327%	236803	SD (10)^{OPT}	11.993%	352305	--	5.595%	0	SD (7)^{OPT}	11.449%	108346	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	+0.034%***	-3813	SD (1)	-0.015%***	-172	--	5.595%	0	SD (2)	+0.089%*	-3786	--	6.352%	0	--	5.797%	0
Medium Quick (MQ) PWOM Message	**Weak**	**Weak**	MQ (110)	-0.104%***	-7718	MQ (240)	-0.281%*	-12304	MQ (20)^{OPT}	7.970%	31922	MQ (350)	-0.335%***	-27926	MQ (200)	-0.677%***	-42616	MQ (180)	-0.896%***	-51475
		Medium	MQ (4)^{OPT}	12.047%	126191	MQ (3)	-0.211%*	-547	--	-0.526%***	-31922	MQ (10)	+0.013%***	-1	MQ (10)^{OPT}	11.886%	119298	MQ (15)^{OPT}	11.080%	99323
		Strong	MQ (1)	+0.029%***	-2459	MQ (2)^{OPT}	10.967%	101453	--	-0.526%***	-31922	MQ (1)^{OPT}	11.969%	116516	MQ (2)	+0.100%***	-548	MQ (4)	+0.236%*	-3041
	Medium	**Weak**	MQ (180)	-0.152%***	-12785	MQ (5)^{OPT}	6.829%	16664	--	5.744%	0	MQ (500)	-0.284%***	-30056	--	-1.661%***	-45261	--	6.458%	0
		Medium	MQ (5)^{OPT}	11.993%	156218	MQ (1)	-0.085%^{ns}	-6013	--	5.744%	0	MQ (10)^{OPT}	11.951%	118901	MQ (70)^{OPT}	9.346%	45261	--	6.458%	0
		Strong	MQ (1)	+0.029%***	-1616	--	-0.276%***	-16664	--	5.744%	0	MQ (1)	-0.017%***	-276	MQ (4)	-0.469%***	-1057	--	6.458%	0
	Strong	**Weak**	MQ (400)	-0.392%***	-32784	--	6.188%	0	--	5.595%	0	MQ (1000)	-0.589%***	-65679	--	6.352%	0	--	5.797%	0
		Medium	MQ (10)^{OPT}	11.812%	203913	--	6.188%	0	--	5.595%	0	MQ (15)^{OPT}	11.832%	132444	--	6.352%	0	--	5.797%	0
		Strong	MQ (1)	-0.017%**	-275	--	6.188%	0	--	5.595%	0	MQ (2)	+0.022%*	-1245	--	6.352%	0	--	5.797%	0
SD versus MQ PWOM Message	**Weak**	**Weak**	SD (40)	-0.043%***	-2673	SD (130)	-0.071%***	-5573	SD (230)	+0.083%^{ns}	-1606	SD (140)	-0.128%***	-9606	SD (100)	-0.206%***	-15302	SD (100)	-0.182%^{ns}	-9499
		Medium	SD (2)^{OPT}	12.359%	141097	SD (5)^{OPT}	12.306%	190857	SD (3)^{OPT}	8.385%	49915	SD (5)^{OPT}	12.221%	129340	MQ (10)^{OPT}	11.886%	119298	MQ (15)^{OPT}	11.080%	99323
		Strong	SD (1)	+0.025%***	-4414	SD (1)	+0.009%^{ns}	-2890	SD (1)	-0.234%^{ns}	-19959	SD (1)	+0.029%***	-1593	MQ (2)	+0.100%***	-548	MQ (4)	+0.236%*	-3041
	Medium	**Weak**	SD (40)	-0.047%***	-2911	SD (220)	-0.290%***	-19792	--	5.744%	0	SD (150)	-0.136%***	-10520	SD (60)	-1.121%***	-20663	SD (8)^{OPT}	6.785%	13217
		Medium	SD (2)^{OPT}	12.349%	174742	SD (9)^{OPT}	12.073%	335083	--	5.744%	0	SD (5)^{OPT}	12.163%	130005	MQ (70)^{OPT}	9.346%	45261	--	-0.327%***	-13217
		Strong	SD (1)	+0.029%***	-4181	SD (1)	-0.019%**	-1253	--	5.744%	0	SD (1)	+0.036%***	-1187	MQ (4)	-0.469%***	-1057	--	-0.327%***	-13217
	Strong	**Weak**	SD (40)	-0.060%***	-3722	SD (240)	-0.335%***	-22612	--	5.595%	0	SD (190)	-0.695%***	-45731	--	6.352%	0	--	5.797%	0
		Medium	SD (2)^{OPT}	12.327%	236803	SD (10)^{OPT}	11.993%	352305	--	5.595%	0	MQ (15)^{OPT}	11.832%	132444	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	+0.034%***	-3813	SD (1)	-0.015%***	-172	--	5.595%	0	MQ (2)	+0.022%*	-1245	--	6.352%	0	--	5.797%	0

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant, SD = strong delayed PWOM message, MQ = medium quick PWOM message, -- = no reaction

Table 33. Optimal countermeasure strategy decisions for seed costs of $0.1 per 1000 followers.

			Recommended countermeasure strategies in terms of message strategy, seed quantity, and seed quality, where the optimal decision for a constellation across PWOM seed quality classes is marked with ^{OPT}																	
			Individualistic Market (β=0.3)									**Collectivistic Market (β=0.7)**								
			Weak NWOM Message			**Medium NWOM Message**			**Strong NWOM Message**			**Weak NWOM Message**			**Medium NWOM Message**			**Strong NWOM Message**		
	NWOM Seed Quality	**PWOM Seed Quality**	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***	**Message Strategy (Optimum Seeds)**	**Share of Buyers *Difference to Optimum***	**Profit ($) *Difference to Optimum***
Strong Delayed (SD) PWOM Message	**Weak**	**Weak**	SD (250)	-0.029%***	-2079	SD (230)	-0.079%***	-4703	SD (230)^{OPT}	8.468%	56809	SD (1000)	-0.049%***	-5091	SD (240)	-0.221%**	-12669	SD (100)	-0.149%^{ns}	-9065
		Medium	SD (9)^{OPT}	12.386%	143713	SD (15)^{OPT}	12.342%	196147	SD (3)	-0.083%^{ns}	-4601	SD (25)^{OPT}	12.290%	135879	SD (50)	-0.033%^{ns}	-4004	SD (9)^{OPT}	11.047%	102585
		Strong	SD (1)	-0.002%***	-112	SD (2)	-0.002%^{ns}	-385	SD (3)	-0.167%^{ns}	-11969	SD (3)	-0.001%^{ns}	-218	SD (3)^{OPT}	11.941%	122363	SD (9)	+0.025%^{ns}	-4551
	Medium	**Weak**	SD (300)	-0.030%***	-2277	SD (240)	-0.397%***	-22779	--	5.744%	0	SD (1000)	-0.071%***	-6079	SD (60)	-0.080%^{ns}	-4046	SD (110)^{OPT}	6.834%	16199
		Medium	SD (10)^{OPT}	12.381%	177614	SD (40)^{OPT}	12.190%	346741	--	5.744%	0	SD (30)^{OPT}	12.263%	138038	SD (15)^{OPT}	8.305%	30862	SD (25)	-0.060%^{ns}	-5457
		Strong	SD (1)	-0.003%***	-134	SD (5)	-0.003%^{ns}	-607	--	5.744%	0	SD (3)	-0.004%^{ns}	-10	SD (4)	-0.193%^{ns}	-14064	SD (10)	-0.009%^{ns}	-7788
	Strong	**Weak**	SD (350)	-0.040%***	-2682	SD (240)	-0.490%***	-27782	--	5.595%	0	SD (2000)	-0.206%***	-17054	--	6.352%	0	--	5.797%	0
		Medium	SD (15)^{OPT}	12.373%	240135	SD (50)^{OPT}	12.147%	366344	--	5.595%	0	SD (50)^{OPT}	11.748%	128984	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	-0.012%***	-226	SD (6)	-0.003%*	-525	--	5.595%	0	SD (9)	-0.014%^{ns}	-3536	--	6.352%	0	--	5.797%	0
Medium Quick (MQ) PWOM Message	**Weak**	**Weak**	MQ (1000)	-0.037%***	-4770	MQ (240)	-0.451%***	-26477	MQ (20)^{OPT}	7.970%	32661	MQ (2000)	-0.092%***	-11002	MQ (240)	-0.894%***	-53384	MQ (180)	-1.655%***	-90261
		Medium	MQ (20)^{OPT}	12.102%	131411	MQ (50)	-0.039%^{ns}	-3649	--	-0.526%***	-32661	MQ (50)^{OPT}	12.133%	130399	MQ (50)^{OPT}	12.111%	137790	MQ (45)	-0.528%***	-21893
		Strong	MQ (2)	-0.006%***	-228	MQ (4)^{OPT}	11.136%	124495	--	-0.526%***	-32661	MQ (6)	-0.001%^{ns}	-437	MQ (6)	-0.003%^{ns}	-533	MQ (20)^{OPT}	11.839%	144761
	Medium	**Weak**	MQ (1000)	-0.098%***	-8203	MQ (5)^{OPT}	6.829%	16849	--	5.744%	0	MQ (2000)	-0.108%***	-11969	--	-2.951%***	-151890	--	-0.334%***	-16722
		Medium	MQ (25)^{OPT}	12.072%	163377	MQ (1)	-0.085%^{ns}	-5434	--	5.744%	0	MQ (50)^{OPT}	12.120%	133867	MQ (230)	-0.323%**	-5389	MQ (45)	-0.091%^{ns}	-5734
		Strong	MQ (3)	-0.002%^{ns}	-289	MQ (8)	+0.018%^{ns}	-5007	--	5.744%	0	MQ (6)	-0.002%^{ns}	-489	MQ (45)^{OPT}	10.636%	151890	MQ (5)^{OPT}	6.792%	16722
	Strong	**Weak**	MQ (2000)	-0.235%***	-19642	--	6.188%	0	--	5.595%	0	MQ (2000)	-0.436%***	-30892	--	6.352%	0	--	5.797%	0
		Medium	MQ (45)	-0.013%***	-63	--	6.188%	0	--	5.595%	0	MQ (50)	-0.040%***	-617	--	6.352%	0	--	5.797%	0
		Strong	MQ (6)^{OPT}	11.966%	217559	--	6.188%	0	--	5.595%	0	MQ (8)^{OPT}	12.054%	153092	--	6.352%	0	--	5.797%	0
SD versus MQ PWOM Message	**Weak**	**Weak**	SD (250)	-0.029%***	-2079	SD (230)	-0.079%***	-4703	SD (230)^{OPT}	8.468%	56809	SD (1000)	-0.049%***	-5091	SD (240)	-0.391%***	-28096	SD (100)	-0.940%***	-51241
		Medium	SD (9)^{OPT}	12.386%	143713	SD (15)^{OPT}	12.342%	196147	SD (3)	-0.083%^{ns}	-4601	SD (25)^{OPT}	12.290%	135879	MQ (50)^{OPT}	12.111%	137790	MQ (45)	-0.528%***	-21893
		Strong	SD (1)	-0.002%***	-112	SD (2)	-0.002%^{ns}	-385	SD (3)	-0.167%^{ns}	-11969	SD (3)	-0.001%^{ns}	-218	MQ (6)	-0.003%^{ns}	-533	MQ (20)^{OPT}	11.839%	144761
	Medium	**Weak**	SD (300)	-0.030%***	-2277	SD (240)	-0.397%***	-22779	--	5.744%	0	SD (1000)	-0.071%***	-6079	SD (60)	-2.411%***	-125074	SD (110)	+0.042%^{ns}	-523
		Medium	SD (10)^{OPT}	12.381%	177614	SD (40)^{OPT}	12.190%	346741	--	5.744%	0	SD (30)^{OPT}	12.263%	138038	MQ (230)	-0.323%**	-5389	MQ (45)	-0.091%^{ns}	-5734
		Strong	SD (1)	-0.003%***	-134	SD (5)	-0.003%^{ns}	-607	--	5.744%	0	SD (3)	-0.004%^{ns}	-10	MQ (45)^{OPT}	10.636%	151890	MQ (5)^{OPT}	6.792%	16722
	Strong	**Weak**	SD (350)	-0.040%***	-2682	SD (240)	-0.490%***	-27782	--	5.595%	0	MQ (2000)	-0.436%***	-30892	--	6.352%	0	--	5.797%	0
		Medium	SD (15)^{OPT}	12.373%	240135	SD (50)^{OPT}	12.147%	366344	--	5.595%	0	MQ (50)	-0.040%***	-617	--	6.352%	0	--	5.797%	0
		Strong	SD (1)	-0.012%***	-226	SD (6)	-0.003%*	-525	--	5.595%	0	MQ (8)^{OPT}	12.054%	153092	--	6.352%	0	--	5.797%	0

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant, SD = strong delayed PWOM message, MQ = medium quick PWOM message, -- = no reaction

2.9 Conclusion

2.9.1 Summary

The increasing popularity of OSN creates new challenges for firms (Kim et al. 2016, pp. 511-512; van Noort and Willemsen 2012, p. 131). Negative information disseminated by customers can spread very fast in OSN, damage a firm's reputation, and lead to financial losses (Mochalova and Nanopoulos 2014, pp. 1-2; Pfeffer et al. 2014, p. 118; van Noort and Willemsen 2012, pp. 131-132). The aim of this chapter was to analyse and evaluate different countermeasure strategies for adequately dealing with the challenges posed by NWOM in OSN. For answering the three research questions of this chapter, three models were successively developed and numerically analysed by simulation. In the base model, two messages of opposing valence, namely an NWOM and PWOM message, coexisted in the network and competed for the favour of OSN members. The content of a message was characterised by a rational and emotional dimension that constituted its strength and persuasive power. Receivers of a message decided on its credibility based on the persuasiveness of its content and the social pressure emanating from their peers. The effects of NWOM were tested in several markets where customer behaviour differed in terms of message credibility evaluation. In individualistic markets, OSN members paid more attention to the message's content when evaluating its credibility. In collectivistic markets, peer behaviour played a more important role. Only when it appeared to an OSN member that most of its contacts were convinced of the message, he would also perceive it as credible. Depending on which message exerted the greater influence on an OSN member, he believed either in the NWOM or PWOM message. Private messaging was incorporated into the base model to enable OSN members to share messages with their peers. The higher the message's perceived credibility and the more intense the relationship to a potential receiver were, the more likely was the forwarding of the message to that particular receiver. Both the NWOM and PWOM message were prone to ageing in the OSN, which decreased their likelihood of getting forwarded with increasing time. The base model addressed the first research question (RQ1.1: *How important is the reaction speed when countering NWOM?*), for which the diffusion of NWOM and PWOM messages were tested in artificially generated small-world networks with 1000 vertices. The results show that, in general, the reaction speed is not as important as the persuasiveness of the counter-message. A stronger PWOM message can easily make up for potential effectiveness losses caused by a longer delay in the response. A strong delayed PWOM message is in most cases able to outperform weaker counter-messages that are launched immediately or with a short delay. To some extent, this also holds even if multiple seeds are used for the quickly launched messages. Only if the firm faces a very convincing NWOM message, the reaction time becomes more critical as it causes the strong delayed PWOM message to lose its effectiveness.

The purchase model extended the base model by the purchase behaviour of OSN members. In the purchase model, OSN members were characterised by an inherent purchase probability regarding an offered product. The purchase probability of an OSN member was either increased or decreased depending on whether the PWOM or NWOM message had influenced him more. The purchase model also introduced a range of indifference for the credibility evaluation of received messages. If the NWOM and PWOM message were similar in terms of persuasiveness, OSN members could choose to remain indifferent by believing in neither message. Furthermore, incoming messages were able to re-activate formerly received messages irrespective of the valence. If OSN members were already aware of the NWOM message, a later arriving PWOM message caused a rejuvenation of the online discussion. The previously received NWOM message was re-assessed by OSN members with the age of the more recently issued PWOM message, which increased the likelihood of stimulating and triggering new waves of NWOM in the OSN. The purchase model also used artificially generated small-world networks with 1000 vertices and was able to reproduce the findings of the base model. A strong delayed PWOM message does not only reduce the NWOM spread more effectively but also exhibits a greater potential for reversing the economic damage caused by NWOM. By incorporating economic considerations, the purchase model addressed the second research question (RQ1.2: *In which situations is it mandatory to react to NWOM, and under which circumstances is it better to resign from taking any measures?*). Its numerical analysis revealed that weak NWOM messages are characterised by a low spread which hardly affects the share of buyers in the OSN. Because of the low financial risk posed by such messages, a reaction is not mandatory, and the firm may opt for the no-response strategy. The analysis of the conducted experiments could further show that a counter-message disseminated with a certain delay has two opposing effects: (1) a triggering effect that increases the initial NWOM spread leading to fewer sales and (2) a promotional effect that attracts new customers. The latter can usually compensate for the former if the PWOM message is at least as strong as the NWOM message. The stronger the NWOM message is, the less effective will a PWOM message be in utilising the promotional effect for reversing the damage caused by NWOM. If the PWOM message is significantly weaker than its counterpart, the firm should resign from using multiple seeds as they increase the harmful NWOM triggering effect of the response that can lead to additional losses.

The optimal reaction model delivered two extensions to the purchase model. First, in order to comply with the message sharing capabilities provided by OSN like Facebook and Twitter where users are able to publicly share received messages, the optimal reaction model used public instead of private messaging. If an OSN member decided to share a message, he forwarded it to all of his peers at once. Second, the optimal reaction model provided a formulation of the firm’s decision problem regarding the constitution of an optimal reaction strategy that maximised her profit under consideration of a countermeasure's potential revenue and costs. The optimal reaction covered the decisions a firm can take for reducing the negative impact of an online crisis caused by NWOM: (1) the strength of the counter-message, (2) the number of seeds who initially disseminate the counter-message in the OSN, and (3) the quality of seeds that is based on nodal characteristics stemming from the seeds' positions and relationships in the OSN. It was taken into account that the response delay results from the chosen level of message strength, e.g. more time is required for composing a highly persuasive message that can consequently only be launched with a longer delay. Unlike the previous models, the optimal reaction model was not tested in artificially generated small-world networks but in a sub-graph of Facebook consisting of 63392 vertices. In the non-competitive setting, the experiments were also conducted in another Facebook sub-graph with 3097165 vertices. The experiments could show that the findings of the previous models also hold in a much larger network with public messaging. For answering the third research question (RQ1.3: *When should a firm focus on the quality of the response, and when should it prefer a quick reaction at the expense of quality?*), two contrasting message strategies were defined where a strong PWOM message that was launched after 24 hours competed against a medium PWOM message that was disseminated only two hours after the emergence of the NWOM message in the OSN. The costs of the message strategies were compared to the revenue they generated by potentially increasing the share of buyers in the OSN. The findings demonstrate that in individualistic markets the strong delayed PWOM message always outperforms a quickly launched weaker response. In collectivistic markets, the firm might be better off with the latter because the collectivistic environment requires a quick reaction. A delayed response is confronted with negatively influenced and consolidated clusters in the OSN where peer pressure could prevent the PWOM message from taking root. Our results indicate that the more affordable the activation of multiple seeds is, the more the firm should prefer a quick response at the expense of the counter-message's quality in collectivistic markets.

2.9.2 Managerial Implications

Several managerial implications can be deduced from the analyses of the three developed diffusion models. Our findings show that messages diffuse differently in different markets. Persuasive NWOM messages reach a higher spread in individualistic markets, where the message content is higher valued by OSN members. If a message lacks persuasiveness, it hardly diffuses in individualistic markets but can reach and preserve a relevance in collectivistic markets. As long as the message's topicality does not drop quickly and is kept up to date, OSN members will forward the message. In the beginning, this might occur at a very slow pace, but eventually the message can reach a high spread in the OSN. Hence, firms should pay attention to enduring negative online discussions in collectivistic environments.

Even if the shared messages do not provide substantial content, they might prevail and convince many OSN members in the long term. However, if the topicality decay is high, i.e. messages age very quickly, the spread of an NWOM message is generally lower in collectivistic markets. As this also applies to PWOM messages, taking countermeasures can be more difficult in this kind of markets, which is reflected in lower recovery rates from NWOM.

As our findings demonstrate, it is not always necessary for a firm to counter NWOM. For instance, a weak NWOM message launched by a weak seed requires no reaction because it hardly affects the share of buyers in the OSN. In other cases, a reaction is not recommended because it is not financially worthwhile. This mostly applies to scenarios of strong NWOM messages in individualistic markets and strong NWOM seeds in collectivistic markets. In these situations, a firm might be better advised to refrain from taking any of the examined measures. Although a countermeasure could lessen the negative impact of NWOM, the potential revenue would not be able to recoup the campaign's costs. Firms should therefore closely monitor these types of messages and members in the respective markets. The monitoring of the latter requires less effort because the network structure can be used for their identification as exemplarily demonstrated in Section 2.8.4. Controlling and observing the NWOM emergence in OSN is, by contrast, a greater challenge since any member can disseminate a strong message that may potentially reach a high spread in the OSN. This would require a permanent monitoring and continuous analysis of all OSN members' posts. Because of limited technical and financial feasibility, a firm should instead concentrate on clusters in the OSN (e.g. fan pages) for early detection. Although it was not part of this study, a strong PWOM message that is not only disseminated by multiple seeds but also launched very quickly in the OSN could help to limit the damage in these critical scenarios.

Our results emphasise the importance of message strength in countermeasures. In general, the firm's response should be at least one level stronger than the NWOM message but does not necessarily need to be much stronger if the firm only aims for damage control. For instance, if a weak NWOM message is to be countered, both the medium and strong PWOM message are able to reverse the damage and reach the initial share of buyers in the OSN. Only if the NWOM message is strong, an equally strong PWOM message should be deployed as weaker counter-messages are mostly ineffective.

The message strength also plays an important role in conjunction with the activation of multiple seeds. In general, using multiple seeds can only yield a considerable improvement if the firm's response is stronger than the NWOM message. If a strong NWOM message is countered, it is inevitable to use more seeds for the strong PWOM message in order to fully reverse the caused economic damage. When facing NWOM, firms should also be aware of the fact that the activation of multiple seeds could be counterproductive. This particularly applies to situations where a firm responds to an NWOM message inadequately with a poorly designed counter-message, which bears the risk of provoking new waves of NWOM in the OSN (Rafiee and Shen 2016, p. 2; Thomas et al. 2012, p. 92; van Noort and Willemsen 2012, p. 132). As proven by our experiments, using a few more seeds will hardly compensate for a lack of persuasiveness in the firm's response but will instead increase the NWOM spread and thereby cause additional damage. According to our results, firms should therefore remain silent if they are not able, for whatever reason, to respond with a well-developed counter-message.

The optimal reaction to NWOM is highly dependent on contextual factors. In individualistic markets, a firm should always take time to develop a well-founded and persuasive response. This is because people tend to value the message content over the opinions of their peers, which empowers strong delayed PWOM messages to outperform weaker counter-messages that are launched with a shorter delay in the OSN. The situation is different in collectivistic markets, where a delayed reaction, even if it is highly convincing, could encounter difficulties in winning back already negatively influenced parts of the OSN. Hence, in collectivistic markets a firm should carefully consider reacting quickly at the expense of message quality. Our decision matrices in Table 29 may serve as guidelines for selecting appropriate countermeasure strategies in given NWOM scenarios. As a rule of thumb, the cheaper the publishing of sponsored post gets, the more profitable it is to react quickly with a multitude of seeds, who are able to compensate for the lack of persuasiveness and achieve better results. Surprisingly, strong seeds are mostly too expensive to be considered as starting points for disseminating the firm's response in the OSN. Particularly in individualistic markets, medium seeds are in most examined scenarios sufficient for launching the PWOM message. Only in collectivistic markets, the use of strong seeds can be reasonable if their activation costs are extremely low as compared to today's standards.

2.9.3 Limitations and Future Research Directions

There are some limitations of this study that need to be considered. First of all, we made assumptions about some parameters for which empirical data needs to be derived. One example is the individual weighting factor γ_i between the argument quality and expressiveness of a message. We chose $\mu(\gamma_i) = 0.5$ for our experiments, which makes both factors to be perceived, on average, as equally important. An empirical study should be carried out in order to examine how the dimensions of a message interact with each other and if counterbalancing effects exist. In this regard, it is conceivable that the expressiveness can, to a certain extent, make up for a lack of argument quality. It may also be possible that the expressiveness has a non-linear effect on the receiver, e.g. a reversed U-curve, where too much or too little expressiveness negatively impacts the perceived credibility. The weighting factor γ_i could also be dependent on the market. For instance, in markets for production innovations many members of the target group could have low expertise about a newly introduced product. In such cases, as stated in Section 2.3.4, people pay more attention to utility-based and easily comprehensible information, which might result in the expressiveness being higher valued in the credibility evaluation. In future revisions, the model could also incorporate a possible reciprocal relationship between the NWOM and PWOM message regarding their influence on the receiver. It can be assumed that the argument quality of an NWOM message is lowered by the argument quality of the opposing PWOM message. But it is likewise conceivable that a PWOM message with incomprehensible or wrongful arguments adds to the NWOM message's strength. Empirical tests are required to identify all potential interrelationships between the messages. Secondly, in our experiments the new NWOM waves that were triggered by the PWOM message consisted of the same NWOM message that was originally disseminated in the OSN. In reality, however, a not well-countered customer concern might provoke a more negative reaction of OSN members, which could result in an online firestorm (Mochalova and Nanopoulos 2014, pp. 1-2; van Noort and Willemsen 2012, p. 132). These are usually emotionally charged and characterised by a lack of well-founded arguments (Pfeffer et al. 2014, p. 118). Applied to our developed model, this would enable OSN members to modify the argument quality and expressiveness of a message before forwarding it to their peers. A model extension of this kind would yield a more realistic representation of the lively discussions in OSN as members not only share links or posts but usually also express their own opinion, which could either increase or decrease the message's credibility. However, incorporating this into the implementation of the model would cause challenges in the simulation because it hampers the progressiveness of the messages' spread in the OSN. Since members could constantly discuss with each other, the opinions would continuously swing between the two messages. This would require the definition of appropriate stop criteria by which the simulation could be, for instance, automatically stopped if a steady state of opinion changes is maintained over a given period of time. Thirdly, in this regard, the model could be extended by considering the forming of determination over time: the longer someone believes something, the more difficult it might get to convince him of the opposite. By modelling this, the model could also be used for analysing the effects of proactive measures where the PWOM message starts before the NWOM message's emergence in the OSN. Finally, for our experiments we used artificially generated networks and two extracted Facebook sub-graphs of different size. The results of the larger sub-graph indicate that the network topology may play a key role in the propagation behaviour of NWOM messages.

Our model should therefore also be tested with other graph datasets including graphs of directed OSN such as Twitter in order to determine if and how the results differ.

Chapter 3:

Different Prices for Different Customers – Optimising Individualised Prices in Online Stores by Artificial Intelligence

3 Different Prices for Different Customers – Optimising Individualised Prices in Online Stores by Artificial Intelligence

3.1 Introduction

With recent years' improvements and increased use of information tracking technology, firms are becoming more and more capable of gathering behavioural information about their customers (Aydin and Ziya 2009, p. 1523; Chen and Chen 2015, p. 725; Liu and Zhang 2006, p. 97). The data collected in this way can be used to create accurate profiles that help to understand the needs of customers (Thakur et al. 2011, p. 311). This process is facilitated by the large amounts of data generated in the age of big data. Accurate customer-related information enables firms to deploy *price discrimination*, where different customers are charged different prices for the same product or service (Aloysius et al. 2009, pp. 4-5; Bourreau et al. 2017, p. 39; Chen and Chen 2015, p. 725; Ghose et al. 2002, p. 305; Krämer et al. 2018, pp. 116-117). The term price discrimination has no negative connotation and is synonymous with *price differentiation* (Phlips 1983, p. 17). Firms apply price discrimination in order to maximise their profit (Bourreau et al. 2017, p. 39; Ghose et al. 2002, pp. 305-306). Research on consumer welfare indicates that customers may profit from differential pricing as well (Bourreau et al. 2017, pp. 43-44; Richards et al. 2016, pp. 139-140). With price differentiation, firms can provide affordable prices to customers with lower purchasing power who otherwise would not be able to afford the good.

In general, three different types of price discrimination are distinguished: first-degree (personalised pricing), second-degree (volume discounts or bundling), and third-degree (group pricing) price discrimination (Bourreau et al. 2017, pp. 39-40; Chang and Yuan 2007, p. 297; Pigou 1920, pp. 278-279; Varian 1989, p. 600). Personalised pricing is applied when customers are offered individualised prices that are tailored to them based on available individual-level information (Aydin and Ziya 2009, p. 1523; Shapiro and Varian 1998, p. 39). Personalised pricing is referred to as *perfect price discrimination* if customers are charged exactly their willingness-to-pay (Varian 1989, p. 600), which is defined as the maximum amount of money a customer would spend on a product or service (Wertenbroch and Skiera 2002, p. 228). Third- and second-degree price discrimination are already widely adopted in the real world (e.g. student discounts or bundle pricing), but there is a trend towards personalised pricing (Bourreau et al. 2017, pp. 40-41; Chen and Chen 2017, p. 154). While volume discounts or bundling require the least amount of information, the adoption of group and personalised pricing is characterised by a significantly higher requirement for customer data (Bourreau et al. 2017, p. 40). For a precise estimation of the customers' willingness-to-pay, accurate customer profiles are needed. These consist of two parts: (1) the *static customer profile* that is based on static long-term oriented personal data such as gender, age, or income and (2) the *dynamic customer profile* that depends on dynamic data concerning the short-term behaviour of customers in online stores including visit frequency/history, total visit duration, shopping cart analysis data etc. (Niu et al. 2002, p. 1076; Thakur et al. 2011, p. 312). The more data a firm collects about its customers, the higher is the estimation accuracy of the willingness-to-pay and the more individualised are the prices offered to customers. However, the application of such pricing strategies also involves risks. A substantive problem of price discrimination and the resulting price heterogeneity concerns the low acceptance of customers who could feel disadvantaged by being offered higher prices (Xia et al. 2004, p. 1). In the age of social media, online social networks (OSN), and electronic word of mouth (EWOM), negative information spread faster and can reach a substantially higher level of network dissemination (Beneke et al. 2015, pp. 70-71; Mochalova and Nanopoulos 2014, pp. 1-2; Pfeffer et al. 2014, pp. 117-118). A high level of price transparency regarding other customers being privileged in terms of prices can lead to perceived price unfairness, which, in turn, can negatively affect sales (Koschate-Fischer and Wüllner 2017, p. 841). Various incidents in the past have shown that first-degree price discrimination can initiate large waves of customer complaints. As an infamous example, in 2000 Amazon had been widely criticised by its customers for selling a DVD at different prices depending on whether cookie information was available for a visiting customer (Bourreau et al. 2017, p. 41; Enos 2000; Xia et al. 2004, p. 1). Recent developments and trends have also shown that the acceptance of pricing based on collected data is still low when it was revealed that Amazon changed prices up to 300 times during a few days (Hirsch 2015). As a result, EWOM and the resulting price transparency in the market should be considered as a risk factor for a firm's pricing decisions. Derived from these opportunities and challenges, we investigate the following research questions (RQ):

RQ2.1: *How should a decision model for price differentiation be formalised that considers customer data and EWOM effects?*

RQ2.2: *Is artificial intelligence suitable for finding adequate solutions to complex pricing decisions?*

Concerning the first research question RQ2.1, we develop a pricing decision model for offering individualised prices in online stores. The model's theoretical underpinning is based on findings from the relevant theoretical and empirical literature. For obtaining realistic results, the model is required to comprise the multifaceted interdependencies between the store's decision variables and the response behaviour of customers. The resulting complexity of such models usually prevents analytical solutions for practical problem sizes. For numerical analyses, powerful solution methods are needed as found in the research field of artificial intelligence (AI). Therefore, as an answer to the second research question RQ2.2, we propose the use of an evolution strategy belonging to the class of evolutionary algorithms (Emmerich et al. 2018, p. 90; Herrero et al. 2003, p. 772). To test the power and applicability of this method, we solve the developed decision model numerically for exemplary scenarios under realistic conditions as EWOM is incorporated into our model. For assessing the quality of the results generated by the evolution strategy, we benchmark them against the results of other AI and non-AI solution methods. Hence, from a practitioner's point of view, this study contributes to the development and deployment of practical individualised pricing strategies in e-commerce. Furthermore, only a few studies have examined information sharing and EWOM effects in the relevant price discrimination literature (see next section). Most of these studies consider the sharing of product information but neglect that price information can also be passed among customers. In our study, customers can get informed about prices offered to both directly and indirectly connected market participants who are interconnected in an OSN and may react to price discrepancies and disadvantageous price discrimination, i.e. perceived price unfairness, in different ways. Thereby, this study contributes to the price discrimination literature by providing insights into when EWOM may harm a firm's profit and when it may be beneficial in the presence of individualised prices.

The remainder of this chapter is organised as follows. Section 3.2 gives an overview of related literature. In Section 3.3, we develop the pricing decision model that is solved in Section 3.4 for numerical examples by various solution methods. The examined examples include different price discrimination strategies that are compared to uniform pricing. In Section 3.5, a summary of the results is given, from which managerial implications are drawn. The section closes with limitations and future research directions.

3.2 Literature Review

In our approach, the prices of the seller will vary depending on a visiting customer's static and dynamic attributes leading to a heterogeneous price situation in the market. This study is therefore closely related to the research on reference price effects, which is a sub-stream of price discrimination literature. Reference prices are formed by customers based on market observations and experiences (Koschate-Fischer and Wüllner 2017, p. 830; Popescu and Wu 2007, pp. 413-414; Winer 1986, p. 251). Customers use reference prices as an anchor point to evaluate offered prices (Hu et al. 2016, p. 150; Kalyanaram and Little 1994, p. 408). In this context, Hu et al. (2016) examine a monopolistic market setting where the customers' reference prices are based on past prices that are exponentially smoothed depending on a memory factor. The authors could show that a cyclic pricing policy is optimal for a myopic pricing strategy where the seller only seeks to maximise the profits in the current period without planning strategically for future periods. The model of Hu et al. (2016), among others, considers reference prices to be the same for all customers in each period (e.g. Fibich et al. 2003; Greenleaf 1995; Kopalle et al. 1996; Popescu and Wu 2007). In contrast to this, Wang (2016) uses heterogeneous reference prices in his model, which enables the formation of different reference prices on an individual level. Wang (2016) also considers a monopolistic market setting where different groups of customers have heterogeneous store arrival schedules. Each customer is characterised by a reference price that is based on the exponentially smoothed prices that were offered to him on previous visits. The results of the model analysis suggest that more frequently visiting customers should be charged higher prices to keep their willingness-to-pay high for later periods. For less frequently visiting customers, it is optimal to extract the momentarily available surplus by offering lower prices. Our work is closely related to Wang (2016), but contrary to the author's model, we do not limit the updating of the reference prices to store visits. While being outside the store, customers are able to receive information about the prices offered to other customers via EWOM. Hence, we distinguish between internal and external reference prices. The former is analogous to the reference prices used in the above-mentioned studies and represents the exponentially smoothed prices offered to a customer on his store visits. The latter is formed based on price information the customer obtains by observing the market and receiving information via EWOM. Another key distinction of our model is that the visiting schedule is not fixed per group but changes on an individual level. Customers who decline the store's price offer may decide on their next visit based on the difference between the observed prices and their willingness-to-pay.

This study is also related to the price discrimination literature that incorporates the effects of information sharing and EWOM. In this stream of literature, several papers have examined the optimal pricing strategy in an OSN with interconnected individuals. Table 34 gives an overview of these papers with their research objectives and key findings. Most studies investigate price discrimination based on network centrality measures and show that influential customers with a greater number of peers or with a more centralised position in the network should be offered lower prices for incentivising them to engage in EWOM (e.g. Bloch and Quérou 2013; Campbell 2008; Candogan et al. 2012; Chen et al. 2018; Fainmesser and Galeotti 2016). These studies implicitly assume that EWOM has a solely positive effect on the firm's profit by informing other customers of the product's existence or quality. Because of this, their research objective is often related to increasing the level of

EWOM in the network. However, they do not consider that EWOM can be financially harmful as it may also be used for passing information about prices. It is conceivable that price information itself is sufficient to change the demand by either attracting customers to visit the store or deterring them from doing so. Different prices for the same good may also lead to perceived price unfairness as mentioned in the introduction section. An exception to the aforementioned studies is the work of Bloch and Quérou (2013), who allow the sharing of prices, but only in the direct neighbourhood of customers. In the model of Bloch and Quérou (2013), customers form their reference prices based on the surrounding price offers and gain a positive utility if they get charged lower prices than their peers. The authors could show for a monopolistic market setting that customers with a high degree centrality should be offered higher prices for increasing the overall demand in the network. The model, however, neglects that in the age of EWOM a customer may also get informed about the prices of distant and indirectly connected OSN members, which we will consider in our study. Contrary to the authors' model, we will also incorporate the customers' similarity to each other, which might entail different levels of acceptance for others paying less.

A frequent feature of the papers listed in Table 34 is their game-theoretic approach. Most of the reviewed studies use a two-staged game where at first the seller sets a price, and then all market participants simultaneously decide on whether to purchase the product. This causes challenges for adequately modelling EWOM and its dynamics. If all customers decide on purchasing a product at the same time, the information dissemination and its effects in the OSN are not sufficiently considered. To address this, in our model the customers act independently of each other in terms of store visits, product purchases, and sharing of prices via EWOM.

Table 34. Related price discrimination studies that incorporate information sharing and EWOM effects.

Author(s)	Research Objective	Degree of Price Discrimination	Market Setting	Customer Communication (Electronic Word of Mouth)	Findings
Bloch and Quérou (2013)	effects of node centrality on optimal discriminatory prices	first-degree	monopoly and oligopoly	customers have knowledge about the product consumption and prices in their local neighbourhood	• a monopolist should charge higher prices to influential customers (hubs) if customers compare prices via EWOM in their neighbourhood • in directed networks, prices are higher for customers who are more susceptible to influence
Campbell (2008)	optimal pricing strategies in a random network	first-degree	monopoly	customers tell their peers about the existence of the product depending on their product valuation and the offered price; lower prices lead to more EWOM	• customers with a greater number of peers should be offered lower prices to increase the level of EWOM
Candogan et al. (2012)	optimal pricing strategies in social networks	first-degree	monopoly	customers pass the information on the product's quality to their local neighbourhood	• the more influential a customer is, the greater is the discount • authors provide an algorithm for finding an optimal set of customers who should get a discount
Chen et al. (2018)	optimal pricing strategies in social networks that are varied in density	first-degree	monopoly and duopoly	customers have knowledge about the product consumptions in their local neighbourhood	• in a monopoly, more EWOM always benefits the seller in terms of profits • in a duopoly, EWOM has opposing effects: although more EWOM increases demand, it also leads to intense competition reducing the prices on the market

Author(s)	**Research Objective**	**Degree of Price Discrimination**	**Market Setting**	**Customer Communication (Electronic Word of Mouth)**	**Findings**
Fainmesser and Galeotti (2016)	optimal pricing strategy and its effects on consumer surplus if the seller uses information about customers' influence (out-degree) and susceptibility (in-degree) in the social network	first-degree	monopoly	customers have knowledge about the product consumption in their local neighbourhood and the whole network	• the seller should offer discounts to influential customers in the social network to initiate EWOM and charge susceptible customers higher prices
Kamada and Öry (2017)	optimal contracting (bundling) in a social network with referral interaction among customers	second-degree	monopoly	customers only send referrals to other customers if their expected utility is greater than their opportunity costs	• for increasing the level of EWOM, the seller should offer free product features to customers who would otherwise not make a purchase
Gramstad (2016)	optimal contracting (bundling) in a social network where the seller has no knowledge about its structure	second-degree	monopoly	customers have knowledge about the product consumption in their local neighbourhood	• a share of the customers should be offered prices below the seller's marginal costs in order to increase the EWOM activity leading to greater overall profits

3.3 Model

3.3.1 Specifying the Pricing Decision Problem

To decide on individualised prices and investigate their consequences, we consider an online store setting where a seller (hereafter referred to as *she*) offers a durable good over a finite time horizon $t = 0, \dots, T$ to her customers. A customer (hereafter referred to as *he*) is denoted by $i = 1, \dots, I$ and is interconnected with other customers in an OSN. Let $b_{it} \in \{0,1\}$ denote if customer i buys the product at time step t for the individualised price $p_{it}, 0 < p_{it}$, that is offered to him on a store visit. Then, the objective function of the seller can be formulated as a maximisation problem of her total profit Π where the marginal costs for each sold product unit are denoted by $c, 0 \leq c < p_{it}$:

$$\text{Maximise } \Pi = \sum_{t=1}^{T} \sum_{i=1}^{I} (p_{it} - c) \cdot b_{it} \tag{25}$$

The maximisation is subject to the following conditions. The seller assigns all visiting customers to a customer group $x = 1, \dots, X$ where x_i shall describe customer i's group. We assume that the seller has collected and evaluated enough information to classify her customers in regard to their characteristics, e.g. by using decision trees or artificial neural networks (Shim et al. 2012, pp. 7736-7737). Although these groups are disjoint, they exhibit a certain degree of similarity to each other, which may result from similar customer-specific attributes such as age or income. For this, let $s_{xz} \in [0,1]$ denote the similarity between two groups x and z with $s_{xz} = s_{zx}$. The group allocation is based on static customer attributes and therefore constitutes the static customer profile. A group x has Y subgroups to which its arriving customers are dynamically allocated depending on the number of their previous visits that are tracked by the seller. Thus, the subgroup allocation represents the dynamic customer profile. For all possible combinations of groups and visits that can occur in the two-stage profile allocation process, the model needs to provide a specific price. These prices depict the seller's decision variables and can be summarised in a price matrix $PM \in \mathbb{R}_{+}^{XxY}$. The greater the dimensions of PM are, the greater is the degree of price discrimination. The price element pm_{xy} represents the price that will be offered to a member of group x on his yth visit where $y = 1, \dots, Y$ with $Y \leq T$. This means that regardless of when a customer visits the store for the first time, he will be offered the 1st price of his group x (i.e. pm_{x1}). If he has visited the store more than Y times, for any forthcoming visit he will be offered the Yth price (i.e. pm_{xY}). Two distinct customers belonging to the same group can get offered different prices while simultaneously visiting the store because of differences in their visit history. Note that for $X = 1$ and $Y = 1$, there is no price discrimination since all customers are assigned to the same group with one available price. For $X = I$, the pricing strategy equals personalised pricing where each customer has his own group with Y individualised prices. Consequently, $1 < X < I$ describes group pricing. Each customer is characterised by his time-dependent willingness-to-pay $WTP_{it}, 0 \leq WTP_{it}$. The random visiting behaviour of customers is modelled on an individual level and follows a discrete distribution. On average, all customers visit the store every $\lambda, 1 \leq \lambda$, time steps. Investigations regarding customer retention in online stores have shown that prices are the predominant factor in the customers' choice of online retailers (Jadhav and Khanna 2016, p. 22; Reibstein 2002, p. 473). Hence, online stores use low prices in an attempt to attract new customers (Chiou and Pan 2009, p. 327; Jadhav and Khanna 2016, p. 22; Schmitz and Latzer 2002, p. 164). From this, we deduce that the time-dependent individual duration until a customer's next store denoted by $\lambda_{it}, 1 \leq \lambda_{it}$, depends on the difference between the customer's WTP_{it} and his price expectations influenced by the offered price. For smaller differences, he may return sooner anticipating an early buying opportunity, whereas large differences might deter him from revisiting the store again. On a store visit, a customer's static attributes and dynamic visiting behaviour from the past will determine the price offered to him. In this context, let $v_{it} \in \{0,1\}$ indicate if a potential customer i is visiting the store at time step t. Based on his group membership and the number of his earlier visits, the offered price p_{it} is defined as:

$$p_{it} = pm_{x_i y_{it}}, \qquad y_{it} = \min\left\{Y, \sum_{\tau=1}^{t} v_{i\tau}\right\}, \qquad \forall i \in \{1, \dots, I: v_{it} = 1\} \tag{26}$$

At time step t, a visiting customer i purchases the product only if his willingness-to-pay WTP_{it} is greater than or equal to the offered price p_{it}. However, some researchers suggest that the willingness-to-pay of a customer is not a fixed point but rather a range (see Koschate-Fischer and Wüllner (2017, p. 829) and Schlereth et al. (2012, p. 762) for an overview). Because this range may vary from customer to customer, we incorporate this into our model as an individually generated random parameter $\tilde{\varepsilon}_{it}, 0 \leq \tilde{\varepsilon}_{it}$, $\forall i \in \{1, \dots, I: v_{it} = 1\}$ that shall represent customer i's flexibility towards small differences between p_{it} and WTP_{it} on a purchase occasion. This means that even if $p_{it} > WTP_{it}$, the customer might still purchase the product if the difference is sufficiently low, i.e. $p_{it} - WTP_{it} \leq \tilde{\varepsilon}_{it}$. After making a purchase, the customer will not return to the store such that $\sum_{\tau=t+1}^{T} v_{i\tau} = 0$. Based on this, the purchase decision of customer i who visits the store at time step t can be modelled as:

$$b_{it} = \begin{cases} 1 & if \quad p_{it} \leq WTP_{it} + \tilde{\varepsilon}_{it} \\ 0 & else \end{cases}, \qquad \forall i \in \{1, \dots, I: v_{it} = 1\} \tag{27}$$

Customers who are not visiting the store at time step t are not able to purchase the product: $b_{it} = 0 \ \forall i \in \{1, \dots, I: v_{it} = 0\}$.

3.3.2 Willingness-To-Pay Adaptation and Word of Mouth Effects

The willingness-to-pay of a customer is not a fixed parameter and may change over time where $WTP_{i0}, 0 \leq WTP_{i0}$, depicts customer i's exogenously predetermined initial willingness-to-pay:

$$WTP_{it} = WTP_{it-1} + \Delta WTP_{it-1}, \qquad \Delta WTP_{i0} = 0 \tag{28}$$

When evaluating potential changes to their willingness-to-pay, customers are oriented towards so-called reference prices (Grunert et al. 2009, p. 616; Johnson and Cui 2013, pp. 275-276; Koschate-Fischer and Wüllner 2017, p. 853). Customers use reference prices to judge the fairness of offered prices, which can influence their purchase behaviour (Johnson and Cui 2013, p. 276; Winer 1986, p. 255). A reference price RP_{it} forms a customer's price expectations (Hu et al. 2016, p. 150; Mazumdar et al. 2005, p. 85; Winer 1986, p. 251) and causes his WTP_{it} to either increase or decrease (Johnson and Cui 2013, pp. 275-276; Koschate-Fischer and Wüllner 2017, p. 853). In our proposed concept for the modification of the willingness-to-pay, the incremental change ΔWTP_{it} depicts the amount of adaptation of WTP_{it} towards RP_{it} as visualised in Figure 26:

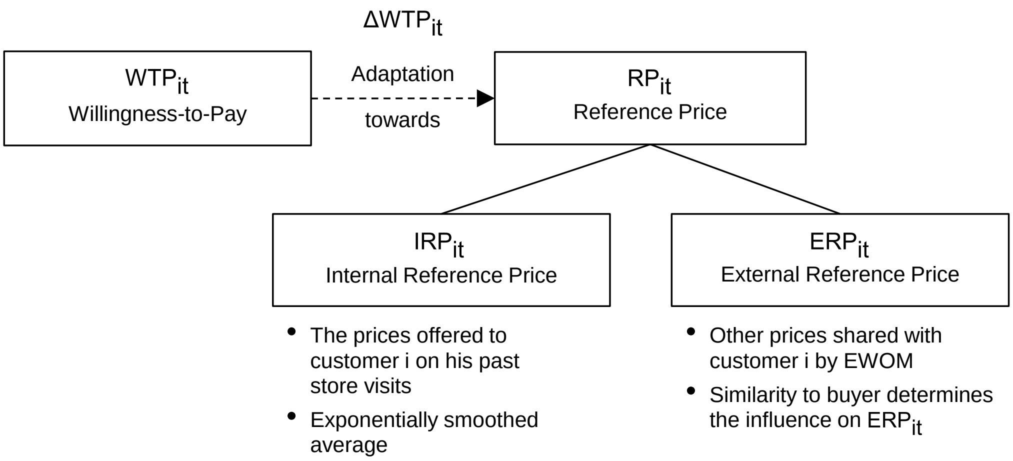

Figure 26. Proposed conceptual framework for the modification of a customer's willingness-to-pay.

Each customer is characterised by an upper limit for his willingness-to-pay $WTP_i^{max}, 0 \leq WTP_i^{max}$, up to which he agrees to make changes to it: $WTP_{it+1} \leq WTP_i^{max}$. In total, a customer may only change his willingness-to-pay n times. A customer's number of modifications that took place until time step t exclusively shall be denoted by n_{it}. We define two cases for triggering a potential modification of the willingness-to-pay that differ regarding whether a customer is inside or outside the store: (1) the customer visits the store and leaves without making a purchase and (2) the customer gets aware of other prices on the market via EWOM. For the latter, let $k_{it} \in \{0,1\}$ indicate if customer i has received information via EWOM and knows about at least one other price at time step t. If neither case (1) nor (2) occurs or if the customer has already surpassed the modification limit, there will be no modification: $\Delta WTP_{it} = 0 \;\; \forall i \in \{1, \dots, I: (v_{it} = 0 \wedge k_{it} = 0) \vee n_{it} \geq n\}$. If case (1) or (2) occurs, the amount by which the willingness-to-pay WTP_{it} changes depends on its difference to the reference price RP_{it}. Grunert et al. (2009, p. 616) provide evidence that the willingness-to-pay linearly increases towards a higher reference price. For a lower reference price, we assume that the willingness-to-pay will likewise decrease linearly. However, customers attach different weights to economic gains and losses according to the prospect theory of Kahneman and Tversky (1979). If the customer increases his WTP_{it}, he will pay more than initially intended, which can be seen as an economic loss (Johnson and Cui 2013, p. 276; Mazumdar et al. 2005, p. 94). In the converse case, the customer pays less than originally planned, which is perceived as an economic gain (Johnson and Cui 2013, p. 276; Mazumdar et al. 2005, p. 94). Due to the customers' loss aversion (Mazumdar et al. 2005, p. 94), it is inferable that a customer will decrease his WTP_{it} considerably faster than increasing it. We therefore define the slope of the linear decrease to be greater. For this, let the coefficients $\alpha^{increase} \in [0,1]$ and $\alpha^{decrease} \in [0,1]$ denote the slope of the linear increase and decrease respectively with $\alpha^{increase} < \alpha^{decrease}$. For $\alpha^{increase} = 1$ or $\alpha^{decrease} = 1$, the customer will immediately adapt his WTP_{it} to RP_{it}. We define the difference $\alpha^{decrease} - \alpha^{increase}$ as the degree of loss aversion. Furthermore, let $\alpha^{limit}, 0 < \alpha^{limit}$, denote a threshold value for the increasing case. If the customer's price expectations denoted by RP_{it} are considerably higher than his current WTP_{it}, i.e. $\alpha^{limit} < RP_{it} - WTP_{it}$, we assume that he will not increase his WTP_{it} at all:

$$\Delta WTP_{it} = \begin{cases} \alpha^{decrease} \cdot (RP_{it} - WTP_{it}) & if \quad RP_{it} - WTP_{it} \leq 0 \\ \alpha^{increase} \cdot (RP_{it} - WTP_{it}) & if \quad 0 < RP_{it} - WTP_{it} \leq \alpha^{limit} \\ 0 & if \quad \alpha^{limit} < RP_{it} - WTP_{it} \end{cases}, \tag{29}$$

$$\forall i \in \{1, \dots, I: (v_{it} = 1 \vee k_{it} = 1) \wedge n_{it} < n\}$$

A visualisation of the operationalisation of ΔWTP_{it} is presented in Figure 27:

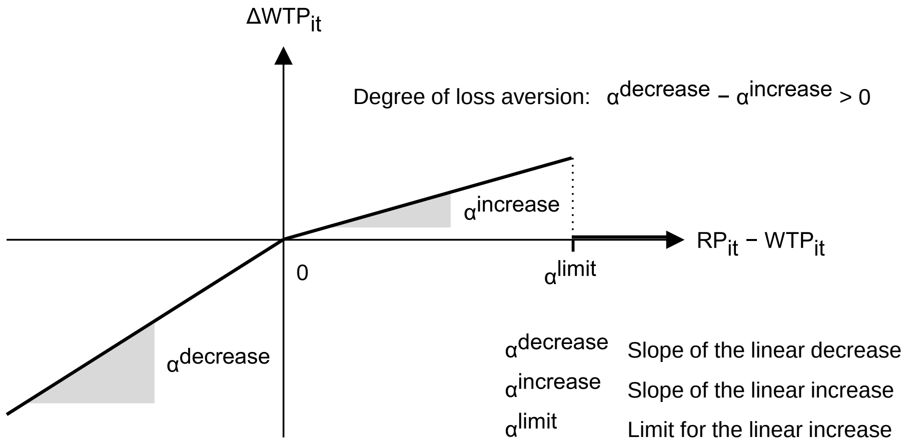

Figure 27. Function for the adaptation of the willingness-to-pay towards the reference price.

Reference prices can be differentiated into internal and external reference prices (Koschate-Fischer and Wüllner 2017, pp. 829-832; McCarville et al. 1993, p. 116). The internal reference price IRP_{it} reflects a customer's memory for prices from past or current purchase occasions (Kopalle and Lindsey-Mullikin 2003, p. 226; Mazumdar et al. 2005, p. 86). The external reference price ERP_{it} refers to price information that is available externally (Mazumdar et al. 2005, p. 89). It depicts a regular price that a product is usually sold at and can be provided by the seller for allowing customers to compare the offered price with competitors' prices (Johnson and Cui 2013, p. 276; Kopalle and Lindsey-Mullikin 2003, p. 226; Krishna et al. 2002, p. 101; Mazumdar et al. 2005, p. 89; McCarville et al. 1993, p. 116). Because of this, the internal and external reference price are also referred to as the memory-based reference price and stimulus-based reference price respectively (Moon et al. 2006, pp. 1-2). In our study, we do not confine the definition of the external reference price to price stimuli presented in the store but rather define it to reflect price information made available via EWOM. Thereby, the external reference price is not treated as a seller-controlled variable in this study, which enables customers to get an unbiased impression of the regular price on the market. This is a more realistic approximation of today's world influenced by EWOM, where customers do not have to rely on the provided in-store comparison prices but can easily compare the offered prices online at any time.

The internal reference price IRP_{it} of a customer gets updated when he visits the store. Research concerning reference prices is not unequivocal. Some papers use all offered prices and exponentially smooth them when calculating IRP_{it} (e.g. Hu et al. 2016, p. 151; Wang 2016, pp. 290-293. Others argue that there is a lack of substantial evidence for exponentially smoothed average prices in behavioural research (Koschate-Fischer and Wüllner 2017, p. 830; Nasiry and Popescu 2011, pp. 1361-1362) and that customers are unlikely to remember past offers well except for the most recent purchase situation (Kopalle et al. 1996, p. 62). We follow the former and exponentially smooth the internal reference price IRP_{it} that gets updated when the customer visits the store. The smoothing factor $\psi_i \in [0,1]$ is modelled on an individual level and determines customer i's memory for price offers in the past. The parameter ψ_i is also called the assimilation parameter that specifies the sensitivity to differences between the newly offered price p_{it} and the old internal reference price IRP_{it-1} (Mazumdar et al. 2005, p. 86). For $\psi_i = 1$, a customer only remembers the very last price offered to him (Wang 2016, pp. 290-293) or, in other words, completely assimilates new prices (Mazumdar et al. 2005, p. 89). Let $av_{it} \in \{0,1\}$ denote if customer i has already visited the store at least once until time step t inclusively: $av_{it} = \min\{1, \sum_{\tau=1}^{t} v_{i\tau}\}$. If the customer visits the store for the first time at time step t, his internal reference price will equal the offered price: $IRP_{it} = p_{it} \ \ \forall i \in \{1, \dots, I: \sum_{\tau=1}^{t} v_{i\tau} = 1\}$. On subsequent visits, IRP_{it} will be updated in the following way:

$$IRP_{it} = \begin{cases} IRP_{it-1} & if \quad v_{it} = 0 \\ IRP_{it-1} + \psi_i \cdot (p_{it} - IRP_{t-1}) & if \quad v_{it} = 1 \end{cases}, \qquad t \geq 2, \qquad \forall i \in \{1, \dots, I: av_{it} = 1\} \tag{30}$$

In our model, the external reference price ERP_{it} is determined by the prices that customer i observes in the market at a given time step t. A customer is only aware of prices offered to other customers if they have been passed to him via EWOM. Let $k_{ijt} \in \{0,1\}$ denote if customer i has received price information from customer j at time step t, i.e. if he knows about the price p_{jt} paid by the customer j at the same time step t (i.e. $b_{jt} = 1$). Based on k_{ijt}, the binary EWOM activation indicator k_{it}, which denotes that customer i knows about at least one other price paid by others at time step t, is calculated as: $k_{it} = \min\left\{1, \sum_{j \in \{1,\dots,I\} \setminus i} k_{ijt}\right\}$. Furthermore, let $ak_{it} \in \{0,1\}$ denote if customer i has already been activated by EWOM at least once until time step t inclusively: $ak_{it} = \min\{1, \sum_{\tau=1}^{t} k_{i\tau}\}$.

According to the theory of social comparison, customers focus more on the prices paid by customers who are in a comparable situation (Bloch and Quérou 2013, p. 245). To some extent, people accept price differences for certain groups like students or retirees (Aydin and Ziya 2009, p. 1524; Garbarino and Lee 2003, p. 498). In analogy to the above-defined assimilation parameter, a customer's old ERP_{it-1} should change depending on the similarity to the sender from whom he has obtained price information. More (less) similar customers have a greater (smaller) influence on the formation of his updated external reference price ERP_{it}. To put it differently, receiver i's similarity $s_{x_i x_j}$ to a sender j determines the degree of assimilation to the sender's price. We assume that the interaction between customer i and j suffices for an adequate assessment of the mutual similarity. If customer i has received multiple prices, the average of all similarity-weighted price differences will be used for updating his external reference price. If the obtained prices come from highly dissimilar customers, the external reference price will hardly be modified. If a customer gets activated by EWOM for the first time, his external reference price will correspond to the average of the shared prices known to him: $ERP_{it} = (\sum_{j\in\{1,\dots,I\}\setminus i} k_{ijt} \cdot p_{jt})/(\sum_{j\in\{1,\dots,I\}\setminus i} k_{ijt})\ \forall i \in \{1,\dots,I\colon \sum_{\tau=1}^{t} k_{i\tau} = 1\}$. Afterwards, we define the updating of ERP_{it} as follows:

$$ERP_{it} = \begin{cases} ERP_{it-1} & if \quad k_{it} = 0 \\ ERP_{it-1} + \dfrac{\sum_{j\in\{1,\dots,I\}\setminus i} k_{ijt} \cdot s_{x_i x_j} \cdot \left(p_{jt} - ERP_{it-1}\right)}{\sum_{j\in\{1,\dots,I\}\setminus i} k_{ijt}} & if \quad k_{it} = 1 \end{cases}, \tag{31}$$

$$t \geq 2, \qquad \forall i \in \{1,\dots,I\colon ak_{it} = 1\}$$

The actual reference price RP_{it}, which the customer adapts his WTP_{it} towards, is based on the internal and external reference price. IRP_{it} and ERP_{it} are known to the customer as soon as he has visited the store or has been activated by EWOM respectively. If both conditions are met, the customer is aware of both reference prices. In this case, the relative weight between both reference prices is determined by customer i's price sensitivity (Koschate-Fischer and Wüllner 2017, p. 832; Moon et al. 2006, p. 8), which shall be denoted by the parameter $\varrho_i \in [0,1]$. Highly price-sensitive customers ($\varrho_i \to 1$) will mainly look at the prices others pay when forming their reference price. It is more likely that customers make a purchase if they personally benefit from discriminatory pricing (Richards et al. 2016, p. 139). We therefore assume that the price sensitivity ϱ_i only plays a role if other customers pay less (i.e. $IRP_{it} > ERP_{it}$). If the customer is privileged or at least equally served in his perception of prices (i.e. $IRP_{it} \leq ERP_{it}$), he will pick his internal reference price as RP_{it}, which will make an increase of his WTP_{it} and thereby a purchase more likely.

$$RP_{it} = \begin{cases} WTP_{it} & if \quad av_{it} = 0 \quad \wedge \quad ak_{it} = 0 \\ ERP_{it} & if \quad av_{it} = 0 \quad \wedge \quad ak_{it} = 1 \\ IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 0 \\ IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 1 \quad \wedge \quad IRP_{it} \leq ERP_{it} \\ \varrho_i \cdot ERP_{it} + (1-\varrho_i) \cdot IRP_{it} & if \quad av_{it} = 1 \quad \wedge \quad ak_{it} = 1 \quad \wedge \quad IRP_{it} > ERP_{it} \end{cases} \tag{32}$$

3.4 Numerical Analysis

3.4.1 Applied Solution Methods

The developed decision model describes in a formalised way the profit caused by the seller's pricing decisions that are summarised in the price matrix $PM \in \mathbb{R}_{+}^{XxY}$. The optimisation of the price matrix elements is a complex task because of the model's profound interdependencies and stochastic variables that, for instance, concern the customers' store visiting and purchase behaviour. This impedes an analytical solution of the decision model for practical problem sizes. To provide numerical solutions to pricing decisions that today's online stores are confronted with, we propose the deployment of an evolution strategy as an AI solution method often used for continuous optimisation problems (Emmerich et al. 2018, p. 92) and regarded as an efficient tool in stochastic optimisation (Herrero et al. 2003, p. 772). We benchmark it against other AI methods (simulated annealing and particle swarm optimisation) and non-AI methods (greedy algorithm and Monte Carlo simulation).

Evolution strategies are based on an analogy to biological processes for the genetic selection and survival of the best-suited features in a population (Hansen et al. 2015, p. 873). Starting with a set of individuals who depict the population and are characterised by their genetic attributes, subsets are chosen to simulate a reproduction procedure for generating new individuals and testing their fitness (Emmerich et al. 2018, pp. 93-94; Hansen et al. 2015, p. 873; Herrero et al. 2003, pp. 772-773). The implementation of an evolution strategy for our decision problem involves two steps. First, an operationalisation of an individual is needed. Because an individual represents a possible solution to our pricing decision model, it can be constructed as a matrix of the dimensions XxY containing positive numerical values. The fitness of an individual is determined by the profit it generates in a given scenario. In order to obtain representative fitness values in a stochastic environment, the simulation of an individual's financial outcome needs to be conducted multiple times. Second, the genetic process of generating new individuals and the survival conditions that specify the transition to the next generation need to be defined. The evolution strategy (ES) was conducted as $(\mu^{ES} + \lambda^{ES})$-ES where μ^{ES} and λ^{ES} denote the number of parental individuals and their generated children respectively (Hansen et al. 2015, p. 874). A "+" survival strategy was used for modelling an elitist selection where parents do not automatically die out but can survive if they outperform their offspring (Hansen et al. 2015, p. 874). We parameterised the evolution strategy with $\mu^{ES} = 10$ parents where each parent generated multiple children by mutating its elements with a step size of $\sigma^{ES} = 5$. For reducing the risk of getting trapped in local optima, additional children were generated by recombining randomly selected parents. We implemented two variants of the recombination process: (1) children inherited the average of the numerical values of their parents for each of their price elements and (2) a binary mask was generated that determined which element was inherited from which parent. In order to enrich the population with good genes, a "kindergarten" was added where three randomly created individuals were protected from dying out for five generations. In total, $\lambda^{ES} = 139$ children were generated in each generation whose fitness was calculated according to the profit calculation formulated in Equation (25). For all scenarios, the evolution strategy was stopped after 100 generations. Afterwards, the best-performing individual among the survivors was identified and represented the found solution to the seller's decision problem.

The particle swarm optimisation developed by Kennedy and Eberhart (1995) mimics animal swarm behaviour found in nature such as the movement of birds (Chopard and Tomassini 2018, p. 97; Kennedy and Eberhart 1995, p. 1942). Animals belonging to the swarm are in the optimisation process represented by so-called particles depicting possible solutions that move around in the problem's solution space (Chopard and Tomassini 2018, p. 97). The velocity of each particle's movement depends on the previous velocity, the personally found best position in the solution space, and the global best position identified by the swarm (Bonyadi et al. 2014, pp. 420-421; Chopard and Tomassini 2018, pp. 97-98; Kennedy and Eberhart 1995, p. 1944).

Simulated annealing was independently developed and introduced by Kirkpatrick et al. (1983) and Černý (1985) and is based on the metallurgical annealing process (Johnson et al. 1989, p. 865; Wee and Nayak 2019, p. 226). Simulated annealing has the advantage of avoiding and being able to leave local optima (Dekkers and Aarts 1991, p. 369; Johnson et al. 1989, pp. 865-867). Depending on a decreasing temperature level that determines the step size and the currently known best solution, a trial solution is generated and evaluated (Dowsland and Thompson 2012, p. 1628; Johnson et al. 1989, pp. 867-868). If it performs better, it is henceforth defined as the best known solution (Dowsland and Thompson 2012, p. 1628; Johnson et al. 1989, pp. 867-868). In the converse case, it may still be defined as the so far best-performing solution with a certain probability that decreases with the temperature and eventually reaches zero (Dowsland and Thompson 2012, p. 1628; Johnson et al. 1989, pp. 867-868; Wee and Nayak 2019, p. 226).

As a non-AI solution method, a greedy algorithm was tested where the prices of a possible solution were consecutively optimised. We also performed a Monte Carlo simulation where potential solutions were randomly generated and evaluated according to their fitness. For achieving performance comparability, each solution method was granted approximately the same simulation time as the evolution strategy. The average profits generated by the best-performing solutions were determined by re-conducting the fitness calculation 1000 times and provide the basis for the numerical analysis in the following subsections.

3.4.2 Parametrisation and Scenario Development

To examine the performance of the solution methods and to analyse different scenarios, we developed and solved a numerical example for an exemplary online store. Some of the parameters constituting the numerical example were fixed, and others were varied for carrying out a sensitivity analysis. The former include a fixed time horizon of $T = 100$ and the customer segmentation. We defined three different customer groups A, B, and C that formed disjunct subsets of members in the OSN and represented the store's customer segment structure. We normalised the number of potential buyers in the OSN to 100, of whom 10% belonged to group A, 20% to group B, and 70% to group C. The customer groups are denoted by the indices $x \in \{1, 2, 3\}$. Each group x was set to have a similarity of $s_{xx} = 1$ to itself. The group of A customers had a similarity of $s_{12} = s_{21} = 0.5$ and $s_{13} = s_{31} = 0.1$ to the groups of B and C customers respectively. The groups of B and C customers had a similarity of $s_{23} = s_{32} = 0.5$ to each other. Customers belonging to group A represented the seller's most loyal customers and had a significantly higher initial willingness-to-pay WTP_{i0}. We assumed that the initial willingness-to-pay of customers was normally distributed with a mean μ and standard deviation σ. For generating WTP_{i0}, we defined a market price level $PL = 100$ that can be interpreted as a scaling factor. Based on PL, the willingness-to-pay of A customers was generated by using a mean of $\mu(WTP_{i0}) = 2 \cdot PL$. Customers of group B had a considerably lower willingness-to-pay with $\mu(WTP_{i0}) = 1.25 \cdot PL$. Customers with the lowest willingness-to-pay belonged to group C with $\mu(WTP_{i0}) = PL$. For all customer groups, a standard deviation of $\sigma(WTP_{i0}) = 5$ was used, and the upper limit of their willingness-to-pay was fixed at $WTP_i^{max} = 1.1 \cdot WTP_{i0}$. The market price level PL was also used for defining reasonable boundaries $[0, 3 \cdot PL]$ for the decision problem's solution space in order to improve the quality of the candidate solutions determined by the applied solution methods. The smoothing factor was set to $\psi_i = 0.9$ so that newly offered prices were quickly adopted as internal reference prices by the customers. The marginal costs for each sold product were $c = 0$. The parameter $\tilde{\varepsilon}_{it}$, which depicts a customer's flexibility regarding small differences between the offered price and his willingness-to-pay, was drawn from a right-sided triangular distribution in the range of [0,3]. This made a purchase more likely if the offered price is greater than the willingness-to-pay only by a small amount. Furthermore, we chose $\alpha^{limit} = 0.5 \cdot PL$ so that the difference between WTP_{it} and RP_{it} had to be less than 50 in order to initiate an increase of WTP_{it}. The price sensitivity of all customers was set to $\varrho_i = 0.8$ inducing them to have a low tolerance for similar customers paying less.

The set of non-fixed model parameters that were varied in the sensitivity analysis comprises the customer's visit frequency and loss aversion as well as the price transparency in the market resulting from the EWOM activity in the OSN. To test different visit frequencies, the base level for the expected duration until the next store visit was varied: $\lambda \in \{1, 5, 20\}$. A value of $\lambda = 20$ represents, for instance, a low visit frequency scenario and means that without modification of the customer arrival times (i.e. $\lambda_{it} = \lambda$), each customer would visit the store every 20 time steps. The expected duration λ_{it} was modified depending on the weighted difference between the reference price and willingness-to-pay. As a weighting factor, we chose 0.5, meaning that a customer with an encountered difference of $RP_{it} - WTP_{it} = 10$ would increase his expected duration λ_{it} until the next store visit by $10 \cdot 0.5 = 5$ time steps. For generating the actual random durations based on λ_{it}, a geometric distribution was used. In the following, we will refer to the above-defined visit frequency scenarios as *high visit frequency* (HF), *medium visit frequency* (MF), and *low visit frequency* (LF) respectively. To test various degrees of loss aversion, we set the increasing slope of the willingness-to-pay to $\alpha^{increase} = 0.1$ and varied the decreasing slope: $\alpha^{decrease} \in \{0.2, 0.5, 1.0\}$. Greater values of $\alpha^{decrease}$ lead to higher degrees of loss aversion where customers reduce their willingness-to-pay faster upon observing lower prices. These three cases will be called *low loss aversion* (LLA), *medium loss aversion* (MLA), and *high loss aversion* (HLA) respectively.

In order to examine the effects of different price transparency levels, an operationalisation of the binary EWOM reception indicator k_{ijt} is needed. For mimicking the information sharing in real OSN, we developed an analogous EWOM model that replicates the customer interaction in the following way. Real social networks are characterised by clustered areas where customers are densely connected to each other and so-called bridges or short cuts that represent connections between the clusters leading to a faster information dissemination (Chen and Li 2017, p. 959; Granovetter 1973, pp. 1363-1366; Onnela et al. 2007, p. 7334). An artificial network that shares these characteristics is the small-world network model of Watts and Strogatz (1998). We used the algorithm provided by the authors (Watts and Strogatz 1998, p. 441) for creating small-world networks consisting of 1000 vertices with a lattice parameter of six and a rewiring probability of 10%. Messages emitted in OSN are subject to decay depending on a half-life (Nugroho et al. 2015, p. 143) that determines the distance $\Lambda, 0 < \Lambda$, they reach in the network. We define the distance as the longest possible walk originating from a random sender in the OSN. For $\Lambda = 1$, a sender would only reach his directly connected neighbours, whereas for $\Lambda = 2$ his second-degree neighbours would be informed, too and so forth. Messages with a high half-life have a low distance because they quickly lose their topicality and thereby reach only a small fraction of the network and vice versa. We define $\Omega \in [0,1]$ as the edge pass-through probability in the identified walks. If a random receiver i is two edges away from the sender j, the likelihood that i knows of j's paid price p_{jt} equals Ω^2. Both potential buyers and non-buyers can equally forward price information they received from others even while being outside the store. In a conducted pretest, for different values of Λ and Ω we numerically determined the likelihood of $k_{ijt}(\Lambda, \Omega) = 1$, which describes that a randomly selected customer i receives price information sent by a likewise randomly selected distinct customer j. The results are presented in Figure 28. For the following experiments, we chose $\Lambda = 6$ and $\Omega \in \{0, 0.25, 0.4, 0.55, 1\}$. These scenarios led to rounded price transparencies of 0%, 21%, 54%, 82%, and 100% in the market and hereafter will be referred to as *no price transparency* (NT), *low price transparency* (LT), *medium price transparency* (MT), *high price transparency* (HT), and *full price transparency* (FT) respectively.

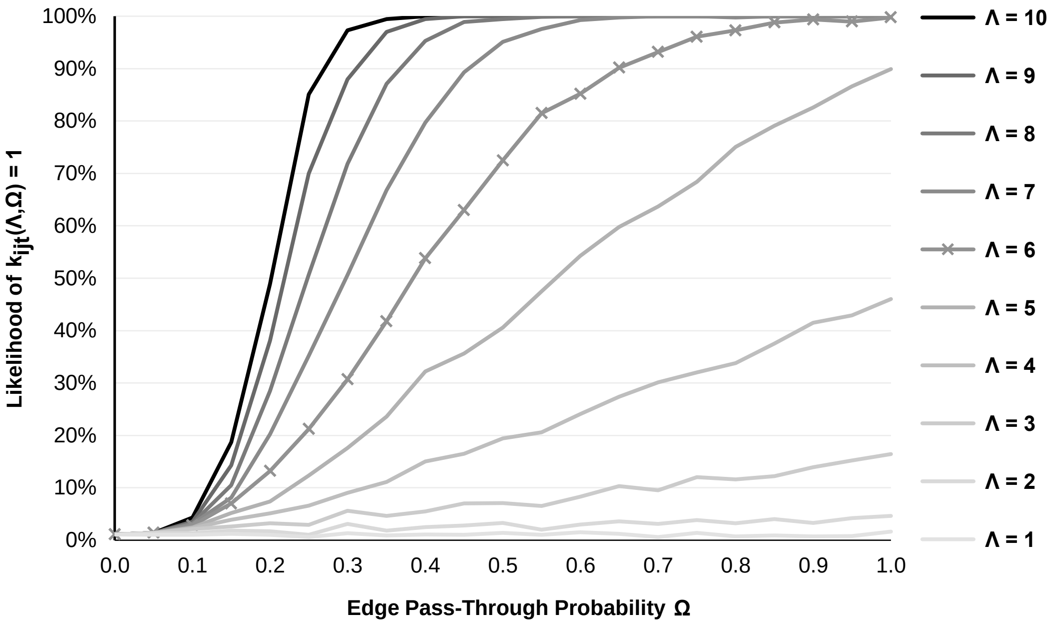

Figure 28. Likelihood of getting informed via EWOM about another customer's paid price.

3.4.3 Benchmark Case: Uniform Pricing

To validate the plausibility of the model and for the purpose of comparison, we define uniform pricing (UP) as our benchmark case where price differentiation is not deployed. With UP, there is only one group that includes all customers, who are offered one price (i.e. $X = 1, Y = 1$). The profits generated by the evolution strategy for UP are depicted in Figure 29 and vary between 8264.41 and 9212.62. The standard error (SE) in all depicted UP scenarios ranged from 4.38 to 19.68. The graphs demonstrate that the loss aversion of the customers has no effect on the outcome since all customers are offered the same price. The price transparency, on the other hand, seems to have a solely positive impact on the profit. However, it can only accrue if customers exhibit a low visit frequency ($\lambda = 20$). For higher visit frequencies, there is no observable effect of the price transparency. In all examined UP scenarios, the evolution strategy suggested setting approximately the same price. The mean of all offered prices was 94.26 with a standard deviation of 0.49. The prices slightly increased with the visit frequency (LF: 93.71, MF: 94.41, HF: 94.66).

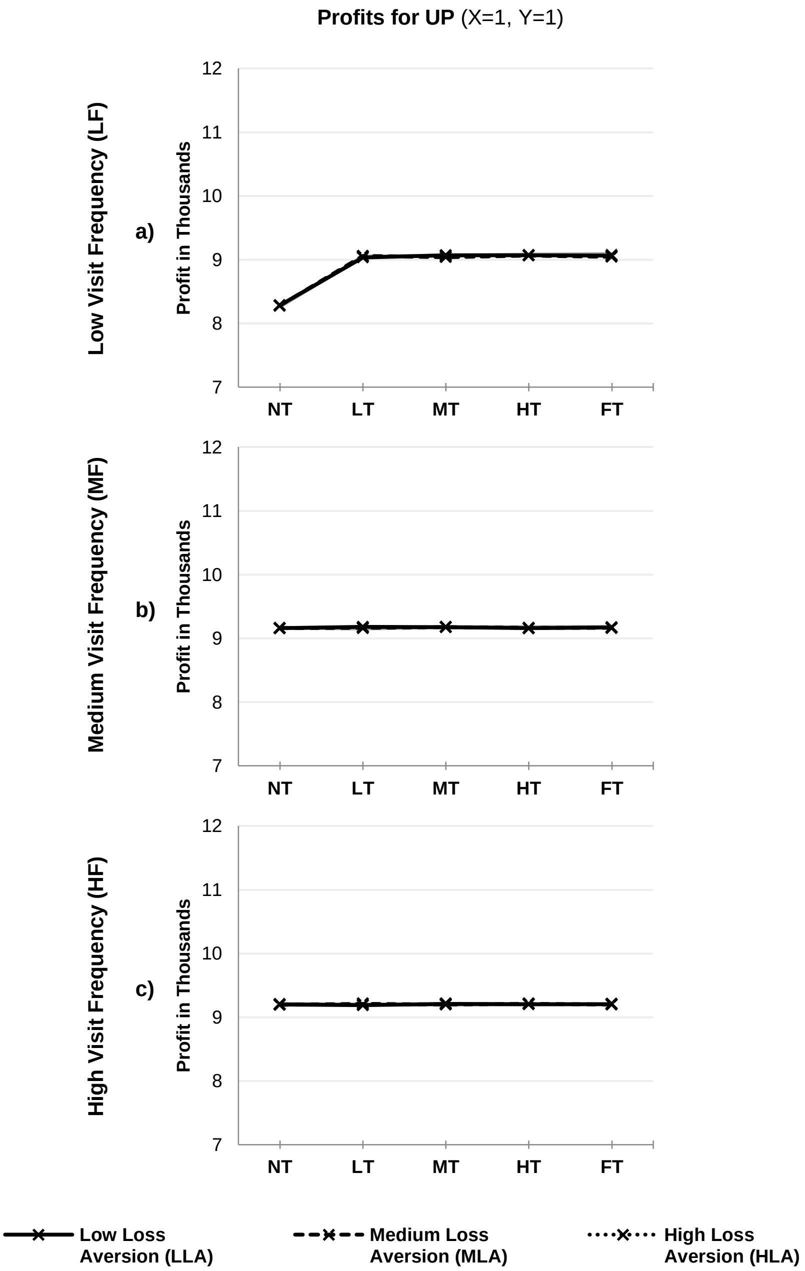

Figure 29. Profits generated by the evolution strategy for uniform pricing.

3.4.4 Price Discrimination Based on Customer Data

To test the effects of differential pricing, we define different price discrimination (PD) strategies that differ in terms of available price subgroups $Y \in \{1,3\}$ to which a group x's members are assigned depending on the number of their previous visits. These strategies will be called PD1 and PD3 respectively, where the level of price individualisation increases with the number of available prices per group. The profits of PD1 and PD3 are depicted in Figure 30, for which the SE ranged from 4.39 to 20.82 and from 2.34 to 82.90 respectively. The SE decreased with increasing visit frequency, i.e. it was generally smaller for higher visit frequencies.

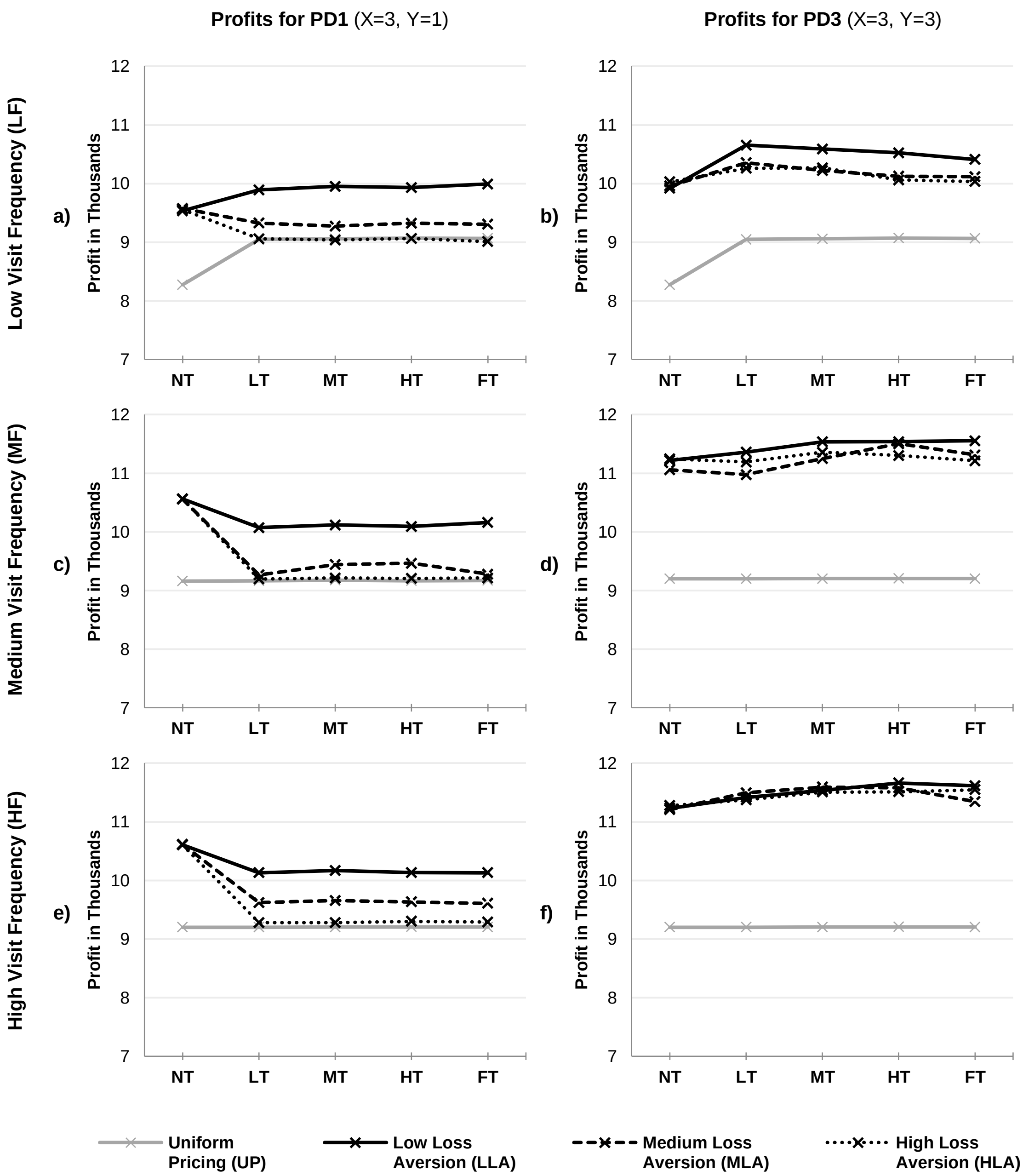

Figure 30. Profits generated by the evolution strategy for price discrimination.

PD1 can be described as a "one price per group" strategy, which is equivalent to traditional group pricing. As shown in Figure 30a/c/e, PD1 always outperforms UP significantly if there is no price transparency. The degree of loss aversion does not seem to affect the profit in the no price transparency cases as all data points overlap. This is because customers are only aware of their own prices and therefore cannot adapt their willingness-to-pay to potentially lower prices offered to others, which prevents differences in the various loss aversion scenarios.

In general, the effects of price transparency are highly dependent on circumstantial factors regarding the behaviour of customers. For instance, if price transparency exists in cases of low visit frequency and low loss aversion, it has a solely positive impact on the profit as depicted in Figure 30a. In the other cases of PD1, however, the existence of price transparency leads to reduced profits when compared to the no price transparency case. The graphs also reveal that the loss aversion of customers has a moderating effect on the profitability of PD1 under price transparency. The higher the loss aversion is, the smaller is the generated profit and the more PD1 forfeits its superiority to UP. This can be explained by the two opposing effects of EWOM: with lower (higher) prices, more (less) customers are attracted to the store but their willingness-to-pay decreases (increases). This means that EWOM may increase the profit by enticing customers to visit the store sooner than originally planned or more often. At the same time, customers may lower their willingness-to-pay if they observe lower prices on the market, which would reduce the profit of the seller. The higher the customer loss aversion is, the more pronounced is the latter negative effect of EWOM. Because of this, the profit-increasing effect of price transparency in Figure 30a is only observable in the cases with low loss aversion but not in the medium and high loss aversion scenarios, where the negative effect outweighs the positive one due to the faster decreasing of the willingness-to-pay. In some high loss aversion cases, the evolution strategy was able to figure out that differential pricing in the form of PD1 is counter-productive under price transparency and suggested offering the same price (≈ 94) to all groups equalling the UP strategy. This explains why in Figure 30a/c/e the high loss aversion curves of PD1 mostly overlap with the UP curve but hardly fall below it.

The PD3 price discrimination strategy provides three subgroups per group and thereby distinguishes between first-time, second-time, and third-time visitors of the online store. Figure 30b/d/f show that in comparison to PD1, the application of PD3 leads to higher profits and the price transparency does not result in a significant reduction of the profit. The profits generated in the no transparency cases can mostly be maintained for higher transparency levels. Furthermore, the negative effects of the loss aversion seem to be lessened to the extent that even for highly loss aversive customers, PD3 is able to outperform the UP strategy. The results also indicate that the influence of the loss aversion on the profit gets lessened with increasing visit frequency, which seems to mitigate the effects of higher loss aversion.

The experiments shown in Figure 30 were also re-conducted with the other solution methods. All methods suggested approximately the same prices for UP leading to similar profits. For PD1, most of the methods were able to find equivalent solutions for scenarios with low loss aversion except for simulated annealing, which generated poorer results than UP in some price transparency cases. In the higher loss aversion cases of PD1, the other methods performed worse than the evolution strategy by suggesting solutions that fell below the UP curve generating profits close to 8000. Similar observations were made for PD3, where the application of the other solution methods led to smaller profits, particularly in the high loss aversion and low visit frequency scenarios. Among the tested methods, the particle swarm optimisation was the closest to the evolution strategy in terms of generated profits.

For determining the performance of the solution methods in a greater solution space, we tested them by deploying a price discrimination strategy with $Y = 6$ prices per group that we will refer to as PD6. The profits of PD3 and PD6 generated by the applied solution methods in selected low and high visit frequency scenarios are depicted in Figure 31 and Figure 32 respectively with their 95% confidence intervals. The SE ranged from 1.76 to 94.13 for PD3 and slightly increased for PD6, where it varied between 1.64 and 110.99. A comparison among the non-AI solution methods reveals that the greedy algorithm obtained significantly better results than the Monte Carlo simulation, particularly in the high visit frequency scenarios. In most cases, the greatest profits were generated by either the evolution strategy or particle swarm optimisation. As the third AI solution method, simulated annealing performed considerably worse and often generated even less profit than the non-AI methods, which suggests that its optimisation approach does not suit the given problem structure well.

We tested the differences for statistical significance with a two-sample heteroscedastic t-test (*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant). In terms of maximising the profit by deploying PD3, the evolution strategy was, on average, able to outperform the Monte Carlo simulation (+6.455%%***), greedy algorithm (+3.402%**), simulated annealing (+10.549%***), and particle swarm optimisation (+1.157%^{ns}). The differences increased with PD6 in the greater solution space, and the evolution strategy was able to consolidate its lead in particular over the Monte Carlo simulation (+8.289%***) and greedy algorithm (+5.425%***). Smaller performance difference changes were observed for simulated annealing (+11.578%***) and particle swarm optimisation (+1.187%^{ns}).

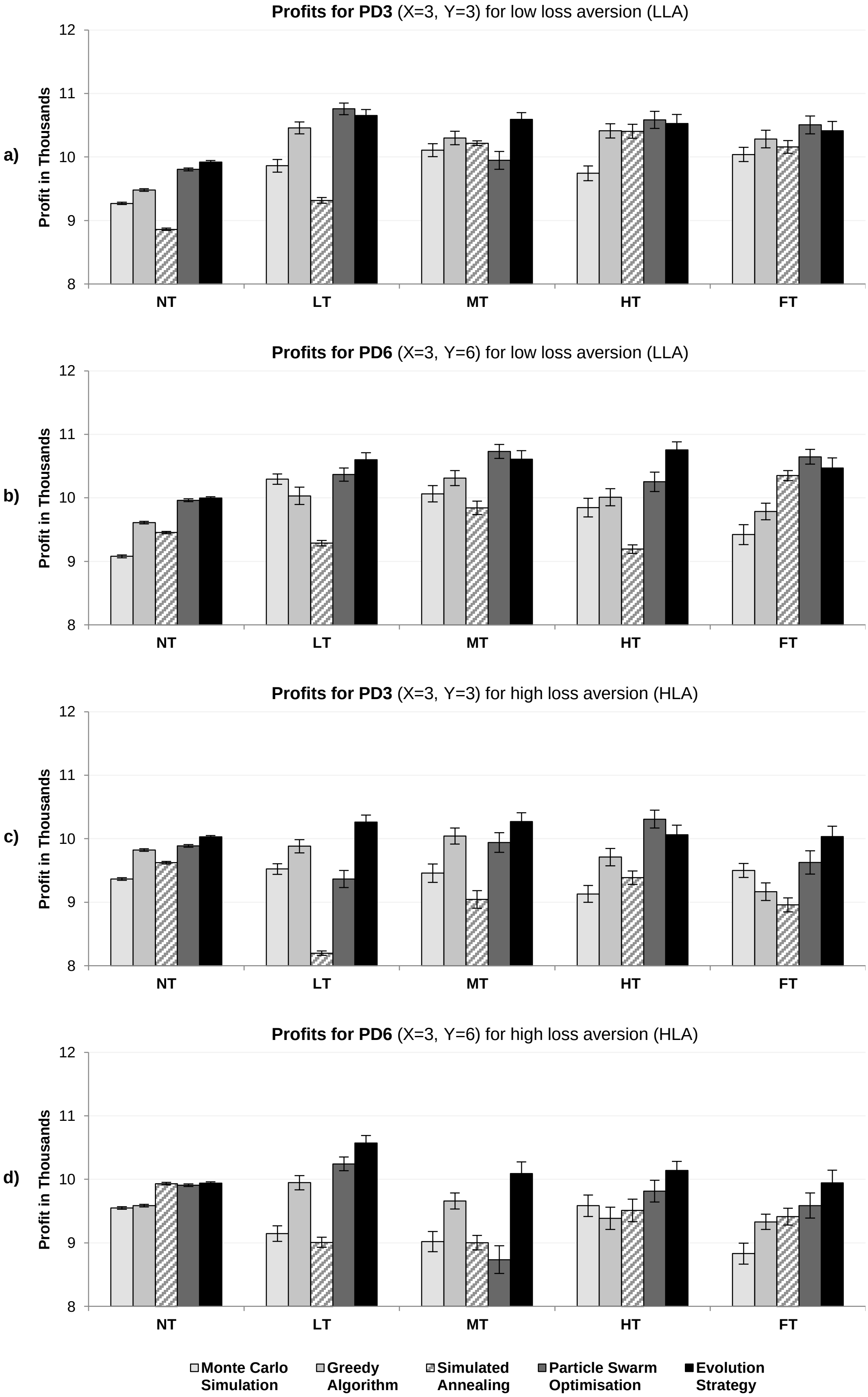

Figure 31. Benchmark of the evolution strategy against other solution methods in selected low visit frequency scenarios with 95% confidence intervals.

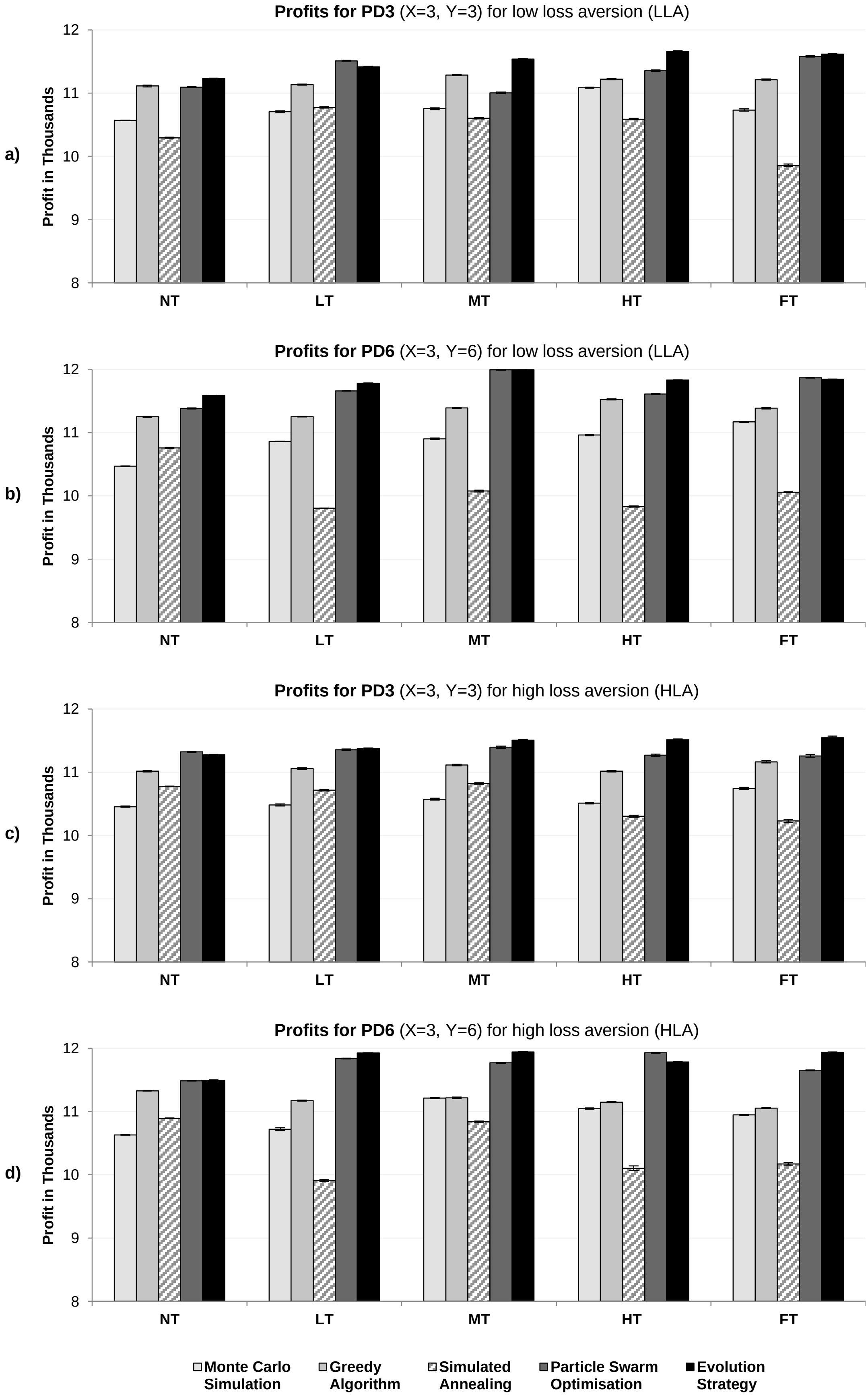

Figure 32. Benchmark of the evolution strategy against other solution methods in selected high visit frequency scenarios with 95% confidence intervals.

Table 35 and Table 36 list the PD1 and PD3 prices found by the evolution strategy for low and high loss aversion scenarios respectively. In each table, low and high visit frequencies are compared to each other in terms of generated profits and average sales. The profits increase from low to high visit frequency and decrease from low to high loss aversion, i.e. the highest profits can be expected in high visit frequency and low loss aversion scenarios.

The tables disclose the pricing strategies that should be deployed by the seller in the listed scenarios. For instance, the price data in Table 35 shows for the low loss aversion scenarios that if price transparency exists, the offered PD1 prices to A customers should be lowered, while the prices for B and C should remain fairly constant. This applies to both the low and high visit frequency cases. Table 36 reveals for the high loss aversion scenarios that as soon as price transparency exists, the deployment of PD1 becomes counter-productive in the low visit frequency cases, where price discrimination should be abandoned by the seller in favour of setting UP prices. In the high visit frequency cases, differential pricing with PD1 is still suggested under price transparency, but the generated profits are only slightly higher than the UP profits (≈ 9200).

In the pricing strategies suggested for PD3, three different types of pricing schemes can be identified. *Successive lowering* (SLO) of prices is applied when the seller sets a high initial price to first serve customers with a high willingness-to-pay and then monotonically decreases the price to sell to those customers who are characterised by a lower willingness-to-pay. In the *pull up* (PUL) pricing scheme, the seller sets one or more initial prices as high as to hinder almost all visitors of a customer group from buying the product on their first visit. These prices increase the willingness-to-pay of customers so that they can be charged higher prices on subsequent visits. After the willingness-to-pay has been pulled up to a sufficient extent, the prices are successively lowered to generate more profitable sales. Differing from the PUL scheme, the *cyclic* (CYC) scheme offers a high price intended to pull up the willingness-to-pay not on the first but on a later visit. Thereby, it presupposes that sales were realised by preceding prices.

The price data in Table 35 and Table 36 reveals that for A customers, the SLO pricing scheme is the dominant pricing scheme and should preferably be applied by the seller, particularly if customers frequently visit the store. The price transparency level hardly changes this recommendation as in 70% of the shown cases SLO is suggested for A customers. The situation is different for B customers, for whom SLO is only found to be optimal for relatively low levels of price transparency. For higher levels of price transparency, the PUL scheme is listed more often. For C customers, price transparency exhibits an even higher degree of separation regarding the selection of an appropriate pricing scheme. In scenarios without price transparency, SLO should be deployed by the seller except for the low loss aversion scenario with a high visit frequency, where CYC is recommended instead. As soon as price transparency exists, PUL is applied without exception.

To summarise, the impact of price transparency on the pricing schemes increases from A to C customers. If there is no price transparency, SLO is the dominant scheme for most customers. If price transparency exists, SLO is in most cases only suggested for A customers, while the PUL scheme is more often recommended for B and C customers.

The listed prices also explain the aforementioned rather surprising result that a higher degree of price discrimination mitigates the negative effects of higher customer loss aversion. The reason for this is reflected, for instance, in the prices of PD1 and PD3 that are suggested for highly loss aversive customers in the high visit frequency case under medium price transparency (HF MT) in Table 36. With the PD1 price discrimination strategy, approximately 50% of A customers buy the product at a relatively high price. The other half adapt their willingness-to-pay to a much lower level due to the more affordable prices offered to B and C customers and therefore refuse to pay a significantly higher price. The deployment of PD3 increases the profit by 24.01% as compared to PD1. For accomplishing this, the suggested pricing strategy for PD3 indicates that first A customers should be served by deploying the SLO pricing scheme. In the meantime, B and C customers should be hindered from making a purchase by applying the PUL scheme, which offers them high first-time visitor prices for two reasons: (1) their willingness-to-pay increases and (2) the willingness-to-pay of A customers does not immediately decrease as it is the case under the deployment of PD1. This serving order can also be identified in most of the other pricing strategies that are listed for PD3 in Table 35 and Table 36.

Table 35. Profits and prices (average number of sales) of price discrimination strategies in selected low loss aversion scenarios.

Cus-tomer Group	Low Visit Frequency (LF) Case	PD1 Profit (Ø Sales)	PD1 1st Price (Ø Sales)	PD3 Profit (Ø Sales)	PD3 Pricing Scheme	PD3 1st Price (Ø Sales)	PD3 2nd Price (Ø Sales)	PD3 3rd Price (Ø Sales)	High Visit Frequency (HF) Case	PD1 Profit (Ø Sales)	PD1 1st Price (Ø Sales)	PD3 Profit (Ø Sales)	PD3 Pricing Scheme	PD3 1st Price (Ø Sales)	PD3 2nd Price (Ø Sales)	PD3 3rd Price (Ø Sales)
A			186.27 (9.148)		**SLO**	193.48 (8.537)	189.00 (0.548)	143.71 (0.044)			191.53 (9.914)		**PUL**	224.95 (0.000)	199.81 (7.930)	185.55 (2.049)
B	**No Price Transparency (NT)**	9536.02 (89.734)	116.02 (17.954)	9920.65 (90.206)	**SLO**	124.52 (11.201)	119.40 (5.475)	115.72 (1.092)	**No Price Transparency (NT)**	10607.38 (98.174)	118.56 (19.525)	11230.60 (99.450)	**SLO**	124.55 (12.221)	120.80 (5.185)	112.58 (2.593)
C			91.79 (62.632)		**SLO**	98.57 (43.610)	85.55 (19.699)	85.55 (0.000)			93.02 (68.735)		**CYC**	101.43 (32.875)	127.67 (0.000)	95.39 (36.597)
A			148.84 (9.713)		**CYC**	174.11 (8.464)	220.24 (0.000)	125.45 (1.195)			172.41 (8.624)		**SLO**	180.54 (9.427)	136.12 (0.573)	136.12 (0.000)
B	**Low Price Transparency (LT)**	9892.64 (96.023)	110.72 (19.154)	10654.86 (94.438)	**SLO**	122.97 (14.905)	112.98 (4.793)	112.98 (0.000)	**Low Price Transparency (LT)**	10131.35 (96.554)	112.02 (19.830)	11416.68 (99.498)	**SLO**	126.95 (9.714)	122.20 (7.464)	114.43 (2.816)
C			94.20 (67.156)		**PUL**	128.95 (0.000)	104.21 (49.733)	96.06 (15.348)			94.32 (68.100)		**PUL**	136.11 (0.000)	106.54 (40.035)	98.54 (29.469)
A			148.64 (9.851)		**SLO**	184.52 (5.388)	154.55 (4.375)	154.55 (0.000)			163.75 (9.231)		**SLO**	191.56 (9.098)	163.17 (0.899)	163.17 (0.000)
B	**Medium Price Transparency (MT)**	9951.09 (96.164)	111.45 (19.128)	10590.18 (93.081)	**CYC**	122.06 (16.748)	166.16 (0.000)	102.46 (2.708)	**Medium Price Transparency (MT)**	10169.20 (97.027)	114.34 (19.449)	11536.99 (99.260)	**SLO**	136.66 (0.502)	125.73 (14.031)	120.01 (5.373)
C			94.59 (67.185)		**PUL**	131.27 (0.000)	105.48 (46.636)	97.47 (17.226)			94.13 (68.347)		**PUL**	134.40 (0.000)	106.44 (40.699)	99.03 (28.658)
A			149.43 (9.851)		**CYC**	190.19 (8.572)	236.87 (0.000)	169.82 (0.887)			172.88 (8.452)		**SLO**	192.28 (9.358)	174.58 (0.642)	174.58 (0.000)
B	**High Price Transparency (HT)**	9933.15 (95.303)	112.38 (19.012)	10525.24 (90.407)	**PUL**	161.98 (0.000)	126.71 (16.965)	104.76 (1.824)	**High Price Transparency (HT)**	10132.50 (96.272)	114.24 (19.552)	11660.49 (99.053)	**PUL**	160.07 (0.000)	130.59 (13.834)	123.72 (6.066)
C			95.19 (66.440)		**PUL**	134.83 (0.000)	108.62 (29.956)	97.81 (32.203)			94.30 (68.268)		**PUL**	137.66 (0.000)	107.01 (40.571)	99.73 (28.582)
A			149.84 (9.806)		**CYC**	183.97 (9.367)	205.13 (0.000)	178.49 (0.363)			172.66 (8.410)		**SLO**	189.91 (9.680)	156.79 (0.320)	156.79 (0.000)
B	**Full Price Transparency (FT)**	9991.71 (96.605)	111.66 (19.167)	10410.77 (89.780)	**SLO**	136.69 (1.559)	127.94 (10.277)	118.64 (6.705)	**Full Price Transparency (FT)**	10130.15 (96.725)	112.73 (19.826)	11614.49 (99.347)	**PUL**	154.90 (0.001)	130.94 (11.728)	122.99 (8.165)
C			94.37 (67.632)		**PUL**	135.98 (0.000)	110.37 (22.978)	97.66 (38.531)			94.07 (68.489)		**PUL**	136.72 (0.000)	106.38 (42.870)	98.77 (26.583)

SLO = successive lowering, PUL = pull up, CYC = cyclic

Table 36. Profits and prices (average number of sales) of price discrimination strategies in selected high loss aversion scenarios.

Customer Group	Low Visit Frequency (LF) Case	PD1 Profit (Ø Sales)	PD1 1st Price (Ø Sales)	PD3 Profit (Ø Sales)	PD3 Pricing Scheme	PD3 1st Price (Ø Sales)	PD3 2nd Price (Ø Sales)	PD3 3rd Price (Ø Sales)	High Visit Frequency (HF) Case	PD1 Profit (Ø Sales)	PD1 1st Price (Ø Sales)	PD3 Profit (Ø Sales)	PD3 Pricing Scheme	PD3 1st Price (Ø Sales)	PD3 2nd Price (Ø Sales)	PD3 3rd Price (Ø Sales)
A			190.31 (9.045)		**SLO**	198.22 (6.527)	190.23 (2.445)	186.15 (0.076)			192.65 (9.837)		**CYC**	203.71 (3.041)	218.29 (0.000)	194.17 (6.919)
B	**No Price Transparency (NT)**	9559.24 (89.740)	116.27 (17.989)	10030.01 (90.400	**SLO**	121.92 (14.407)	114.21 (3.667)	81.88 (0.085)	**No Price Transparency (NT)**	10602.00 (97.949)	118.26 (19.541)	11275.03 (99.538)	**CYC**	126.32 (9.599)	161.45 (0.000)	121.59 (10.167)
C			91.64 (62.706)		**SLO**	97.99 (46.223)	91.72 (15.680)	83.10 (1.290)			93.27 (68.571)		**SLO**	104.79 (16.022)	99.43 (31.256)	92.15 (22.534)
A			93.53 (9.641)		**SLO**	191.73 (7.484)	115.40 (1.674)	115.40 (0.000)			189.58 (4.932)		**SLO**	192.53 (8.873)	148.93 (0.823)	90.97 (0.304)
B	**Low Price Transparency (LT)**	9057.41 (97.447)	92.89 (19.949)	10260.85 (91.003)	**PUL**	175.06 (0.000)	127.02 (10.076)	108.65 (8.111)	**Low Price Transparency (LT)**	9280.65 (93.253)	96.02 (20.000)	11372.74 (99.459)	**PUL**	161.47 (0.000)	123.62 (17.435)	101.71 (2.565)
C			92.88 (67.857)		**PUL**	242.23 (0.000)	107.66 (25.832)	97.57 (37.826)			94.05 (68.321)		**PUL**	132.25 (0.000)	106.57 (33.069)	98.21 (36.390)
A			93.94 (9.960)		**CYC**	192.58 (7.686)	255.86 (0.000)	161.64 (1.054)			189.43 (4.995)		**SLO**	192.21 (8.631)	188.34 (0.277)	142.27 (1.073)
B	**Medium Price Transparency (MT)**	9038.06 (95.969)	94.42 (19.703)	10268.23 (89.860)	**PUL**	258.66 (0.000)	128.39 (12.955)	117.68 (4.939)	**Medium Price Transparency (MT)**	9278.41 (92.187)	99.26 (19.193)	11506.16 (99.368)	**PUL**	153.38 (0.000)	126.26 (16.523)	110.51 (3.470)
C			94.14 (66.306)		**PUL**	188.04 (0.000)	105.89 (30.535)	96.04 (32.691)			94.52 (67.999)		**PUL**	137.59 (0.000)	106.58 (40.597)	98.83 (28.797)
A			93.27 (9.969)		**SLO**	186.64 (7.999)	169.48 (0.876)	169.48 (0.000)			191.37 (4.969)		**SLO**	194.47 (8.255)	186.43 (1.356)	169.94 (0.357)
B	**High Price Transparency (HT)**	9062.54 (97.108)	93.67 (19.606)	10061.65 (88.015)	**PUL**	217.21 (0.000)	129.68 (10.384)	117.63 (7.042)	**High Price Transparency (HT)**	9302.07 (91.754)	100.32 (19.260)	11511.61 (98.905)	**PUL**	157.90 (0.000)	171.50 (0.000)	125.05 (19.814)
C			93.23 (67.533)		**PUL**	183.83 (0.000)	106.08 (28.175)	97.10 (33.539)			95.06 (67.525)		**PUL**	138.10 (0.000)	108.81 (25.993)	99.39 (43.130)
A			94.88 (9.729)		**SLO**	181.03 (6.942)	146.21 (1.950)	118.94 (0.227)			187.61 (4.987)		**SLO**	194.70 (7.882)	180.03 (1.418)	166.05 (0.482)
B	**Full Price Transparency (FT)**	9009.78 (95.382)	94.76 (19.576)	10035.34 (88.892)	**PUL**	226.65 (0.000)	127.24 (13.790)	103.47 (4.456)	**Full Price Transparency (FT)**	9288.74 (92.109)	99.99 (19.308)	11546.93 (98.608)	**PUL**	161.21 (0.000)	129.48 (14.314)	121.53 (5.473)
C			94.31 (66.077)		**PUL**	140.94 (0.000)	108.04 (28.528)	96.03 (32.999)			94.71 (67.814)		**PUL**	138.54 (0.000)	108.22 (32.140)	99.74 (36.899)

SLO = successive lowering, PUL = pull up, CYC = cyclic

3.5 Conclusion

3.5.1 Summary

One of the most relevant and difficult decisions for firms is the adequate pricing of their products and services (Bitran and Caldentey 2003, p. 203; Stahl et al. 2016, p. 139). In this context, big data opens up new opportunities for e-commerce (Akter and Wamba 2016, pp. 173-174; Victor et al. 2019, pp. 140-141). The more information a seller collects about her customers, the better she will be able to estimate their individual willingness-to-pay in order to offer them tailored prices (Bourreau et al. 2017, p. 40). When offering individualised prices, EWOM can have adverse consequences for the seller. The paid prices could be shared in OSN causing customers to feel disadvantaged if their peers pay less for the same product or service. Disadvantageous price discrimination could provoke customers, for instance, to lower their willingness-to-pay and leave the online store without making a purchase. However, EWOM may also have a favourable impact on the seller's profit by attracting new customers who got informed of low prices. As an answer to our first research question (RQ2.1: *How should a decision model for price differentiation be formalised that considers customer data and EWOM effects?*), we developed a pricing decision model for an online seller who had profound knowledge about the static and dynamic data of her customers. In the model, the static customer data constituted the similarity between customers, and the dynamic data was based on their online store visit history. Both types of information were used by the seller to assign visitors to customer groups that were offered different prices. The objective function of the decision model was to maximise the total profit of the seller by optimising the prices for each customer group. EWOM was incorporated into the model for enabling customers to share their paid prices with directly and indirectly connected OSN members, which resulted in a certain price transparency in the market. We investigated the performance of different price discrimination strategies that differed in their level of price individualisation. Our findings prove that, despite the sharing of price information via EWOM, in many cases it can be profitable to offer different prices to different customers. Our results also indicate that the negative influence of loss aversion can be neutralised by applying a pricing strategy with a higher degree of price discrimination, which gives the seller more flexibility in adequately serving her customer base. We answered our second research question (RQ2.2: *Is artificial intelligence suitable for finding adequate solutions to complex pricing decisions?*) by developing and implementing an evolution strategy and comparing it to other AI and non-AI solution methods. The results demonstrate that AI methods have the potential to generate higher profits for the considered problem structure. Their advantage over non-AI methods increases if pricing strategies with a higher degree of price discrimination are deployed. However, our findings also indicate that not all AI methods are superior and should be thoroughly evaluated regarding their suitability for solving the existing pricing decision problem, e.g. by testing more configurations for their optimisation approach.

3.5.2 Managerial Implications

Several managerial implications can be drawn from the examined scenarios in our study. Our results suggest that a pricing strategy with a higher degree of price discrimination performs best in all scenarios and should therefore be deployed preferably. But the higher the degree of price discrimination is, the more information about the store's customers is required. If the collection and analysis of customer-related information are limited (e.g. due to data protection by law), a firm might be compelled to use pricing strategies with a lower degree of price discrimination. In such cases, firms should be cautious as price discrimination is not always beneficial and might lead to less profit than UP.

If a firm has to some extent control over EWOM, additional implications can be derived. For instance, if UP instead of price discrimination is deployed, initiating EWOM is only financially worthwhile if the visit frequency is low. If a firm opts for traditional group pricing (PD1), for higher degrees of loss aversion and higher levels of visit frequency, EWOM has mostly negative effects and should be prevented as far as the circumstances permit. This is contrasted by pricing strategies with a higher degree of price discrimination (e.g. PD3), where EWOM hardly changes the profits as compared to the no price transparency case. As demonstrated by the numerical results for these cases, EWOM can benefit the firm by increasing the profits in the tested scenarios.

The results of our numerical example provide insights into the optimal structure and composition of pricing strategies that are capable of increasing the firm's profit under price transparency. Depending on the chosen degree of price discrimination and contextual factors, the determined pricing strategies reveal how different customer groups should be served by the firm. If, for instance, PD1 is applied in markets with low customer loss aversion, price transparency induces a price reduction for A customers, while the prices for B and C customers are hardly influenced and should remain close to their initial willingness-to-pay. This strategy is found to be optimal irrespective of the customer visit frequency. However, a higher visit frequency generally increases the prices, which is in line with the findings of Wang (2016). If the firm is confronted with highly loss aversive customers, PD1 should not be applied as UP is superior or performs similarly well when price transparency exists.

The deployment of a price discrimination strategy like PD3 with multiple prices per group gives the firm more flexibility in serving different groups of customers, which can counteract the damaging effects of higher loss aversion under price transparency. The SLO pricing scheme, where higher prices are offered to customers on their first store visits and afterwards successively lowered, is often suggested for A customers irrespective of the existing price transparency. Similarly, the SLO scheme is the dominant strategy for C customers, but only if there is no price transparency. As soon as price transparency exists, for C customers the PUL pricing scheme should be deployed, where high prices on initial visits increase their willingness-to-pay and enable charging them higher prices on subsequent visits. B customers should also be served with the PUL pricing scheme, but only for higher levels of price transparency. For lower levels, SLO or the CYC pricing scheme, where high prices are offered to returning visitors for intermediately increasing their willingness-to-pay, are suggested more often.

Online stores may not always be able to accurately assess the characteristics of incoming customers. Erroneous assessments in this matter can lead to misjudgements of the customers' correct group membership. Each pricing decision therefore involves the risk of management mistakes by offering wrong prices to wrong customers. For instance, a customer with a low willingness-to-pay could be mistakenly assigned to the group of customers who usually exhibit a high willingness-to-pay and thereby get offered too high prices. In order to disclose how a partially wrong customer classification would influence the outcome, we tested with our developed model the effects of misclassification based on static customer attributes. For this, we re-ran the profit calculation with the individualised prices the evolution strategy had suggested for PD3. The seller assigned customers with a misjudgement probability of 5%, 10%, and 30% not to their fitting group but to another randomly selected group. On average, the profits of price discrimination were reduced by -3.222%**, -6.192%***, and -16.159%*** respectively. Although the profits decreased, differential pricing still performed significantly better than UP in the 5% and 10% misjudgement cases by +16.908%*** and +13.304%*** respectively. With a misjudgement probability of 30%, the generated profits exceeded the UP strategy's results only slightly by +1.223%^{ns}.

We also tested the effects of misjudging dynamic customer attributes that are represented in our model by the customers' visit history. Customers were assigned to the correct group, but with the same above-mentioned probabilities they were offered a random price of their group. The profits were decreased by an average of -2.638%*, -4.522%***, and -7.761%*** respectively but always outperformed UP significantly by +17.670%***, +15.420%***, and +11.559%***. The smaller decreases can be explained by the higher similarity of prices within a group causing less damage.

These results show that up to a certain level of uncertainty, the profits are only marginally reduced und thereby indicate a robustness of the found solutions against small to medium estimation errors. Only if customers are greatly misjudged in terms of group membership, the profits are substantially reduced but may still perform better than or as well as the UP strategy.

3.5.3 Limitations and Future Research Directions

Our study aims to provide a conceptual basis for future research where the combined effects of price discrimination and EWOM are investigated more thoroughly. Because the study explores new frontiers in this field, some limitations need to be considered when assessing its numerical results. First of all, more constellations regarding customer behaviour should be tested to investigate how the results change and ascertain when the positive influence of higher degrees of price discrimination on neutralising loss aversion is reduced. Secondly, the model should be extended by incorporating a "general acceptance factor" for price discrimination depicting the probability by which differential pricing is either accepted or rejected by customers. More than 50% of customers would refrain from shopping on Amazon if they got aware of individualised prices that are based on their willingness-to-pay (Kalka and Krämer 2016). Thirdly, the model should also be extended by the emotional reaction upon observing a high degree of price discrimination (i.e. greater values of X and Y). By this, a pricing strategy like PD3 or PD6 may not always perform better than their counterparts with a smaller degree of price discrimination since customer dissatisfaction leads to negative EWOM (Xia et al. 2004, p. 1), which, in turn, may result in fewer sales. Fourthly, in our model the strategic behaviour of customers is currently limited to the planning of the next store visit. When a customer visits the store, his buying behaviour is myopic: he only buys the product if the price is less than or equal to his willingness-to-pay, but he does not consider that the seller could offer him a lower price on a subsequent visit. As the offered prices are fixed in their amount and order, it would be easy to see through this sort of pricing strategy. Our model should therefore be extended by future research to support strategically acting and forward-looking customers who also plan future purchases. It should be tested how the applied AI solution methods perform under these circumstances and how the produced results differ. An advanced cyclic pricing scheme that requires a high degree of price discrimination might help to deal with such challenges. Fifthly, the role of the network structure and its impact on setting individualised prices should also be investigated by future research. As the literature review revealed, many studies that incorporate EWOM effects suggest that OSN members with a large number of contacts should be offered lower prices for advertising purposes. The deployment of our model could yield contrary results since OSN members in central positions would be able to inform more people about their potentially lower prices and thereby harm the firm's profit. It should be examined under which circumstances offering lower prices to influential OSN members is financially worthwhile with the developed model. Sixthly, the model and simulation scenarios should be extended in a way that the varied parameters in our experiments (e.g. loss aversion) do not apply to all customers but vary on a group or individual level. For instance, it is conceivable that customers with low purchasing power generally have a lower willingness-to-pay and are more sensitive to disadvantageous price discrimination, which might result in a faster lowering of their willingness-to-pay upon observing lower prices. Applied to our current experiments, this would probably evoke a more strict serving order for the customer groups A, B, and C. In order to reduce the negative effects of high loss aversion among C customers, at first A and thereafter B customers should be encouraged to make a purchase by offering prices that are higher than the mean willingness-to-pay of C customers. Finally, in future investigations, the importance of the correct assessment of customer characteristics should be examined in greater depth. The more diverse customers are, the greater is the probability that they exhibit a different willingness-to-pay. This would justify a higher degree of customer separation leading to the definition of more customer groups and ultimately personalised pricing. In this respect, the impact of the estimation and classification errors on the profit could be amplified because the probability of offering the wrong price to the wrong customer would increase. This could make price discrimination lose its superiority to UP already at smaller estimation errors. Future research should therefore investigate when this point is reached for different constellations. It should also be investigated how the solution methods perform in optimising prices under uncertainty about customers, i.e. when customers are not correctly classified from the outset.

Chapter 4:

The Diffusion of Social Media Apps and Services in Online Social Networks

4 The Diffusion of Social Media Apps and Services in Online Social Networks

4.1 Introduction

Today, social media and online social networks (OSN) enjoy great popularity among Internet users (Statista 2020c). OSN like Facebook, Twitter, and Instagram offer a variety of *social media services* (e.g. sharing of information, photos, or videos) and are usually available in the form of applications (apps) for smartphones and tablets (Köse et al. 2018, p. 1046; Penni 2017, pp. 500-501). Such *social media apps* are used by the vast majority of users to access their favourite social media services leading to an omnipresent reachability of OSN (Chen and Li 2017, p. 958; Lamberton and Stephen 2016, p. 146; Stieger and Lewetz 2018, p. 618). We define social media services as an aggregation of OSN functionalities that create a *social utility* for users and thereby increase the attractiveness of an OSN. The more users a social media service has, the greater is the attraction of adoption for non-users because the social utility derived from using the offered service increases with the number of reachable members. New social media services do not have to be a part of the OSN's website or app but can also be framed as stand-alone apps. For instance, Facebook offers a messenger service that enables users to share direct messages with contacts, for which a stand-alone app was released in 2011 (Kincaid 2011). The service was also kept preliminary in Facebook's main smartphone app until it got removed in 2014 (Gibbs 2014). Similarly, in 2018 Instagram introduced a new social media service called Instagram TV (IGTV) that is optimised for the sharing of longer videos with vertical orientation (Constine 2018; Instagram 2018). IGTV functionality is built into the main Instagram app, and the full-featured service is also offered separately as an app (Constine 2018; Instagram 2018). We therefore define apps that include social media services as social media apps, which act as a framing tool for them. An OSN like Facebook can consist of a website and multiple social media apps that encapsulate its offered social media services. It is possible, however, that the whole OSN with its social media services is contained in one social media app like in the case of the instant messenger WhatsApp.

Today, there are numerous social media apps and services that compete for the attraction of users. Newly introduced social media apps and services can face difficulties in establishing themselves in the market because users could discard them due to insufficient social activity. In this study, we aim to investigate how different kinds of social media apps and services diffuse in OSN in order to identify factors of success and failure. By simulating the diffusion in an extracted sub-graph of Facebook, different launch strategies are examined and compared to each other regarding their ability to maximise the number of active users.

Based on the offered social media apps and services, OSN enable the creation of user-generated content and facilitate the sharing of information via electronic word of mouth (EWOM), e.g. for exchanging experiences with products or services (Beneke et al. 2015, p. 68; Jung and Kim 2012, p. 343; Yoo et al. 2013, p. 669). The intensive usage of an OSN by its members enables the collection of large amounts of user-related data. The obtained data can be used by the OSN vendor for performing analyses that help to assess and predict the interests and behaviour of users (Bello-Orgaz et al. 2016, pp. 53-54; Chen et al. 2012, p. 1169; Fowler et al. 2013, p. 512; Pangrazio and Selwyn 2018, p. 1). These serve as a basis for applying personalised advertising in OSN by which users get shown advertisements that are tailored to their estimated individual preferences (Lax and Russo 2019, p. 1174; Ribeiro et al. 2019, p. 140). For firms that want to promote their products and services, OSN therefore represent an easy way to implement targeted advertising for reaching their target groups at lower costs and more quickly than by advertising in traditional media (Dawson and Lamb 2015, p. 106; Lax and Russo 2019, p. 1174; Wang et al. 2015, p. 17; Xu et al. 2012, p. 318). The more users an OSN has and the more accurately it can assess their interests, the more attractive it gets as an advertising and promotion platform for firms (Hanna et al. 2011, p. 267; Metcalfe 2013, p. 30; Zhang et al. 2015, p. 248). Hence, the acquisition of new users and the maintenance of an active user base can be identified as two main objectives of OSN vendors as they exert a direct influence on the OSN's enterprise value. One approach for reaching these goals is the continuous development of the OSN since the users' desires and needs are subject to continuous change (Wilkinson and Thelwall 2010, p. 2311). Innovative social media apps and services can lead to new ways of member interaction and thereby help to adapt to changing circumstances. Vendors should therefore pay attention to how members use the OSN in order to identify latent needs, be it by analysing the collected user data or by explicitly asking them about their user experience and service improvement wishes. Incidents in the past have shown that capricious users can indeed endanger the popularity of OSN (Arango 2011). For instance, MySpace, as being one of the most popular and successful OSN of its time with more than 76 million users in 2008, has faced a continuous decline since its popularity peak (Mandl 2019, pp. 121-122). This is in part attributed to the lack of innovation and low adaptation to the changing nature of how its members had used the platform (Arango 2011; Lőrincz et al. 2019, p. 44; Mui 2011). Facebook, on the contrary, has been successfully introducing and improving numerous features and services (Mohan 2018) for preventing a decline in user activity. This is underlined by the number of monthly active Facebook users, which has continuously increased over the years and surpassed 2.6 billion users in the first quarter of 2020 (Statista 2020e).

On a meta-level, social media apps and services are comparable to network goods that exhibit an intrinsic value and a network value (Jing 2007, pp. 8-9; Sundararajan 2004, p.

108). These determine the utility that is perceived by potential adopters (Ge 2002, p. 176; Katz and Shapiro 1985, p. 424; Zhao and Duan 2014, p. 56). While the network value equates to the aforementioned social utility, the intrinsic value can be seen as a *personal utility* (He and Lee 2020, p. 29; Hu et al. 2020, p. 1165). In the context of social media apps and services, a user may derive a personal utility from the functionalities of an app or service if these are useful to him irrespective of whether others use them. The diffusion of network goods in a network is subject to so-called *network externalities*, also called *network effects*, that can be differentiated into *direct* and *indirect network externalities* (Chiu et al. 2013, p. 540; Hu et al. 2020, p. 1162; Katz and Shapiro 1985, p. 424; Lin and Lu 2011, p. 1153; Page and Lopatka 1999, pp. 953-955; Top et al. 2011, p. 1576). Direct network externalities refer to the number of existing adopters, who increase the perceived utility of the network good (Chiu et al. 2013, p. 540; Top et al. 2011, p. 1576). Frequently mentioned examples for direct network externalities are communication networks such as telephones or fax machines (Chiu et al. 2013, p. 540; Lin and Lu 2011, p. 1153; Page and Lopatka 1999, pp. 954-955). With each new owner of such technology, network participants gain a new potential communication partner (Page and Lopatka 1999, p. 954). Indirect network externalities pertain to the emergence of complementary goods due to the popularity of the adopted good (Chiu et al. 2013, p. 540; Page and Lopatka 1999, p. 955). Katz and Shapiro (1994, p. 99) give the example of increased supply and quality of software that come with the successful diffusion of a corresponding hardware platform. This, in turn, can increase the sales of the hardware and thereby induce synergetic effects (Katz and Shapiro 1994, p. 99; Page and Lopatka 1999, p. 955). Applied to the context of social media apps and services, indirect network externalities result from the increased usage of these and could, for instance, incentivise the OSN vendor to provide its users with complementary services like analysis or developer tools (Köse et al. 2018, p. 1048; Zhang et al. 2017, p. 285). Additional services can also be supplied by third parties if it is supported by the technological basis of the social media app or service, e.g. via application programming interfaces.

In this study, we focus on direct network externalities. These will enable a user to derive a higher social utility from joining a new social media app or service if more people already actively use it (Chiu et al. 2013, p. 540; Zhang et al. 2017, p. 285). In regard to the source of emergence, direct network externalities are further differentiated into *local* and *global network externalities* (An and Kiefer 1995, p. 104; Jo and Kim 2012, p. 278; Tomochi et al. 2005, p. 274; Zhao and Duan 2014, p. 56). Global network externalities arise if the social utility of an adopted good is based on the total number of adopters (Tomochi et al. 2005, p. 274; Zhao and Duan 2014, p. 56). Local network externalities, by contrast, originate from the adoption in the social neighbourhood of a potential user (Tomochi et al. 2005, p. 275; Zhao and Duan 2014, p. 56). Note that local and global network externalities only refer to the source but do not provide information about the extent of their impact on the perceived social utility (Page and Lopatka 1999, p. 953; Top et al. 2011, p. 1576). Following the terminology of Granovetter (1973), who differentiated relationships in social networks according to their strength, the source of direct network externalities is represented by either *strong ties* (e.g. close friends or family members) or *weak ties* (e.g. indirectly connected individuals such as friends of friends). To encompass the magnitude of their effects, we divide the social utility into a *strong-tie utility* (STU) and *weak-tie utility* (WTU) that emerge from local and global network externalities respectively. The aforementioned indirect network externalities, in the form of additionally offered services, can affect and increase both the personal utility as well as the strong- and weak-tie utility of social media apps and services and thereby induce an increase in the user base. The extent of indirect network externalities, in turn, depends on the popularity and usage intensity of social media apps and services, which may emerge from either type of utility. Figure 33 shows a framework that summarises the above-mentioned interrelationships and dependencies of network externalities in the context of social media apps and services:

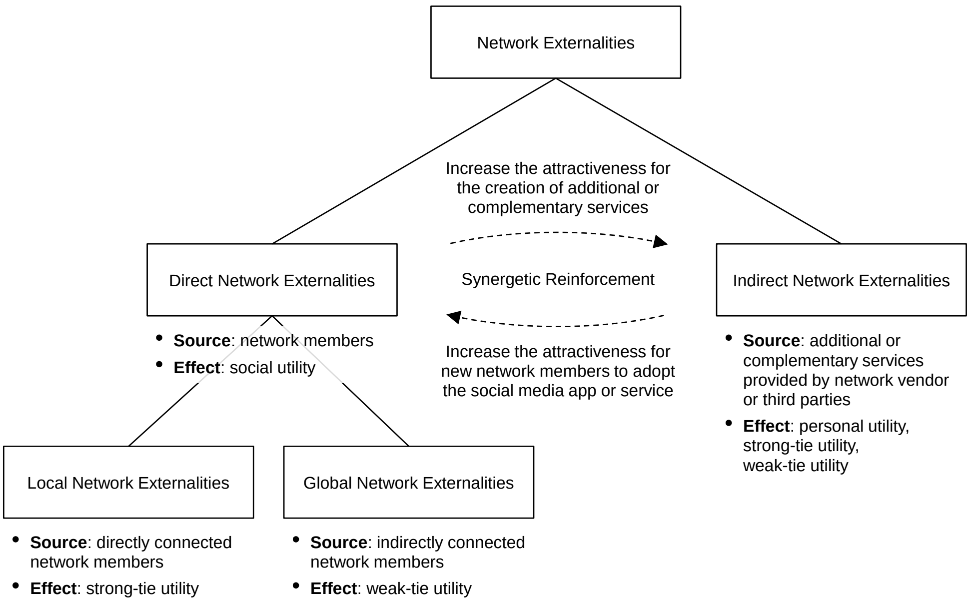

Figure 33. Network externalities in the context of social media apps and services.

Together, the personal, strong-, and weak-tie utility can serve as a basis for classifying social media apps and services. Figure 34 shows our proposed novel classification scheme where selected popular social media apps and services are exemplarily placed according to the estimated personal utility and the relation between the strong- and weak-tie utility. The strong-tie (weak-tie) utility predominates if it is more useful and important from the perspective of a potential adopter that strong (weak) ties use the social media app or service.

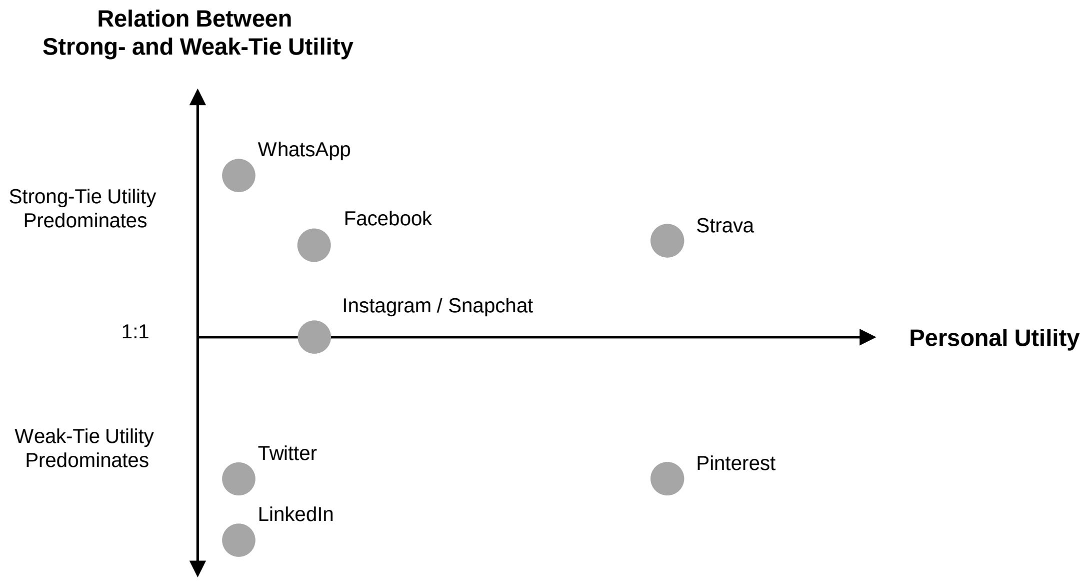

Figure 34. Exemplary classification of social media apps containing social media services according to the proposed classification scheme.

The instant messenger WhatsApp is mostly used for communicating with strong ties and rarely for sharing information with weak ties (Church and de Oliveira 2013, p. 355; Nouwens et al. 2017, p. 730), i.e. the derived social utility is to a great extent influenced by the number of registered close contacts and less by the total number of WhatsApp users, who can be seen as weak ties. As a counterexample, the professional business networking site LinkedIn is used for staying in contact with business partners and finding new ones (Chiang and Suen 2013, p. 17). The attractiveness of LinkedIn mainly increases with the number of total users, i.e. weak ties, and depends less on the adoption among the user’s strong ties. Similar to WhatsApp, Facebook is predominantly used for communicating with strong ties (Alhabash and Ma 2017, p. 4; Lőrincz et al. 2019, p. 44), but its users may also use it for finding new friends based on friendship suggestions (Bulgurcu et al. 2010, p. 7). Facebook’s attractiveness is therefore also influenced by the total number of its users, which enables the establishment of new friendships. Additionally, Facebook exhibits a certain value of personal utility because it offers a marketplace where users can pick from multiple personally usable services like single-player games (Wohn and Lee 2013, p. 176), which have emerged from indirect network externalities. Unlike Facebook, Twitter is mostly used for acquiring news (Akhtar 2017, p. 83) as it is very popular for following politicians and journalists (Dubois and Gaffney 2014, p. 1270). 48% of the Twitter members in the US use the OSN for news and entertainment, while only 34% use it for keeping in touch with family and friends (Statista 2019c). By contrast, Facebook is used by 88% of its members for the latter purpose (Statista 2019b). The more users Twitter have, the greater is the probability of finding interesting and entertaining accounts to follow. We therefore assume that Twitter's weak-tie utility outweighs its strong-tie utility. Instagram and Snapchat are popular photo and video sharing apps that both offer a variety of filters applicable to the shared media (Alhabash and Ma 2017, p. 2; Sheldon and Newman 2019, p. 1). Their users put emphasis on self-portrayal and social identity (Alhabash and Ma 2017, p. 4; Al-Kandari et al. 2016, p. 91; Sheldon and Bryant 2016, p. 90). Users might feel confirmed in these if the shared photos and videos receive many likes from their followers, who can consist of both strong and weak ties. Besides the public sharing of media, the apps are also used for privately communicating with close contacts (Alhabash and Ma 2017, 4; Al-Kandari et al. 2016, p. 91). We therefore estimate the strong- and weak-tie utility of Instagram and Snapchat to be rather balanced out. Because Instagram and Snapchat offer multifaceted photo and video filters that provide a utility for users irrespective of the activity of others, both apps also offer a certain amount of personal utility. The personal utility can be assumed to be much higher for a fitness activity tracking app like Strava that offers functionalities for the measurement of exercises such as elapsed time, burned calories, GPS tracking etc. (Strava 2020). Strava also provides social components and OSN functionalities that enable its users to monitor the activities of their friends or other members who publicly share their data (Strava 2020). It is conceivable that the app's attractiveness depends to a great extent on the number of active users among a potential user's strong ties. Compared to the activity of arbitrary weak ties, a large number of active strong ties might motivate a user more to actively use the app himself. Pinterest is an OSN that is available as a website and an app where creative content can be collected and shared by its users (Ottoni et al. 2013, p. 458; Sheldon and Bryant 2016, p. 90). Pinterest exhibits a high personal utility because these archiving functionalities can be used for personal media collections and are attractive to use even if no interaction to other members existed in the OSN. However, the perceived social utility is strongly shaped by the weak-tie utility because more users mean more creative content to pick from.

Our study can be seen as the diffusion of a new social media app that is launched by the OSN vendor itself or as the diffusion of a social media app that is founded by third parties, e.g. start-ups, and advertised in an existing OSN for winning new users. If a new social media app or service is released, its vendor will try to increase its reach by acquiring as many active users as possible. In order to attract the attention of OSN members, the new social media app or service needs to be advertised in the OSN. In this context, the possible influence of the perceived strong- and weak-tie utility on the diffusion behaviour of an app or service needs to be taken into account. It is possible that social media apps or services with a high strong-tie utility diffuse more cost-efficiently, i.e. require a lower advertising budget for reaching a certain spread in the OSN. A high strong-tie utility means that the total utility of the service is predominantly based on the participation of a potential user's peers.

This, in turn, means that already a small number of app or service adopters can lead to a sufficiently high social utility that could persuade the user to also adopt it. This must not necessarily hold for apps with a high weak-tie utility, where the persuasion of a potential user would require a large number of total adopters.

It can be argued that OSN vendors do not have to be concerned about marketing expenses since the introduction of new social media apps and services can, in theory, be marketed without costs in the OSN. However, it should not be neglected that the provided social utility is the main driver for such apps and services. If users in the OSN are shown the advertisement too early, they might encounter insufficient social activity in the advertised social media app or service. The timing of advertising is thus an important strategy parameter, not least because the users' desire to explore is at its peak when the app or service is opened for the first time and might quickly drop afterwards making a second examination less likely. An appropriate scheduling of the advertising campaign can help to prevent such risks by adequately making use of the user excitement that may act as a catalyst for the diffusion process.

Another aspect that deserves attention in the context of launching social media apps and services is the way the advertisement is conveyed to potential adopters. The least complicated way is a random marketing strategy, where randomly selected OSN members are shown the advertisement. However, social media apps and services could also be launched by more complex targeted advertising strategies such as influencer and cluster marketing. If, for instance, the social media app or service exhibits a high strong-tie utility, it might be more beneficial to deploy cluster marketing, where the advertisement is simultaneously presented to socially coherent areas of the OSN with densely connected members. Influencer marketing could be more suitable for social media apps and services with a high weak-tie utility since influencers are able to reach a multitude of members due to their influential positions in the OSN (Rothe and Wicke 2018, pp. 1637-1638).

Based on these considerations, we formulate the following research questions (RQ):

RQ3.1: *How do social media apps and services that are varied in terms of strong- and weak-tie utility differ in their diffusion behaviour?*

RQ3.2: *How important is the advertising schedule structure?*

RQ3.3: *How effective are influencer and cluster marketing as compared to random marketing in launching social media apps and services?*

In order to answer the first research question RQ3.1, we develop a diffusion model that differentiates between different kinds of utilities according to the proposed classification scheme. This enables the analysis of the diffusion behaviour of social media apps and services that are varied in terms of personal, strong-, and weak-tie utility. We incorporate EWOM in our model by which users will be able to tell their contacts about the app or service as soon as they have adopted it. Thereby, realistic diffusion dynamics are ensured by considering not only different advertising mechanisms but also complex user-individual EWOM behaviour. For answering the second research question RQ3.2, we test and evaluate different structures for advertising schedules where a given advertising budget is split into multiple advertising impulses. The impulses are characterised by their time of activation and intensity, which represents the invested share of the available total budget. To address the third research question RQ3.3, we use a sub-graph of Facebook, where we identify influencers and clusters. Their suitability for effectively distributing the advertisement in the OSN is benchmarked against random marketing, where members are randomly selected and presented the advertised social media app or service. It is investigated which of these targeting strategies performs best in terms of reaching a high share of members in the OSN who actively use the newly introduced social media app or service. Furthermore, the role of EWOM in the context of the targeting strategies is examined by changing the level of EWOM activity among OSN members and measuring its effect on the strategies' performance.

This chapter is organised as follows. In the next Section 4.2, literature streams are presented that are related to our work. In Section 4.3, we introduce our diffusion model, for which a numerical analysis is carried out in Section 4.4. In Section 4.5, we discuss the results, deduce managerial implications, and point out several ways of how our work could be extended in future.

4.2 Literature Review

The present study is related to several areas of research. These include the diffusion of new (innovative) products, technologies, and network goods. These research areas overlap in studies that consider network externalities in the diffusion process. To follow the terminology of the majority of the reviewed papers, the above-mentioned terms will be referred to by the term *technology* in a synonymous sense. As mentioned in the introduction section, network externalities can be differentiated in regard to several aspects. In the following, we will concentrate on related literature that distinguishes between local and global network externalities and point out differences to our study at the end of this section.

While global network externalities have been given much attention by researchers since the 1980s (An and Kiefer 1995, p. 103; Cowan and Miller 1998, p. 286), the research on local network externalities emerged more recently. Table 37 gives an overview of related papers in this field. As depicted in Figure 35, the papers can be broadly divided into three Categories I to III that, to a great extent, are chronologically based on each other showing a shift in the focus of this research field.

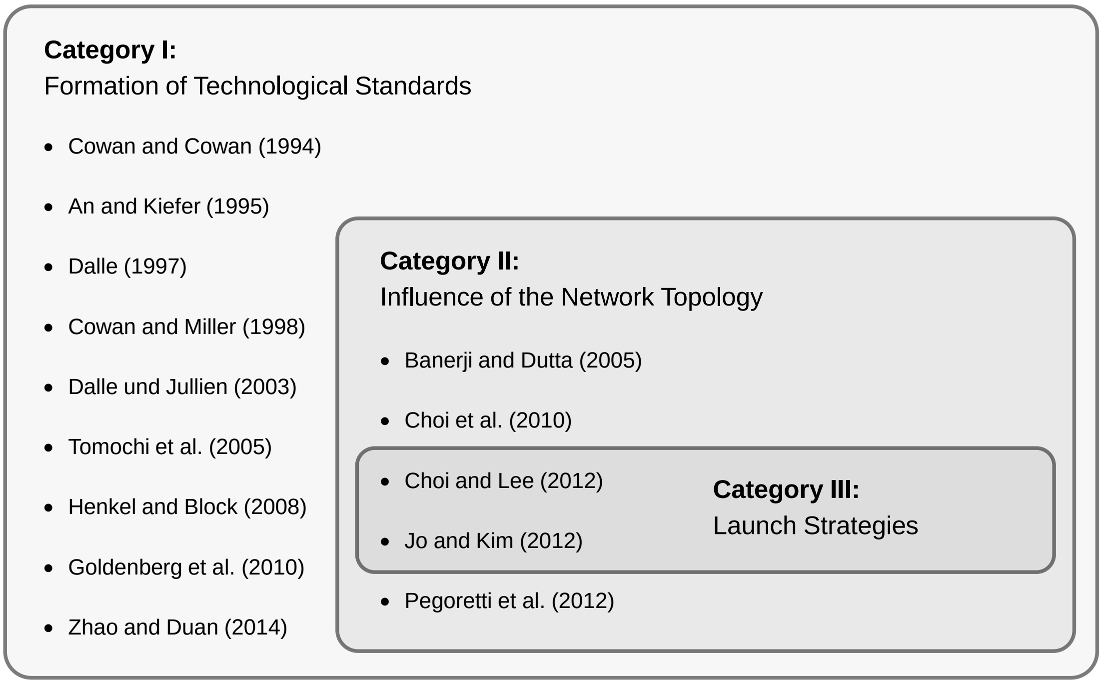

Figure 35. Categorisation of the reviewed papers that distinguish between local and global network externalities.

Category I contains papers that mainly focus on the diffusion of one or multiple competing technologies that are subject to local network externalities. They investigate if and how technological standards are formed where one technology reaches a high spread in a network and dominates the other existing technologies. Category II consists of papers that extend the research carried out in the Category I by examining the impact of the network structure on the diffusion behaviour of technologies and their standardisation. While all of the reviewed studies of Category I either use a one-, two-, or multi-dimensional lattice network, the studies of Category II explicitly test the effects of small-world, random, and scale-free networks. Category III includes papers that examine the effects of different advertising and launch strategies.

Belonging to Category I, the study of Cowan and Cowan (1994) investigates how local and global network externalities impact the market segmentation in the presence of multiple technologies from which users may only pick one. They test different levels of customer heterogeneity that refers to differences in the individual valuation of the existing technologies, i.e. the perception of the offered utility. Their results show that customer heterogeneity leads to an increased probability of failed technological standardisation, which prevents one technology to take over the whole market. In other words, increased customer heterogeneity results in more technological islands that are each dominated by a different technology. If the heterogeneity decreases, the number of technological islands will also decrease but not to the extent that a technological monopoly is created. An and Kiefer (1995) solely focus on local network externalities and their impact on the adoption of a single technology or two competing technologies. They consider a multi-dimensional lattice network where each potential user is spatially surrounded by his neighbours. The attractiveness of adopting the technology depends on the share of adopters in the direct neighbourhood as well as the technology’s quality and price. The authors assume that a potential user meets other users who have already adopted the technology and thereby gets aware of it. Contrary to the findings of prior research on global network externalities, the authors’ results show that it is not always a priori predictable whether a technology will succeed in a monopolistic environment if it only depends on local network externalities. Dalle (1997) considers both local and global network externalities in his model. He follows a different approach than most of the other studies by embodying and treating global network externalities as an additional separate network member who is connected to everyone in the network. The author’s findings indicate that this kind of global network externalities usually leads to standardisation in the market. If only local network externalities exist, standardisation hardly occurs. This result is supported by the findings of Cowan and Miller (1998), who state that, in general, local network externalities do not warrant a standardisation. Henkel and Block (2008) analyse the influence of the peer effect on the diffusion of technologies. The peer effect relates to the intrinsic motivation of adopters to invite non-adopters to increase their own utility derived from the technology. Their results show that the peer effect can considerably increase the diffusion if local network externalities exist. Diverging from the majority of the studies in the research field of local and global network externalities, Tomochi et al. (2005) and Goldenberg et al. (2010) do not additively link the effects of the externalities but opt for a multiplicative modelling. In this regard, Tomochi et al. (2005) investigate a duopolistic market setting and find that this modelling approach can both result in partial and total standardisation. Goldenberg et al. (2010) examine a monopolistic market setting and show that network externalities of either kind enforce a new technology to pass a phase of slowed down diffusion before a high market penetration is reached. This can be explained by the hesitant behaviour of customers who follow a wait-and-see approach before committing to the new technology. Zhao and Duan (2014) analyse the process of standardisation from a different perspective. They consider that an inferior technology already exists on the market and exerts a lock-in effect on adopters who have got used to it and prefer it to a new superior technology that is introduced to the market. Their results show that the lock-in effect can be reinforced by strong local network externalities, which prevent the new technology from taking root in the market.

As one of the first studies belonging to Category II, Banerji and Dutta (2005) test the impact of various simple network topologies like line or ring graphs in a duopoly. They consider nodes of the network not as individuals but groups of customers. Their results indicate that the network structure plays an important role in determining if a technology will dominate the market or if a segmentation of the market will occur. This is supported by the study of Choi et al. (2010), who analyse the diffusion behaviour of technologies in a monopolistic market setting with small-world networks. Following the conceptualisation and small-world network generation algorithm provided by Watts and Strogatz (1998, p. 441), Choi et al. (2010) test various network structures. Their results show that in highly cliquish networks the technology reaches a higher degree of diffusion. The more random, i.e. less cliquish, the network is, the more difficult it gets for the technology to reach a sufficient level of diffusion required for standardisation. Choi and Lee (2012) use a regular and small-world network for their investigations. They introduce a ratio parameter that determines the size of the local network in relation to the global network. Thereby, the local network can be varied in size, and the global network becomes an extreme case of it. The model is tested in a duopoly and reveals that with the increasing size of the local networks, the probability of a technology overtaking the market increases. Pegoretti et al. (2012) could show for a monopoly that the diffusion speed depends on the degree of knowledge about the technology and can be altered by the network structure. For a duopoly, the authors' results suggest that the higher the diffusion speed in a small-world network is, the greater is the probability of standardisation.

With a study that can be assigned to both Category II and III, Jo and Kim (2012) use a scale-free network besides various simple network topologies and distinguish in the duopoly market setting between first and second movers. Their study demonstrates that if the first mover is able to win over a hub in the network with a multitude of connections, the second mover's best choice is to not compete but aim for a niche in the network. The previously mentioned study of Choi and Lee (2012) also belongs to Category III as the authors test the effects of advertising strategies. They compare the random selection of individuals to activating whole clusters as early adopters. In a regular network, the latter outperforms the former by reaching a higher degree of dissemination. The advantage of cluster marketing decreases with the randomness of the network structure.

In general, we will extend and contribute to the reviewed literature by considering local and global network externalities in the context of social media apps and services. For this, we incorporate a usage frequency in our diffusion model that will mimic a realistic opening behaviour of the social media app or service where users check for the activity of others. If they encounter insufficient levels of activity among their strong and/or weak ties, they might discard it and become inactive as well. This can result in cascades of users leaving the social media app or service (Garcia et al. 2013, pp. 40-41; Lőrincz et al. 2019, p. 43). Our model also considers an initial enthusiasm and excitement factor that is subject to decay. Users could be more euphoric when they use the social media app or service for the first time, e.g. out of curiosity or joy of exploring, which will likely not last for a long period of time. Because the model explores new frontiers in this matter, a monopolistic market setting is chosen for the present study.

Our study is particularly related to the Categories II and III of the reviewed literature. We contribute to Category II by testing the proposed diffusion model in a sub-graph of Facebook instead of using artificially generated networks. The number of vertices included in the network excerpt (3097165) is significantly larger than the size of the networks used in the reviewed literature, which mostly consist of only 500 to 1000 vertices. Thereby, insights are provided into how products and services with local and global network externalities diffuse in networks with real-world OSN structure. A contribution to the quite underrepresented Category III is made by examining various launch strategies that will differ in the advertising schedule structure (i.e. how many users are shown the advertisement at a given time step) and ways of targeting (i.e. randomly selected members in the OSN, whole clusters of OSN members, or followers of influencers).

Table 37. Related papers that distinguish between local and global network externalities.

Category	**Author(s)**	**Research Objective**	**Market Setting**	**Network Topology**	**Network Externalities**	**Findings**
I	Cowan and Cowan (1994)	formation of technological standards	oligopoly	two-dimensional lattice	local and global	• if customer heterogeneity increases, many technological islands will occur that preserve their own standard (i.e. adopt a single technology) • with decreasing customer heterogeneity, the number of technological islands will also decrease to a minimum of two accomplished standardisations
I	An and Kiefer (1995)	formation of technological standards	monopoly and duopoly	multi-dimensional lattice	local	• if only one technology exists, it is not always a priori predictable if it will succeed • if two competing technologies exist, the technology with the higher quality will ultimately dominate the market
I	Dalle (1997)	formation of technological standards	duopoly	two-dimensional lattice	local and global	• if only local network externalities exist, a standardisation will hardly occur • if both local and global network externalities exist, a standardisation will occur in almost all cases
I	Cowan and Miller (1998)	formation of technological standards	duopoly	one-dimensional lattice	local	• local network externalities generally do not warrant the accomplishment of a standardisation; many situations exist where non-standardisation prevails
I	Dalle and Jullien (2003)	formation of technological standards in the market of computer operating systems (commercial versus open source)	duopoly	two-dimensional lattice	local and global	• open source software can only dominate if strong local and global network externalities exist; the commercial software provider can counter this by providing lower prices

Category	Author(s)	Research Objective	Market Setting	Network Topology	Network Externalities	Findings
I	Tomochi et al. (2005)	impact of multiplicative effects of network externalities on the formation of technological standards	duopoly	two-dimensional lattice	local and global	• multiplicative effects can lead to both partial and total standardisation
I	Henkel and Block (2008)	impact of the peer effect (i.e. intrinsic motivation of adopters to invite non-adopters) on the diffusion and formation of technological standards	monopoly and duopoly	one- and two-dimensional lattice	local and global	• peer effect positively influences the diffusion of network goods with local network externalities but hardly has an impact on goods with global network externalities • in a duopoly, peer effect increases the likelihood that one network good will dominate
I	Goldenberg et al. (2010)	impact of multiplicative effects of network externalities on the diffusion of technologies	monopoly	two-dimensional lattice	local and global	• both local and global network externalities can delay the diffusion of products when compared to cases without network externalities

Category	**Author(s)**	**Research Objective**	**Market Setting**	**Network Topology**	**Network Externalities**	**Findings**
I	Zhao and Duan (2014)	diffusion of a new superior technology where the total utility increases gradually by local network externalities and learning processes	duopoly (old inferior versus new superior technology)	scale-free network	local	• strong local network externalities can impede the diffusion of the new technology even if users are aware of its advantages
II	Banerji and Dutta (2005)	impact of network structure on the formation of technological standards	duopoly	various simple topologies	local	• some network structures will facilitate the emergence of a dominant technology, while others will lead to a segmentation of the market where multiple technologies co-exist
II	Choi et al. (2010)	impact of network structure on the diffusion of technologies	monopoly	small-world network	local	• the number of failed diffusions increases with the randomness of the network structure
II	Pegoretti et al. (2012)	impact of network structure and degree of knowledge (awareness) about offered products on the formation of technological standards	monopoly and oligopoly	small-world network	local	• if imperfect (perfect) knowledge about the offered technology exists in monopolistic markets, the diffusion is faster in small-world (random) networks • if the average distance in the network is low, the probability of one technology dominating the market increases even if networks are highly clustered

Category	Author(s)	Research Objective	Market Setting	Network Topology	Network Externalities	Findings
III	Choi and Lee (2012)	impact of network structure on the formation of technological standards and the effectiveness of advertising and targeting strategies	duopoly	regular and small-world network	local and global	• the greater the size of the local networks is, the greater is the likelihood that one product will dominate the market • activating whole clusters as initial adopters for advertising is more effective in regular than in small-world networks
III	Jo and Kim (2012)	impact of network structure on the formation of technological standards and the competitive targeting of nodes	duopoly	various simple topologies and scale-free network	local	• if the first mover aims for a hub in the network, the second mover should compete by trying to find a niche

4.3 Model

4.3.1 Network Model

We consider an existing undirected OSN with $i = 1, \dots, I$ members where a new social media app or service is introduced and diffuses within the time horizon $t = 0, \dots, T$. In the following, the terms *social media app* and *social media service* are used interchangeably and in short are also referred to as just *app*. An OSN can be operationalised as a graph $G = (V, E, W)$ where $V = \{1, \dots, I\}$ is a finite set of vertices depicting the OSN members, and $E \subseteq V \times V$ is the set of edges representing the social relationships between them. The graph is connected, meaning that each vertex is able to reach any other vertex in the network. $W: (i, j) \rightarrow [0,1]$ is a function that attributes a weight $w_{ij} = W(i, j)$ to an undirected edge $(i, j) \in E$, which depicts the strength of the social relationship perceived by member i to another member j. Even though an edge is undirected, the perceived respective weights from both end-points may differ such that $w_{ij} \neq w_{ji}$. The direct neighbourhood of member i constitutes his strong ties (ST) and is defined as the set of other OSN members who are directly connected to him: $N_i^{ST} = \{j \in V: (i, j) \in E\}$. These are the members from whom member i will derive his perceived strong-tie utility. We define the remaining members in the OSN, who are only indirectly connected to member i, as his weak ties (WT), who will determine the perceived weak-tie utility: $N_i^{WT} = V \backslash N_i^{ST}$. For larger networks, it can be approximated by $N_i^{WT} \approx V$ where $\left|N_i^{ST}\right| \ll |V|$.

4.3.2 Perceived Total Utility and User Activity Status

An OSN member can be informed about the newly released social media app by advertising or EWOM. For this, let $r_{it} \in \{0,1\}$ indicate if a potential user i has been informed about the app by either way until time step t inclusively. Upon receiving the information, a user examines the functionalities and assesses the social media app's total utility according to his individual preferences. The total utility U_{it} that user i perceives at time step t depends on the perceived personal, strong-, and weak-tie utility that shall be denoted by PU_i, STU_{it}, and WTU_{it} respectively:

$$U_{it} = PU_i + STU_{it} + WTU_{it}, \qquad 0 \leq PU_i, STU_{it}, WTU_{it}, \tag{33}$$

$$\forall i \in \{1, \dots, I: r_{it} = 1\}$$

The activity status $a_{it} \in \{0,1\}$ of user i indicates if at time step t the perceived total utility of the app surpasses his individual time-independent activity threshold value $\theta_i, 0 \leq \theta_i$. OSN members who are unaware of the app cannot become active by definition: $a_{it} = 0 \ \forall i \in \{1, \dots, I: r_{it} = 0\}$. After adopting the app, a user will regularly use the app where the intermediate usage times are randomly generated with a mean value of $\xi, 0 \leq \xi$, which we will refer to as the *usage frequency parameter*. Each time the app is used, the user will re-evaluate its time-dependent utility and compare it to his threshold. As long as the threshold is surpassed, he will continue using the app. Let the set of users who will perform an activity check (AC) at time step t be denoted by $V_t^{AC} \subseteq V$. The activity check is either self-induced due to the regular usage of the app or triggered externally by advertising or EWOM:

$$a_{it} = \begin{cases} 1 & if \quad U_{it} \geq \theta_i \\ 0 & else \end{cases}, \qquad \forall i \in V_t^{AC} \tag{34}$$

The remaining OSN members exhibit the activity status of the previous time step: $a_{it} = a_{it-1} \ \forall i \in V \backslash V_t^{AC}$ with $a_{i0} = 0$. The perceived strong-tie utility STU_{it} and weak-tie utility WTU_{it} depend on the user's valuation for them, which, in turn, depends on how many of his strong and weak ties actively use the app. Because the contacts of a user could stop using the app, his valuation may change over time and the perceived total utility of the app could decrease. This would result in undercutting the required activity threshold, which would induce the user to discard the app and become inactive. Note that the number of changes made to the activity status of a user is not limited. If, later on, the valuation increases and the total utility surpasses the threshold once again, the user will adopt the app a second time. The share of OSN members A_t who are active in the social media app at time step t is given by:

$$A_t = \frac{1}{|V|} \cdot \sum_{i \in V} a_{it} \tag{35}$$

4.3.3 Perceived Personal Utility

OSN members can derive a personal utility from a social media app if it offers personal functionalities that are useful to them irrespective of whether they are used by others. For determining the perceived personal utility PU_i, two aspects need to be considered:

(1) How much utility would a user obtain if he used all personal functionalities?

(2) How many of the functionalities does he actually use?

Aspect (1) leads to the definition of a potential personal utility $PU, 0 \leq PU$, that depicts the maximum personal utility that is obtainable by a user. Aspect (2) takes into account that users usually do not make use of all available functions, e.g. because of a lack of interest or knowledge about their existence. This is represented in user i's individual valuation $v_i^{PU} \in [0,1]$ of the potential personal utility PU resulting in the perceived personal utility PU_i. For the present study, we assume that the valuation does not change over time leading to the perceived personal utility to be time-independent:

$$PU_i = v_i^{PU} \cdot PU, \qquad \forall i \in \{1, \dots, I: r_{it} = 1\} \tag{36}$$

4.3.4 Perceived Weak-Tie Utility

The perceived weak-tie utility describes the social utility that emerges when weak ties use the social media app. Analogous to the perceived personal utility, the perceived weak-tie utility WTU_{it} is based on two aspects:

(1) How much utility would a user obtain if all of his weak ties used the app?
(2) How many of his weak ties do actually use the app?

Aspect (1) concerns the maximum obtainable potential weak-tie utility $WTU, 0 \leq WTU$, while aspect (2) refers to user i's individual valuation $v_{it}^{WTU} \in [0,1]$ of the potential weak-tie utility WTU for determining the perceived weak tie utility WTU_{it}:

$$WTU_{it} = v_{it}^{WTU} \cdot WTU, \qquad \forall i \in \{1, \dots, I: r_{it} = 1\} \tag{37}$$

The valuation is time-dependent because it incorporates a user's number of weak ties in the OSN who have already adopted the app and actively use it. The more of his weak ties use the app, the greater is the perceived weak-tie utility. We assume that the increase is not linear but follows an S-shaped curve where a saturation of the perceived utility is reached after a certain number of adopters. This means that not all users in the OSN are required to be active in the app for generating a high valuation close to one for a potential adopter.

Besides the number of actual users of the app, we define the valuation of the perceived weak-tie utility to also depend on a second component: the initial excitement about the potential weak-tie utility, e.g. evoked by the quality of advertising. The initial excitement will boost the valuation by a determined amount and can be seen as a type of advance praise the social media app receives from users. We will additively link the excitement boost with the first component of the valuation. It is conceivable that the initial excitement for social media apps and services does not last very long and decreases after a certain period of time. This is because users are confronted with a plethora of apps that compete for the users' attraction and time. We also assume that the initial excitement exhibits the form of a reversed saturation curve where the excitement resides at a high initial level for a certain period of time and rapidly decreases thereafter.

Let the valuation that depends on the number of actual weak-tie adopters be expressed by $n_{it}^{WTU} \in [0,1]$ and let the boosted part of the valuation that is based on the initial excitement be denoted by $b_{it}^{WTU} \in [0,1]$. These components are additively linked and therefore limited by a min-function to comply with the normalisation of the valuation v_{it}^{WTU}:

$$v_{it}^{WTU} = \min\{1, n_{it}^{WTU} + b_{it}^{WTU}\}, \qquad \forall i \in \{1, \ldots, I: r_{it} = 1\} \tag{38}$$

For the operationalisation of n_{it}^{WTU}, the share of active users in the weak-tie neighbourhood is needed that is given by $\left|\{j \in N_i^{WT}: a_{jt-1} = 1\}\right| / \left|N_i^{WT}\right|$. In order to avoid sequence problems during the course of a time step, which could occur due to the discrete-time modelling approach, the share is based on the activity status of the weak ties from the preceding time step $t-1$. To create an S-shaped form for n_{it}^{WTU}, we transform the share by using a logistic sigmoid function where δ^{WTU} controls the curve's steepness and ω^{WTU} defines the curve's midpoint position on the abscissa axis:

$$n_{it}^{WTU} = \frac{1}{1 + e^{-\delta^{WTU} \cdot \left(\left|\{j \in N_i^{WT}: a_{jt-1} = 1\}\right| / \left|N_i^{WT}\right| - \omega^{WTU}\right)}}, \tag{39}$$

$$\forall i \in \{1, \ldots, I: r_{it} = 1\}$$

A visualisation of n_{it}^{WTU} for an exemplary parameterisation is depicted in Figure 36:

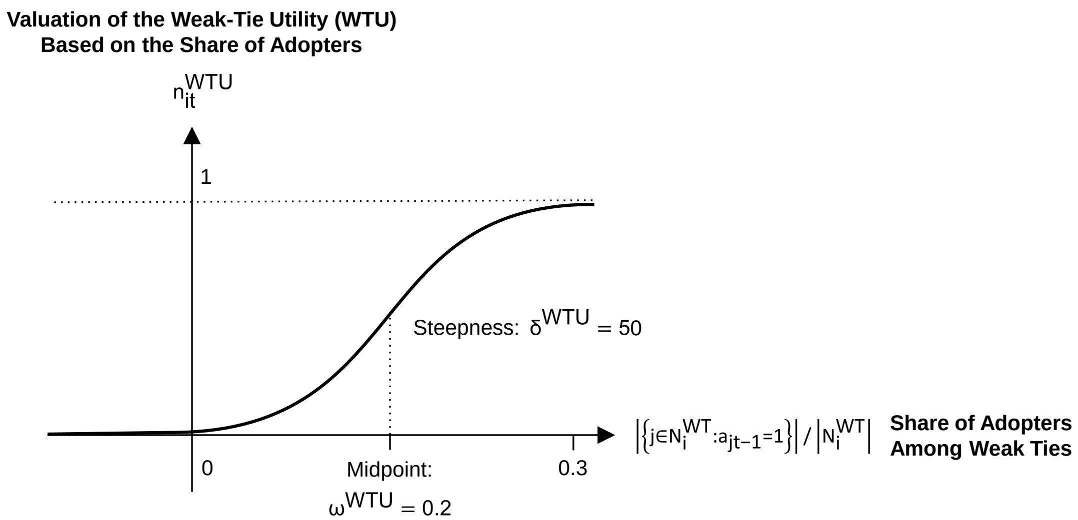

Figure 36. Valuation of the weak-tie utility based on the share of adopters among weak ties.

The boosted part of the valuation b_{it}^{WTU} will begin at an initial excitement level $\beta^{WTU} \in [0,1]$ that will be weighted with a time-dependent normalised factor representing the excitement decay. To accomplish a reversed saturation curve form for the decay, we use an exponential function that depends on the duration d_{it} since user i has gotten aware of the app for the first time: $d_{it} = t - \min\{\tau = 1, \dots, T: r_{i\tau} = 1\} \ \ \forall i \in \{1, \dots, I: r_{it} = 1\}$. The parameter κ^{WTU} controls the curve's steepness and ς^{WTU} is the *decay parameter* that defines the root of the function, i.e. it regulates after how many time steps the excitement will reach zero since the initial reception of the information about the app. Because it may fall below zero, the decay factor is capped at zero by using a max-function:

$$b_{it}^{WTU} = \beta^{WTU} \cdot \max\left\{0, 1 - e^{\kappa^{WTU} \cdot (d_{it} - \varsigma^{WTU})}\right\}, \qquad \forall i \in \{1, \dots, I: r_{it} = 1\} \tag{40}$$

Figure 37 shows an exemplary plot for b_{it}^{WTU}:

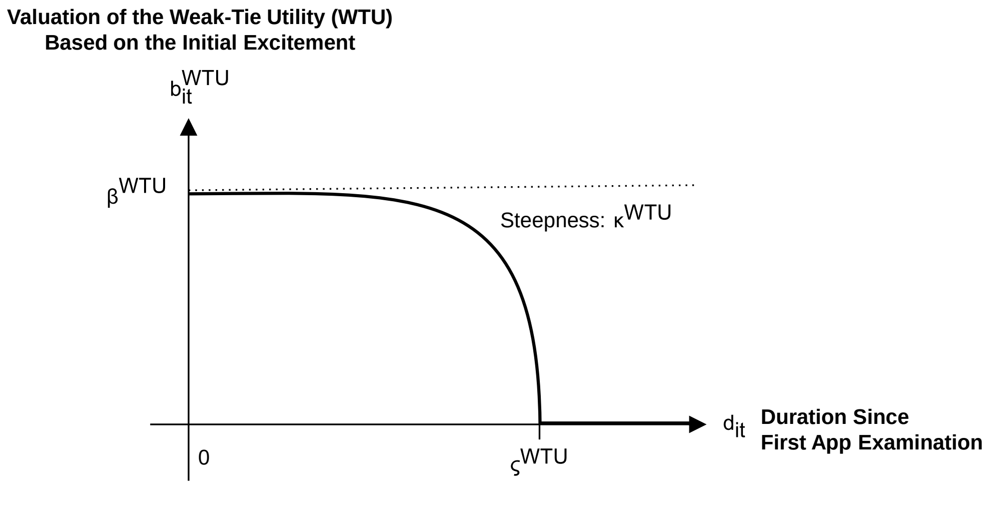

Figure 37. Valuation of the weak-tie utility based on the initial excitement.

The valuation v_{it}^{WTU} of the potential weak-tie utility can be in combination written as:

$$v_{it}^{WTU} = \min\left\{1, \frac{1}{1 + e^{-\delta^{WTU} \cdot \left(\left|\{j \in N_i^{WT}: a_{jt-1} = 1\}\right| / \left|N_i^{WT}\right| - \omega^{WTU}\right)}} + \beta^{WTU} \cdot \max\left\{0, 1 - e^{\kappa^{WTU} \cdot (d_{it} - \varsigma^{WTU})}\right\}\right\}, \tag{41}$$

$$\forall i \in \{1, \dots, I: r_{it} = 1\}$$

4.3.5 Perceived Strong-Tie Utility

As with the perceived weak-tie utility, the perceived strong-tie utility STU_{it} is based on two aspects that concern the potential strong utility $STU, 0 \leq STU,$ and user i's individual valuation $v_{it}^{STU} \in [0,1]$ for it at time step t:

$$STU_{it} = v_{it}^{STU} \cdot STU, \qquad \forall i \in \{1, \dots, I: r_{it} = 1\} \tag{42}$$

Likewise, the valuation is separated into two components that concern the transformed share of adopters among user i's strong ties $n_{it}^{STU} \in [0,1]$ and an initial excitement part that boosts the valuation $b_{it}^{STU} \in [0,1]$, which is also prone to decay. While the latter is modelled in the same way, the operationalisation of n_{it}^{STU} is different as it not only considers the share of active strong ties but also incorporates the strength of the relationship to each strong tie $j \in N_i^{ST}$. The weighted active neighbourhood of strong ties is therefore given by $(\sum_{j \in N_i^{ST}} w_{ij} \cdot a_{jt-1}) / (\sum_{j \in N_i^{ST}} w_{ij})$. Based on this, the compound expression for the valuation v_{it}^{STU} of the potential strong-tie utility is as follows:

$$\begin{aligned} v_{it}^{STU} = \min \Bigg\{ 1, \; & \frac{1}{1 + e^{-\delta^{STU} \cdot \left(\left(\sum_{j \in N_i^{ST}} w_{ij} \cdot a_{jt-1} \right) / \left(\sum_{j \in N_i^{ST}} w_{ij} \right) - \omega^{STU} \right)}} \\ & + \beta^{STU} \cdot \max \left\{ 0, 1 - e^{\kappa^{STU} \cdot (d_{it} - \varsigma^{STU})} \right\} \Bigg\}, \end{aligned} \tag{43}$$

$$\forall i \in \{1, \dots, I: r_{it} = 1\}$$

4.3.6 Advertising and Electronic Word of Mouth

Initially, OSN members are unaware of the new social media app. They can get informed about it via different sources: (1) advertising in the OSN, (2) sponsored posts published by influencers, and (3) EWOM disseminated by OSN members who have already adopted the app. These different ways of informing potential adopters are discussed and operationalised in the following.

For advertising the app in the OSN, a subset of members are chosen to whom the social media app is presented inducing them to evaluate the app's utility for possible adoption. The size of the subset is determined by an advertising budget $AB, 0 < AB,$ that is measured in the number of unique OSN members who are reached by advertising. An advertising campaign usually covers an extended period of time. This means that the budget does not need to be spent at once but can be divided into sub-segments within the time horizon T. These can be summarised in an advertising schedule AS that describes how much of the budget is spent at each time step: $AS = (as_1, as_2, \dots, as_T)$ where $as_t, 0 \leq as_t$, represents a schedule element. The sum of all schedule elements equals the budget: $AB = as_1 + as_2 + \cdots + as_T$. Positive schedule elements will be called *advertising impulses* in the following.

Let the corresponding subsets of OSN members reached by advertising (AD) at each time step be denoted by $V_t^{AD} \subseteq V$. These sets may overlap since a member can be presented the advertisement multiple times. Due to the information overload that is present in OSN (Canali and Lancellotti 2012, p. 28; Liang and Fu 2017, pp. 1-4), recipients could overlook the advertisement or may not be interested in thoroughly examining it. We therefore define a click-through rate (CTR) for advertising $CTR^{AD} \in (0,1]$ that resembles the probability that an OSN member reached by advertising will also examine its content, i.e. evaluate the utility of the social media app. The probability will determine if the advertisement was able to reach and successfully draw the attention of member i at time step t which shall be denoted by $r_{it}^{AD} \in \{0,1\}$. As it can only attain values of zero and one depending on the probability CTR^{AD}, it is subject to a Bernoulli (Ber) distribution (Aizenman et al. 2009, p. 221) and can be written as:

$$r_{it}^{AD} \sim \mathrm{Ber}(CTR^{AD}), \qquad \forall i \in V_t^{AD} \tag{44}$$

By definition, OSN members who are not affected by the advertisement, cannot be activated by advertising: $r_{it}^{AD} = 0 \;\; \forall i \in V \backslash V_t^{AD}$.

Members can also be made aware of the app by sponsored posts that are published by influencers (INF). The subset of OSN members reached by such posts shall be described by $V_t^{INF} \subseteq V$. These resemble the followers of the influencers who are shown the advertisement at a given time step. Usually, the probability of drawing attention is higher if the advertisement is disseminated by influencers (Chen and Knisely 2016, p. 19). We therefore define the click-through rate of influencer marketing to be greater: $CTR^{AD} < CTR^{INF} \in (0,1]$. Likewise, let $r_{it}^{INF} \in \{0,1\}$ denote if an influencer induced advertisement was able to draw the attention of member i at time step t:

$$r_{it}^{INF} \sim \mathrm{Ber}(CTR^{INF}), \qquad \forall i \in V_t^{INF} \tag{45}$$

If member i follows no influencers or if the influencers he follows are not activated as advertisers, he cannot be made aware of the app by influencer marketing: $r_{it}^{INF} = 0 \ \forall i \in V \backslash V_t^{INF}$.

A further possibility to get informed about the social media app is EWOM. This is the case when users try out the app and, due to a sufficient utility, recommend it to their peers. There are numerous motives for inviting one's peers to the social media app. For instance, the sender may make app recommendations based on altruistic reasons to enable his peers to also gain utility from using them. A recommendation can also be made out of self-interest, e.g. because the sender aims to increase his own perceived strong- or weak-tie utility. In this regard, it is conceivable that not all but only a subset of contacts are invited to the app to whom the sender has a closer social relationship. The stronger the perceived strong-tie relationship between the sender and a potential receiver is, the more regularly the sender will communicate with him (Brown et al. 2007, pp. 4-5; Chu and Kim 2011, p. 64; Pescher et al. 2014, p. 47). A more intense communication will, in turn, increase the probability that the sender will tell the receiver about the newly discovered social media app. We therefore define the perceived tie strength w_{ij} as the forwarding probability to a potential receiver $j \in N_i^{ST}$. An adopter has only a single chance to inform his contacts about the app. At each time step, there exists a subset $V_t^{senders} \subseteq V$ of OSN members who are potential senders. The containing users are those who have discovered the app for the first time at time step t: $V_t^{senders} = \{i \in V : r_{it} = 1 \wedge \sum_{\tau=1}^{t-1} r_{i\tau} = 0\}$. Consequently, all subsets of potential senders are disjoint within the time horizon: $V_1^{senders} \cap V_2^{senders} \cap \ldots \cap V_T^{senders} = \emptyset$. For these sets, the actual forwarding decision $FD_{ijt} \in \{0,1\}$ of a sender i to a receiver j at time step t is defined as:

$$FD_{ijt} \sim \mathrm{Ber}(w_{ij}), \qquad \forall i \in V_t^{senders} \tag{46}$$

The receiver of the information will not check the received information immediately but after a certain delay. The delay is randomly generated with a mean value of $\zeta, 0 \leq \zeta$. Let $V_t^{EWOM} \subseteq V$ define the set of members who have received information about the app via EWOM in the past and will possibly evaluate its content at time step t. Because a receiver can be sent information about the app by multiple members of his peer group, the sets may overlap. The likelihood that member i receives information via EWOM increases with the number of his strong ties. However, because of today's information overload, not all messages and information that have been forwarded via EWOM are also clicked on and ultimately evaluated (Canali and Lancellotti 2012, p. 28; Liang and Fu 2017, pp. 1-4;

Mehner 2019, p. 118). Thus, for EWOM we also define a click trough rate $CTR^{EWOM} \in [0,1]$ that will serve as the probability that member i is successfully made aware of the social media app via EWOM at time step t:

$$r_{it}^{EWOM} \sim \text{Ber}(CTR^{EWOM}), \qquad \forall i \in V_t^{EWOM} \tag{47}$$

If member i has not received information by any of his peers, he cannot be activated by EWOM: $r_{it}^{EWOM} = 0 \ \forall i \in V \backslash V_t^{EWOM}$. OSN members who are at time step t activated by either advertising (i.e. $r_{it}^{AD} = 1$), influencer marketing (i.e. $r_{it}^{INF} = 1$), or EWOM (i.e. $r_{it}^{EWOM} = 1$) constitute a subset of the previously defined set of members who will examine the utility of the social media app and decide on whether to adopt it or not: $\{i \in V : r_{it}^{AD} = 1 \vee r_{it}^{INF} = 1 \vee r_{it}^{EWOM} = 1\} \subseteq V_t^{AC}$. The binary reception indicator r_{it} that denotes that member i has been informed about the app until time step t inclusively is also based on r_{it}^{AD}, r_{it}^{INF}, and r_{it}^{EWOM}:

$$r_{it} = \begin{cases} 1 & if \quad \sum_{\tau=1}^{t} r_{i\tau}^{AD} + r_{i\tau}^{INF} + r_{i\tau}^{EWOM} \geq 1 \\ 0 & else \end{cases} \tag{48}$$

4.4 Numerical Analysis

4.4.1 Parameterisation

The stochastic variables of the model impede an analytical analysis of the diffusion of social media apps in practically sized graphs. We therefore conducted a numerical analysis where we determined the diffusion of various social media apps in different scenarios by simulation. As the underlying OSN, we used a sub-graph of Facebook with 3097165 vertices and 23667394 undirected edges (Rossi and Ahmed 2015). Figure 38 shows the cumulative degree distribution of the used network representing the sizes of the existing strong-tie neighbourhoods and reveals that 90% of the members have less than 40 contacts.

Some of the time-independent parameters of the model were fixed for all the following scenarios. The relation between the personal, strong-, and weak-tie utility will be varied, but their sum will be fixed such that $PU + STU + WTU = 100$. Upon receiving information about the app, a potential user compares the perceived utility to his individual threshold θ_i and adopts the app if the provided utility surpasses his threshold. We assume that the individual threshold is normally distributed among OSN members with a mean μ and standard deviation σ. The individual threshold was generated by using $\mu(\theta_i) = 50$ and $\sigma(\theta_i) = 12.5$. The distribution was truncated at zero to ensure the generation of non-negative threshold values. To generate random weights for the edges, we used an exponential distribution with a mean of $\mu(w_{ij}) = 0.2$ truncated at one because OSN members usually have a strong social relationship to a limited number of their contacts (Spiliotopoulos et al. 2014, p. 3). Empirical data indicates that the click-through rate for advertising on Facebook is quite low with 0.0125 (Chen and Knisely 2016, p. 19), meaning that roughly one out of 100 members who are shown the advertisement also clicks on the advertisement. However, in order to reduce the computing time for the following experiments, we fixed the click-through rate for advertising at $CTR^{AD} = 1.0$ unless otherwise specified. The invested budget therefore represents the number of OSN members who are reached and actually affected by advertising. If lower values of CTR^{AD} were used, not all recipients of advertising would evaluate the advertisement, which would require to increase the number of recipients – and thereby the computing time – for achieving the same overall advertising effects as $CTR^{AD} = 1.0$. Because OSN like Facebook offer advertisers to pay for each app installation instead of views (Facebook 2020), the number of OSN members reached by $CTR^{AD} = 1.0$ can be converted to monetary units. For EWOM, the click-through rate was set to $CTR^{EWOM} = 0.2$ by following recent estimations about messenger marketing (Mehner 2019, p. 118).

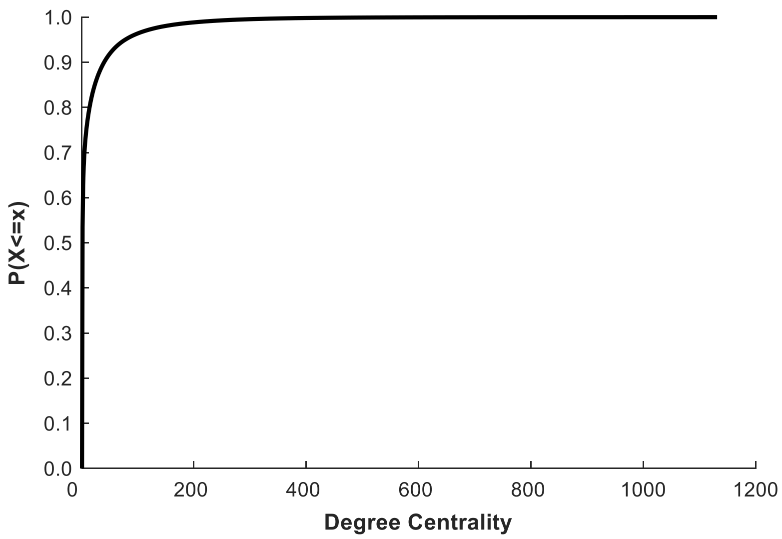

Figure 38. Cumulative degree distribution in the used Facebook sub-graph.

Because users typically do not make use of all the offered functionalities of an app, the valuation v_i^{PU} of the potential personal utility was generated by using a normal distribution truncated between zero and one with $\mu(v_i^{PU}) = 0.5$ and $\sigma(v_i^{PU}) = 0.125$. This means that, on average, a user derives half of the potential personal utility provided by the app. The logistic transformation of the share of weak-tie adopters for the valuation of the potential weak utility was performed with $\delta^{WTU} = 50$ and $\omega^{WTU} = 0.2$. This leads to transformed values close to one as soon as the app adoption reaches a share of approximately 30% in the OSN, which corresponds to approximately 1 million OSN members in the used Facebook sub-graph. For the transformation of the share of strong-tie adopters in the social neighbourhood, we used $\delta^{STU} = 20$ and $\omega^{STU} = 0.25$. Hereby, the valuation of the strong-tie utility reaches values close to one if more than roughly 50% of the strong ties have adopted the app. The initial excitement for both utilities was set to $\beta^{WTU} = \beta^{STU} = 1.0$. The steepness of the excitement decay curve was fixed at $\kappa^{WTU} = \kappa^{STU} = 4$ to keep the excitement at a high level until it quickly drops to zero within the last period of time. The decay parameters ς^{WTU} and ς^{STU} determine the duration until the drop, i.e. how long a high level of excitement will persist. The decay parameters are scenario-specific and will be discussed with the remaining parameters in the following subsections.

For determining the diffusion in the OSN with the selected parameters, a time horizon of $T = 120$ was used. The discrete time steps of the time horizon can be interpreted as days resulting in an observation period of four months. Due to the stochastic variables of the model, all simulation scenarios were conducted 50 times, of which the mean value was calculated. Comparisons between different apps and scenarios are always given in percentage points.

4.4.2 Relation Between Personal and Social Utility

For determining the impact of the personal and social utility on the diffusion behaviour of social media apps, in the first experiment we varied the relation between them. Two different scenarios for the social utility were examined where it consisted solely of either weak- or strong-tie utility. OSN members were made aware of the apps by random marketing. For each app, four different simple advertising scenarios were tested where the available advertising budget was varied: $AB \in \{100000, 200000, 400000, 800000\}$. In each scenario, the whole budget was invested at the beginning of the examined time horizon. After getting aware of the app and potentially adopting it, OSN members used it, on average, every $\xi = 5$ time steps. We defined the average delay ζ between the reception of invitations via EWOM and their evaluation to be always consistent with the app usage frequency, i.e. $\zeta = \xi$, which also applies to all the following experiments. The intermediate random duration times were generated by using a geometric distribution. The decay parameters were both set to $\varsigma^{WTU} = \varsigma^{STU} = 5$ time steps.

The results are shown in Figure 39, where the standard error (SE) was quite small in all depicted cases and ranged from 0.00001% to 0.008%. The graphs in Figure 39a/c/e depict the diffusion of social media apps that offer a personal and weak-tie utility. The app's diffusion is represented by the share of active users in the OSN, which is plotted against time. If the personal utility outweighs the weak-tie utility as given in Figure 39a, a greater budget always increases the final diffusion at time step 120. In the budget scenarios where 400000 and 800000 users are shown the advertisement, a small peak in activity is reached, after which the diffusion slightly decreases and stabilises in a steady state. In Figure 39c/e, the greater dependency on the weak-tie utility seems to have a negative effect on the maintainability of a steady state since in all examined advertising budget scenarios, except for the largest budget, the share of active users declines to almost zero. A higher weak-tie utility, however, increases the maximum diffusion potential of the largest budget, which is in Figure 39c/e more than twice as high as the diffusion depicted in Figure 39a.

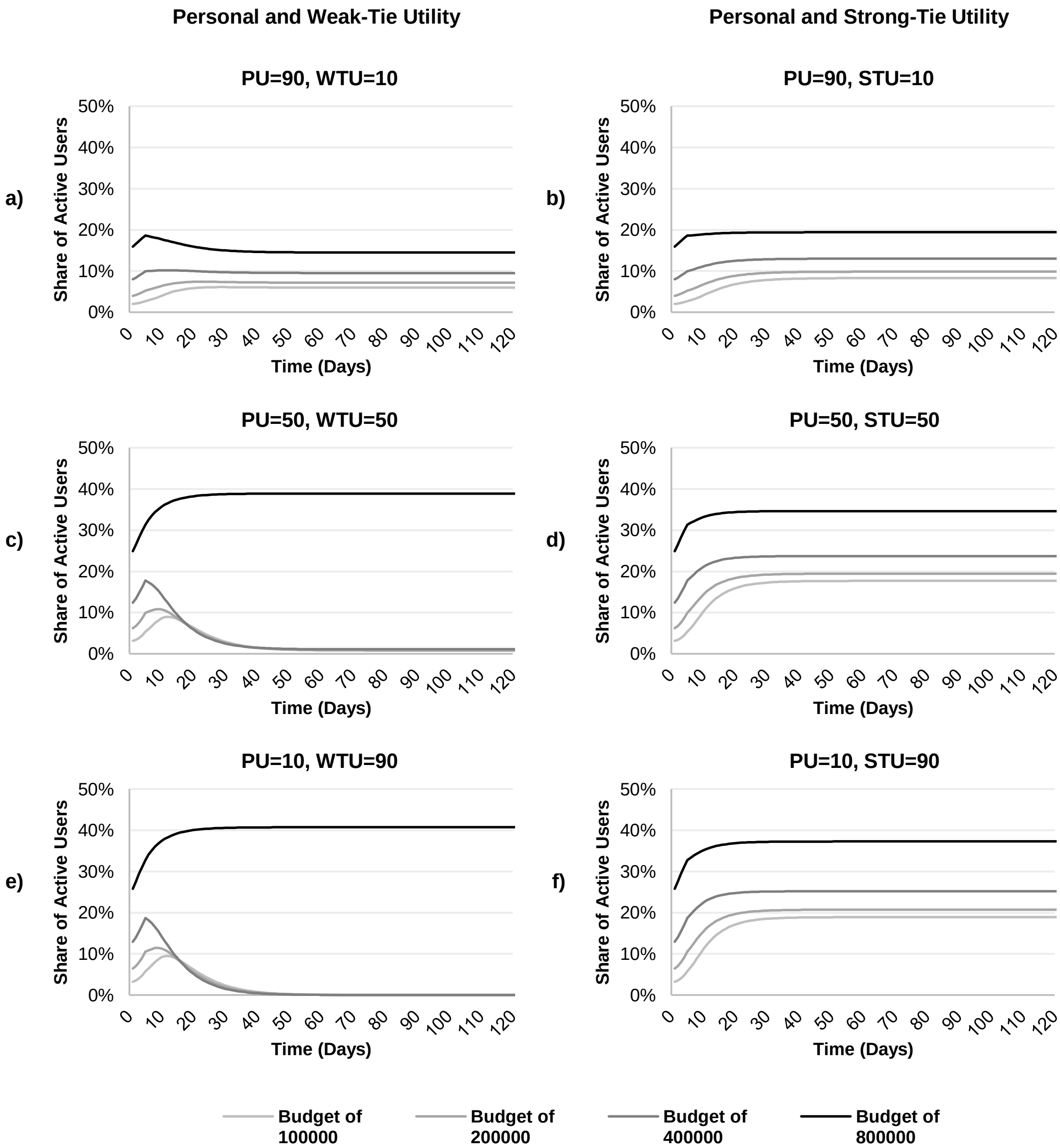

Figure 39. Time-dependent diffusion of different social media apps.

Figure 39b/d/f show the diffusion of social media apps that provide a personal and strong-tie utility. If the former predominates like in the case shown in Figure 39b, similar observations as in Figure 39a can be made. A notable difference is that the diffusion of the largest budget increases monotonically without declines in between. The same applies to the other cases depicted in Figure 39d/f, where a steady state is reached for all tested budget scenarios.

These results indicate that a critical budget exists for apps with a predominating weak-tie utility. We define the critical budget as the minimum number of users who need to be made aware of the app by advertising in order to be able to reach and maintain a steady state where the diffusion is significantly greater than zero. A reason for the emergence of the critical budget is that meeting user expectations is difficult for apps whose attractiveness is mostly based on a weak-tie utility. Adopters can only derive the promised weak-tie utility if the app has a sufficiently large active user base, which requires the investment of an accordingly large advertising budget. If the expectations are not met, OSN members will discard the app causing a decline in the overall activity within the app. Apps with a predominating strong-tie utility show a higher robustness against such decline because users mainly concentrate on the activity in their social neighbourhood. Since the size of the social neighbourhood is quite small, it is easier to reach and maintain a level of activity that suffices for adopters.

4.4.3 Relation Between Strong- and Weak-Tie Utility

Since the personal utility can be interpreted as a reduction of the activity threshold of potential adopters, in the following we will concentrate solely on the relation between the strong- and weak-tie utility. We define three different social media app cases for closer examination. In the first case, the weak-tie utility significantly outweighs the strong-tie utility ($WTU = 90$, $STU = 10$), in the second case both are balanced out ($WTU = 50$, $STU = 50$), and in the third case the strong-tie utility predominates ($WTU = 10$, $STU = 90$). In terms of relation, these apps can be compared to and will be referred to as *Twitter*, *Instagram*, and *WhatsApp* respectively.

For a closer investigation of the critical budget, numerous budgets were tested: $AB \in \{1000, 10000, 50000, 100000, 150000, \dots, 1000000\}$. We also varied the usage frequency and excitement decay for determining their influence on the size of the critical budget. The advertised apps were used, on average, every $\xi \in \{1, 5, 10\}$ time steps. These scenario cases will be called *high*, *medium*, and *low usage frequency* respectively. For the excitement decay, three cases were defined with $\varsigma^{WTU} = \varsigma^{STU} \in \{1, 5, 10\}$, which will be likewise called *high*, *medium*, and *low excitement decay* respectively. Depending on these parameter combinations, the diffusion at the end of the examined time horizon was determined and is depicted in Figure 40, where the SE ranged from 0.003% to 0.207%.

In the low decay case of Twitter shown in Figure 40a, the critical budget is 400000 for a low usage frequency of the app, where a diffusion of 29.910% is reached. The graphs show that by increasing the usage frequency, the critical budget can be significantly reduced in size. In the high usage frequency case, only 150000 users are needed for successfully maintaining a steady state with a final diffusion of 22.731%. Once the critical budget is reached, the graphs overlap and precede congruently, where a linear correlation between the budget and the reached diffusion can be observed. This indicates that the app usage frequency does not affect the maximum diffusion potential for a given advertising budget. The same applies to the excitement decay when the graphs are compared across Figure 40a/b/c in regard to their course above the critical budget, where modified decay values neither increase nor decrease the maximum diffusion potential. However, as the graphs illustrate, an increase in the excitement decay also increases the critical budget. In the medium decay case, a higher usage frequency is able to counteract by decreasing the critical budget. This cannot be observed in the high decay case, where the modification of the usage frequency does not affect the critical budget.

These findings also hold in the Instagram cases in Figure 40d/e/f. A difference can be seen in the high decay case, where the effects of the usage frequency seem to be reversed: unlike in the low and medium decay cases of Instagram, a higher usage frequency does not decrease but instead increases the critical budget if users quickly lose their excitement. A possible explanation for this phenomenon will be discussed in the context of the next subsection's experiments.

The WhatsApp cases depicted in Figure 40g/h/i differ from the results of Twitter and Instagram as a critical budget seemingly does not exist. A higher usage frequency is able to slightly increase the maximum diffusion potential of the app in the low and medium decay cases. In the high decay case, the positive effect of a higher usage frequency is, similar to the Instagram case, reversed and leads to a reduction of the maximum diffusion potential.

Even though the graphs of WhatsApp suggest that the diffusion of apps with a predominating strong-tie utility is easier because even small advertising budgets can maintain a steady state, this comes at the expense of a lower maximum diffusion potential. This emerges from comparing the reached diffusions for a given decay case across the tested apps in Figure 40. A different data representation is presented in Figure 41, where this effect becomes evident. The differences of Twitter to the other apps for the largest examined advertising budget were tested for statistical significance with a two-sample heteroscedastic t-test. The results are listed in Table 38 and show that the highly significant differences increase (decrease) with higher excitement decay (app usage frequency).

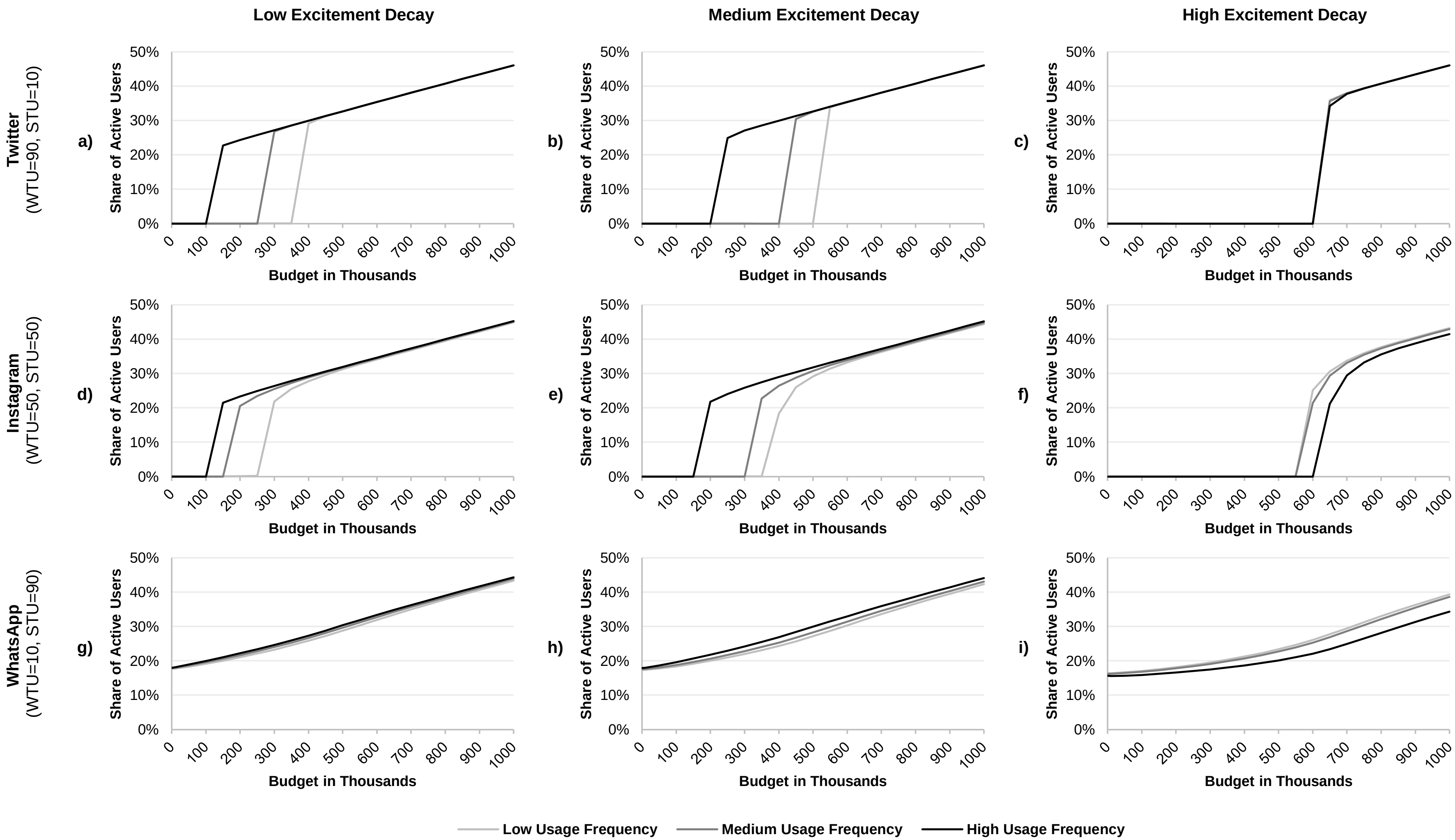

Figure 40. Influence of the app usage frequency and excitement decay on the diffusion of different social media apps.

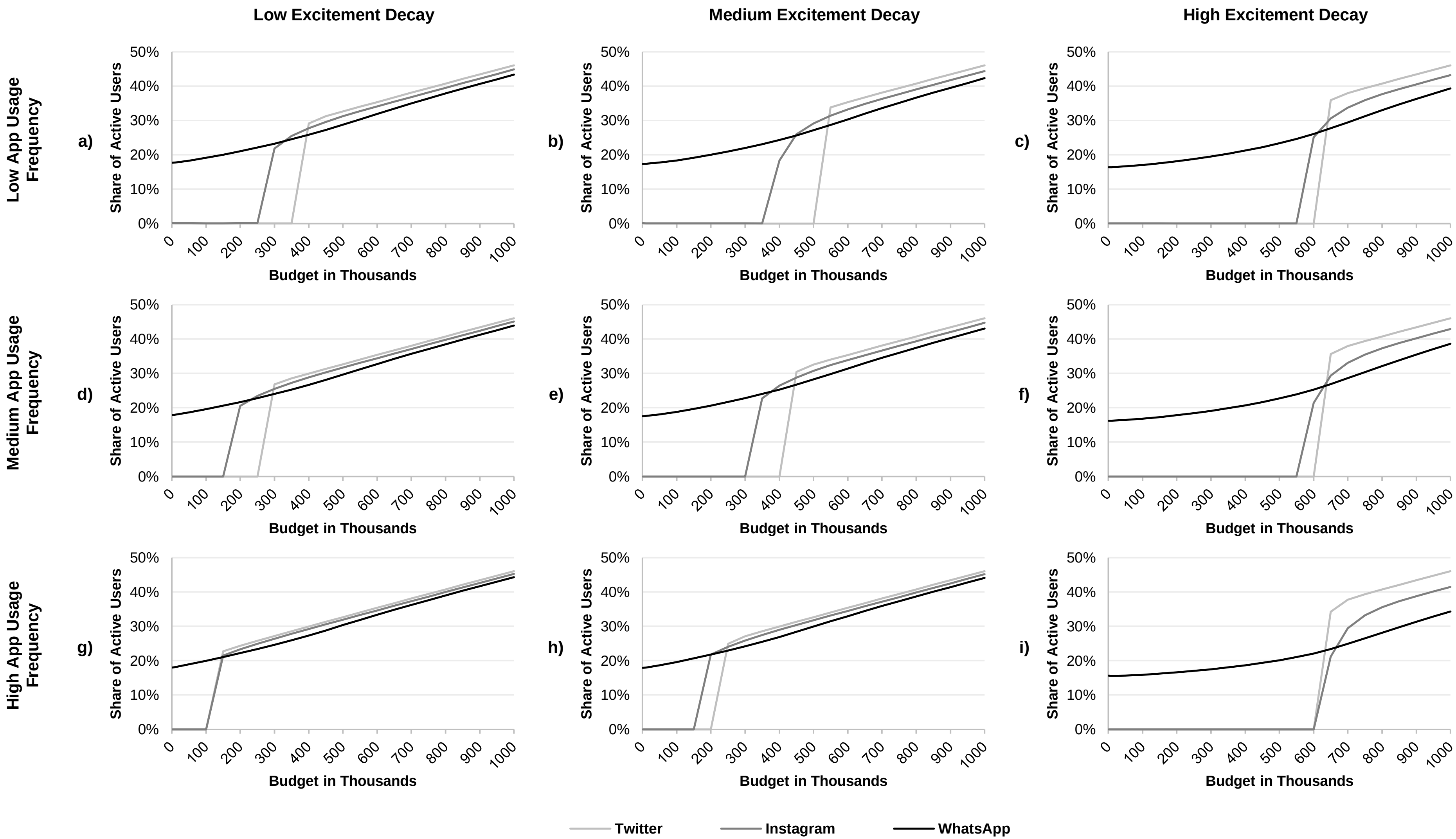

Figure 41. Different data representation of the influence of the app usage frequency and excitement decay.

Table 38. Statistical analysis of the differences between Twitter's diffusion and the reached diffusions of Instagram and WhatsApp.

	Differences between the share of active users of Twitter and the reached diffusions of Instagram and WhatsApp for an advertising budget of 1000000					
	Low Excitement Decay		**Medium Excitement Decay**		**High Excitement Decay**	
App Usage Frequency	**Instagram**	**WhatsApp**	**Instagram**	**WhatsApp**	**Instagram**	**WhatsApp**
Low	+1.221%***	+2.727%***	+1.673%***	+3.770%***	+2.846%***	+6.711%***
Medium	+0.989%***	+2.165%***	+1.362%***	+3.037%***	+3.130%***	+7.471%***
High	+0.799%***	+1.743%***	+0.902%***	+1.982%***	+4.622%***	+11.734%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

4.4.4 Advertising Schedule Structure

For testing different advertising schedule structures and determining their effect on the successful diffusion of social media apps, we split the tested budgets into multiple advertising impulses with temporal distances between them. Because after setting an impulse it will take some time to unfold its impact, we limited the advertising horizon to three months: $T^{AD} = 90 < T = 120$. For each scenario, we defined a uniform advertising strategy where the available budget was uniformly distributed on T^{AD} resulting in 90 advertising impulses. We defined two additional strategies with temporal distances between the impulses of ten and 30 time steps. These are characterised by a total of nine and three advertising impulses respectively. As a benchmark, we chose the "invest all at once" strategy from the previous subsection, which equals a one impulse strategy:

(1) 1 advertising impulse (benchmark case)
(2) 3 advertising impulses with temporal distances of 30 time steps
(3) 9 advertising impulses with temporal distances of 10 time steps
(4) 90 advertising impulses with no temporal distances

The reached diffusions of each scheduling strategy for the low excitement decay case are depicted in Figure 42. The SE was between 0.000002% and 1.975%. For Twitter, it can be observed that multiple impulses seem to be counterproductive as they increase the critical budget and also slightly reduce the maximum diffusion potential after the critical budget is reached. In all depicted Twitter cases, the best results are achieved by the "invest all at once" schedule strategy. Even though similar observations can be made in the depicted Instagram cases, the harmful effect of splitting the budget into multiple impulses is lessened. In the

WhatsApp cases, multiple impulses seem to have no effect at all if the advertising budget is relatively small. Only for budgets larger than 300000, the maximum diffusion potential is slightly reduced if multiple impulses are used instead of one.

An explanation for the inferior performance of the multiple impulse strategies is that each advertising impulse leads to the generation of EWOM in the OSN by which other members get aware of the app. If they open the app and encounter insufficient social activity, they will lose interest in using the app and discard it. When the next advertising impulse is released, these users will be less enthusiastic about the app because they have already tried it out and found it to be unsatisfactory. This endangers the maintainability of a steady state and renders the advertising strategy to be less effective. If, by contrast, the whole budget is spent at once, the risk of disappointment is reduced since many OSN members simultaneously try out the app leading to a higher social activity that is more likely to suffice for maintaining a steady state. Because apps with a relatively high weak-tie utility require a higher share of active users for reaching a steady state, the splitting of the budget into multiple impulses is a greater issue for Twitter and Instagram than for WhatsApp.

The results for the medium and high excitement decay cases are depicted in Figure 43 and Figure 44 with a SE ranging from 0.000002% to 1.672% and from 0.000002% to 0.033% respectively. The graphs show that with increasing decay, the performance of the multiple impulse strategies further worsens in the Twitter and Instagram cases. In the WhatsApp case, however, a higher decay seems to have an opposite effect as it increases the budget limit after which the multiple impulse strategies start to perform worse than the one impulse strategy. Moreover, up to this point, the multiple impulse strategies reach slightly higher final diffusions than the one impulse strategy. The differences increase with the excitement decay and are particularly greater in Figure 44g/h/i making the deployment of multiple impulse strategies in these cases more favourable.

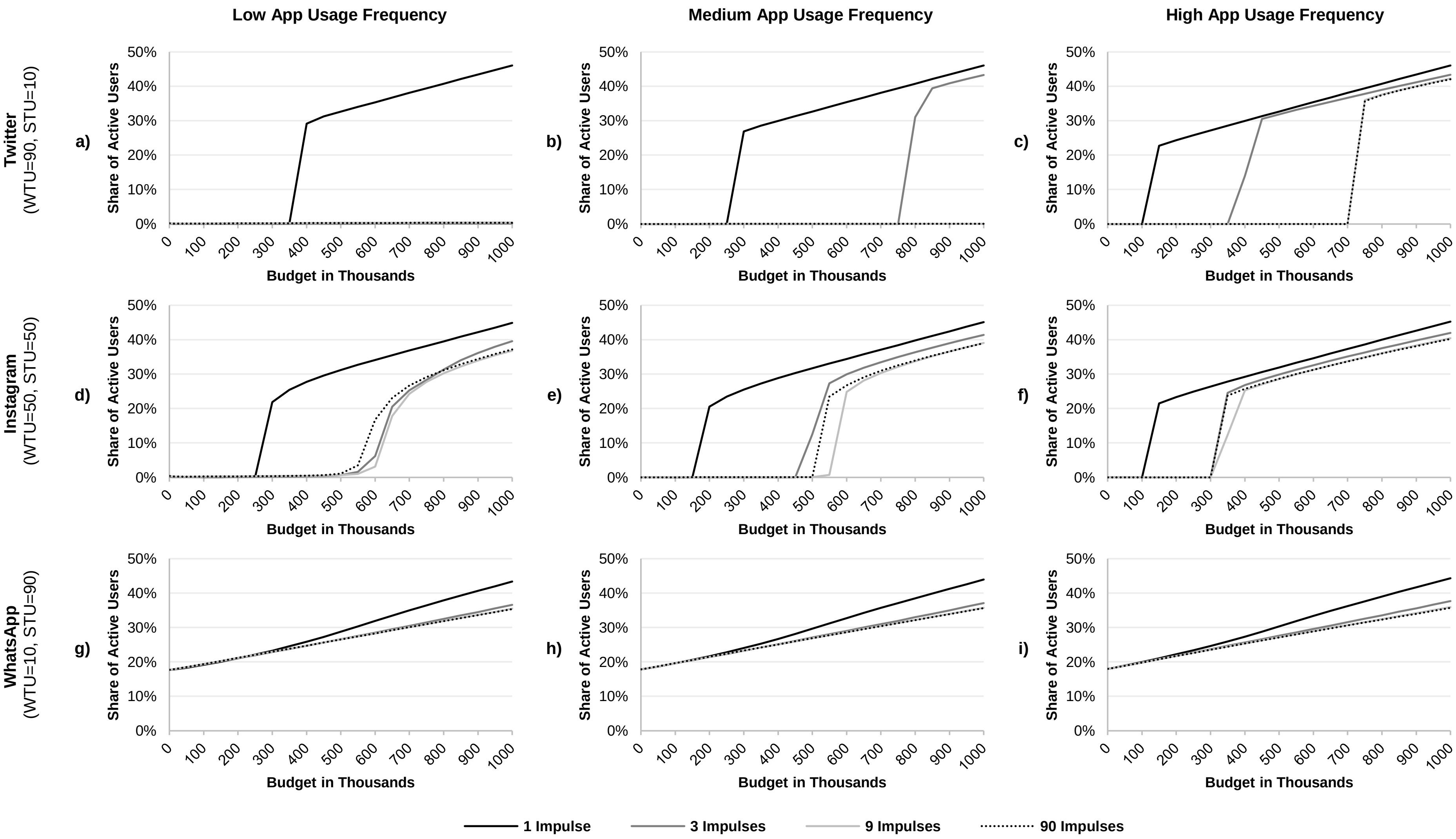

Figure 42. Influence of the advertising schedule structure on the diffusion of different social media apps (low excitement decay).

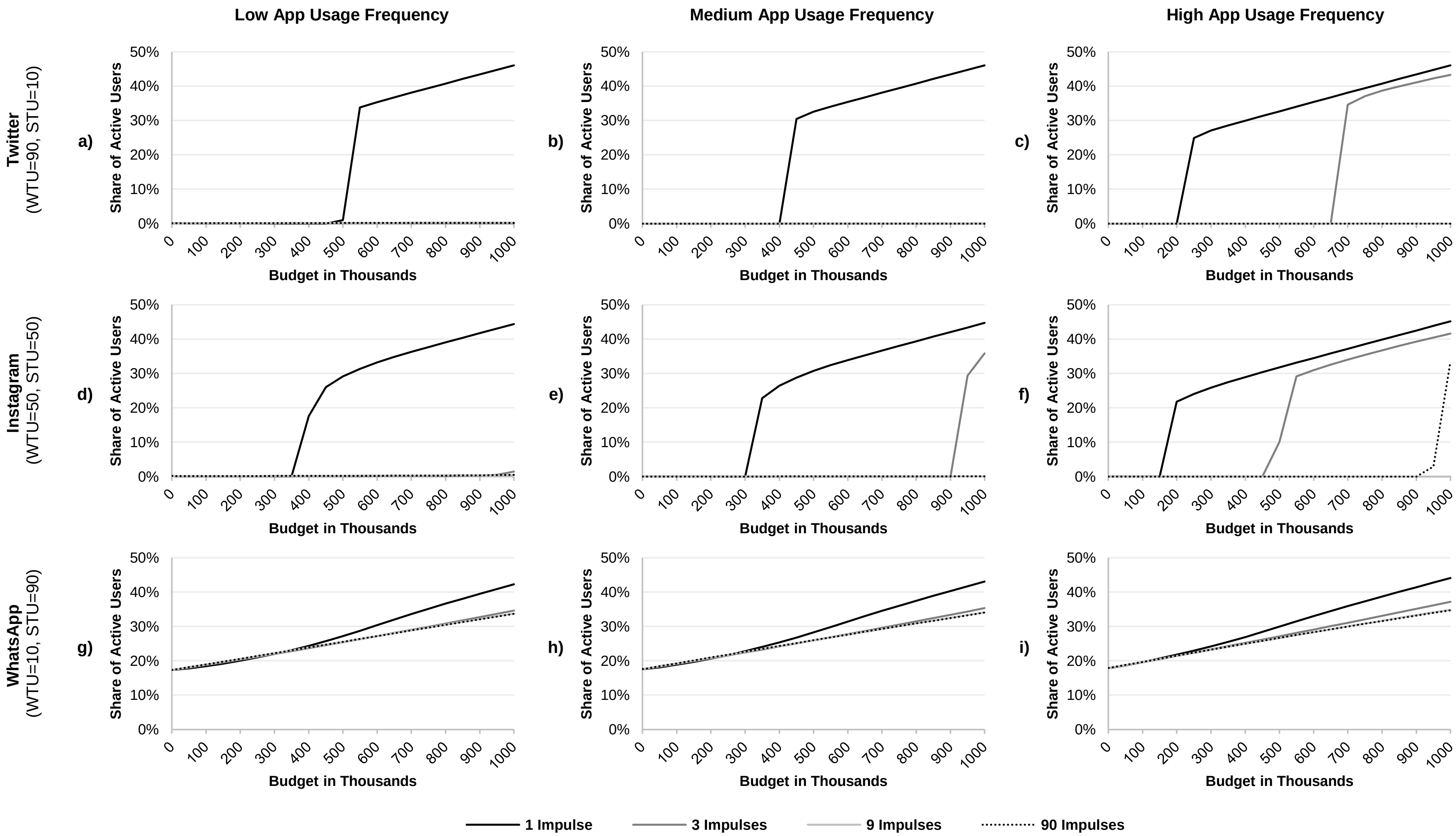

Figure 43. Influence of the advertising schedule structure on the diffusion of different social media apps (medium excitement decay).

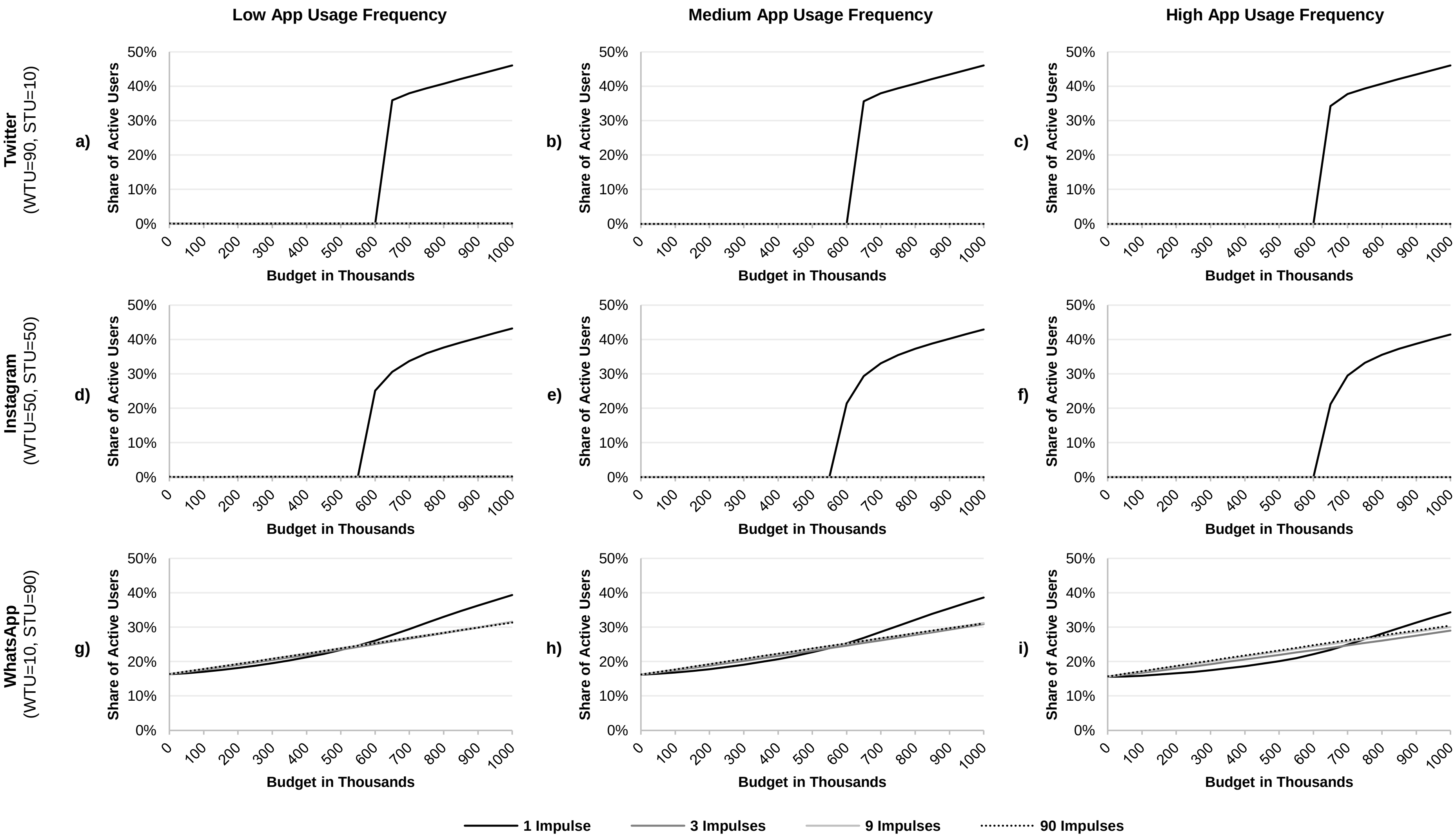

Figure 44. Influence of the advertising schedule structure on the diffusion of different social media apps (high excitement decay).

To investigate the background to this effect, we analysed for the different impulse strategies how the shares of active and inactive users in the OSN changed over time for two selected budget scenarios (500000 and 1000000) from Figure 44g/i. The corresponding graphs for active and inactive users are depicted in Figure 45 and Figure 46 respectively. A statistical analysis of the differences between the one and multiple impulse strategies is given in Table 39.

The data in Figure 45a illustrates for the 500000 budget case that the multiple impulse strategies gradually increase the share of active users of the app. Even if the size of the impulses is small, they do not trickle away but incrementally increase the diffusion. This is because the perceived strong-tie utility is the main driver of diffusion in the case of WhatsApp. If an advertising impulse empowered by EWOM reaches a cluster in the OSN, it is not unlikely that a certain share of the cluster's members will stay active because the activity of their peers is sufficient for them. The higher strong-tie utility therefore acts as a "safety net" for advertising impulses and protects them from ineffectiveness. All strategies perform almost equally well and reach a final diffusion of roughly 23%. The situation is altered to the detriment of the one impulse strategy if a high usage frequency exists as shown in Figure 45b. While the multiple impulse strategies are able to maintain their level of diffusion to a great extent, the one impulse strategy sacrifices a large part of its former performance. In general, the negative effect of the high usage frequency is attributable to the existence of the high excitement decay, which makes users less patient. If impatient users open the app too often, they may get confronted with insufficient levels of social activity, which will increase the risk of disappointment and potentially result in abandoning the app. In this context, the question arises why the negative impact of the high usage frequency in Figure 45b is particularly high for the one impulse strategy and lessened the more impulses an advertising strategy has?

To answer this question, it is first necessary to have an understanding of the different effects EWOM has in OSN from which both potentials and risks arise. While EWOM empowers the advertising impulse and increases the share of active users in the network, it also bears the risk of leaving "scorched earth" behind, which we equate to the share of inactive users who have evaluated the app at least once and decided for discarding the app. As discussed before, if the information about the app reaches areas and clusters in the OSN prematurely where a sufficient level of activity is not present yet, it could deplete the excitement of the users. If, later on, these areas are reached by advertising, its effect will be significantly lessened because of the reduced enthusiasm. The magnitude of the "scorched earth" effect depends on the deployed advertising schedule structure and the invested advertising budget.

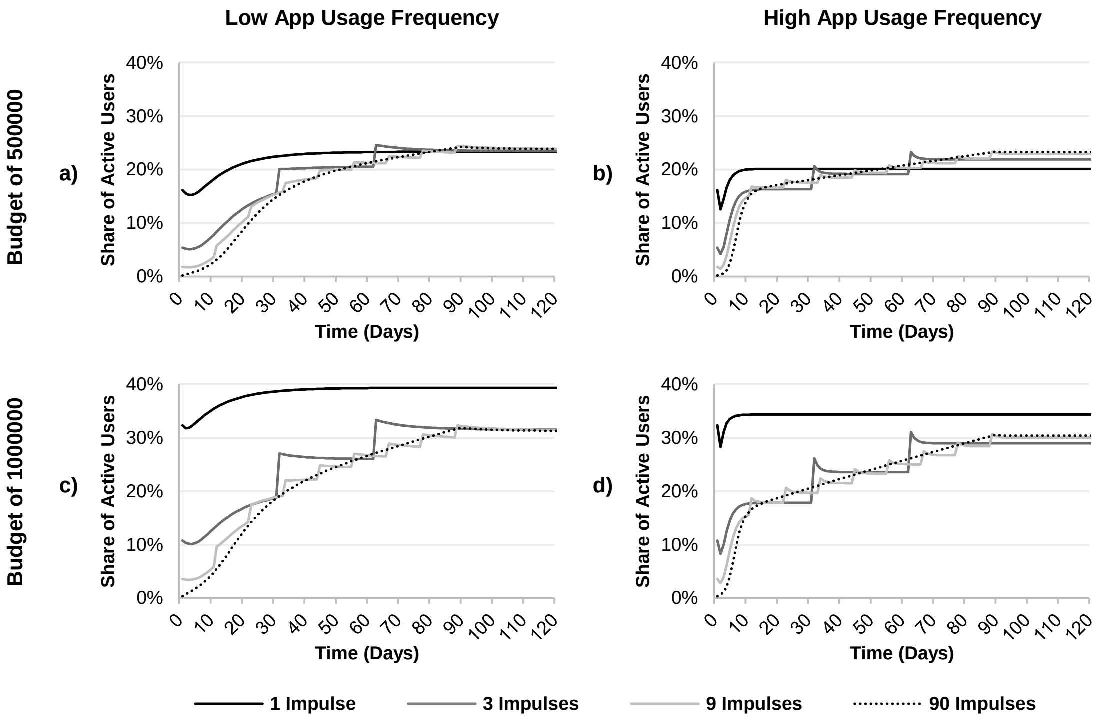

Figure 45. Changes over time in the share of active users of WhatsApp in selected scenarios (high excitement decay).

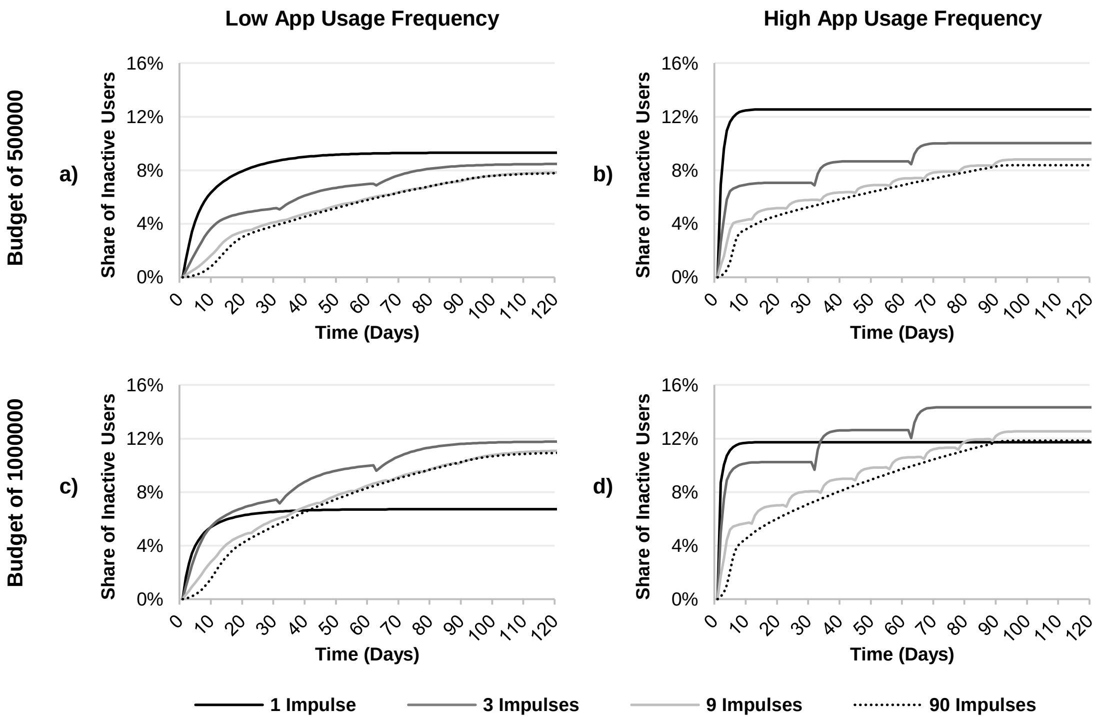

Figure 46. Changes over time in the share of inactive users of WhatsApp in selected scenarios (high excitement decay).

Table 39. Statistical analysis of the one impulse strategy's performance as compared to the performance of the multiple impulse strategies (high excitement decay).

	Changes in the share of active users (the more, the better) evoked by the one impulse strategy in comparison to the multiple impulse strategies for advertising budgets of 500000 and 1000000					
	Low App Usage Frequency			**High App Usage Frequency**		
Budget	**3 Impulses**	**9 Impulses**	**90 Impulses**	**3 Impulses**	**9 Impulses**	**90 Impulses**
500000	-0.125%***	-0.524%***	-0.494%***	-1.810%***	-2.816%***	-3.146%***
1000000	+7.801%***	+7.881%***	+8.047%***	+5.371%***	+4.322%***	+3.935%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, [ns] = not significant

If the whole budget is spent at once in Figure 45b, many unique OSN members who are scattered throughout the network are influenced by the advertisement at the same time. These users tell their peers about the app and thereby initiate EWOM waves. Due to the faster decrease in excitement, the EWOM waves come quickly to a standstill resulting in small reaches. This lowers the likelihood that the EWOM waves overlap and reinforce each other, which, in turn, increases the "scorched earth" effect, where users lose their excitement. Splitting the budget into multiple impulses has the advantage that these are able to successively unfold their impact. Since the high strong-tie utility acts as a "safety net", smaller impulses create a "breeding ground" of social activity for subsequent impulses that can increase the overall reach. Because of this, the likelihood of creating damage by "scorched earth" is reduced.

This is a possible explanation for the robustness of multiple impulses against the damaging effects of the high usage frequency in the presence of a high excitement decay and is supported by the graphs shown in Figure 45a and Figure 46a. After setting the impulse, there is a drop in activity resulting from disappointed users as depicted in Figure 45a. The greater the impulse is, the greater is the immediate decline in activity afterwards. The inactivity graphs in Figure 46a, which represent the magnitude of the "scorched earth" effect, show that the disappointment is particularly high for the one impulse strategy. The higher usage frequency increases the drop and leads to more inactivity as Figure 45b and Figure 46b reveal.

The situation changes if a higher budget is available. The one impulse strategy surprisingly shows the best performance both in the low and high usage frequency scenarios as depicted in Figure 45c/d. The one impulse strategy is also characterised by the lowest inactivity shares as Figure 46c/d prove. This enhanced performance can be explained by the expanded reach of the EWOM waves. If the number of unique OSN members who are shown the advertisement is increased, this results in a denser network of activated small areas and clusters throughout the OSN. The gaps and distances between them are reduced in size, which increases the likelihood of their overlapping and mutual reinforcement. Thereby, the risk of leaving "scorched earth" is reduced. This is underlined by Table 40, which lists the ratios between the shares of active and inactive users for the analysed cases. A higher ratio indicates that the share of active users is increased more efficiently by minimising the "scorched earth" that is left behind, which is inevitably created as an undesirable by-product during the advertising of the app. A lower ratio, on the contrary, implies that the applied schedule strategy yields a less desirable return in activity by increasing the relative size of the "scorched earth". In the 500000 budget case, the one impulse strategy shows the worst ratio among the tested advertising strategies, whereas in the 1000000 budget case it achieves the best ratio. These results suggest that for higher advertising budgets, the potentials of overlapping and mutual reinforcement of EWOM waves achieved by the one impulse strategy outweigh the potentials of the "breeding ground" that is utilised by the multiple impulse strategies.

Table 40. Comparison of the shares of active and inactive users at the end of the time horizon in selected budget scenarios (high excitement decay).

		Reached shares of active and inactive users by the one and multiple impulse strategies and the corresponding ratios (the higher, the better) for advertising budgets of 500000 and 1000000					
		Low App Usage Frequency			**High App Usage Frequency**		
Budget	**Impulses**	**Active**	**Inactive**	**Ratio**	**Active**	**Inactive**	**Ratio**
500000	**1**	23.338%	9.310%	**2.507**	20.101%	12.548%	**1.602**
	3	23.463%	8.463%	**2.773**	21.911%	10.015%	**2.188**
	9	23.863%	7.835%	**3.046**	22.917%	8.800%	**2.604**
	90	23.833%	7.769%	**3.068**	23.247%	8.375%	**2.776**
1000000	**1**	39.337%	6.718%	**5.855**	34.333%	11.722%	**2.929**
	3	31.536%	11.767%	**2.680**	28.961%	14.342%	**2.019**
	9	31.456%	11.081%	**2.839**	30.010%	12.540%	**2.393**
	90	31.290%	10.925%	**2.864**	30.397%	11.838%	**2.568**

4.4.5 Premature Advertising

The results of the previous subsection could show that, except for a few particular high excitement decay cases of WhatsApp, in most of the examined scenarios it is better to deploy the "invest all at once" advertising strategy and avoid the splitting of the budget into multiple impulses. In reality, however, a social media app vendor may not always be able to deploy the correct strategy from the beginning. Start-ups, in particular, might be inclined to test the general response to the app on a small scale by initially investing only a small share of their available advertising budget, e.g. for examining the effectiveness of different marketing approaches by performing A/B tests. This raises the question of how harmful a premature advertising campaign could be to the successful diffusion of an app.

In order to investigate this more closely, we defined three scenarios for a premature advertising impulse where one, ten, and 100 OSN members were shown the advertisement at the beginning of the time horizon. For ensuring that the premature impulse had enough time to unfold its impact, the second impulse with the main advertising budget was set to be activated at time step 90. The time horizon for examination was therefore extended from $T = 120$ to $T = 210$. We focused on the medium excitement decay case, for which we varied the usage frequency like before. The final values of the share of active users altered by the premature advertising impulse are benchmarked against the "invest all at once" advertising strategy in Figure 47, where the SE ranged from 0.000002% to 2.619%. The premature impulse caused instability in the outcome of the experiments as the standard deviation (up to 18.517%) was considerably higher than in the previous experiments.

In the low usage frequency case of Twitter shown in Figure 47a, a premature impulse decreases the diffusion even if only a few users are reached by the advertisement. While the damage of one prematurely reached user is comparatively limited, ten users already show signs of a considerable reduction. If 100 users are activated, the critical budget is increased to 800000. As Figure 47b/c reveal, a higher app usage frequency can still bring a certain benefit by decreasing the critical budget, but only if one or ten users are affected by the premature impulse. If 100 users are prematurely reached, the critical budget remains at 800000 and cannot be reduced by an increased usage frequency.

Premature advertising also poses a risk to Instagram as the graphs in Figure 47d/e/f demonstrate. Particularly in the case where 100 users are too early informed about the app, premature advertising can severely harm the follow-up campaign as none of the tested budgets are able to reach a steady state. This is contrasted by the WhatsApp cases shown in Figure 47g/h/i, where the outcome of the main advertising campaign is hardly affected by the premature advertising impulses.

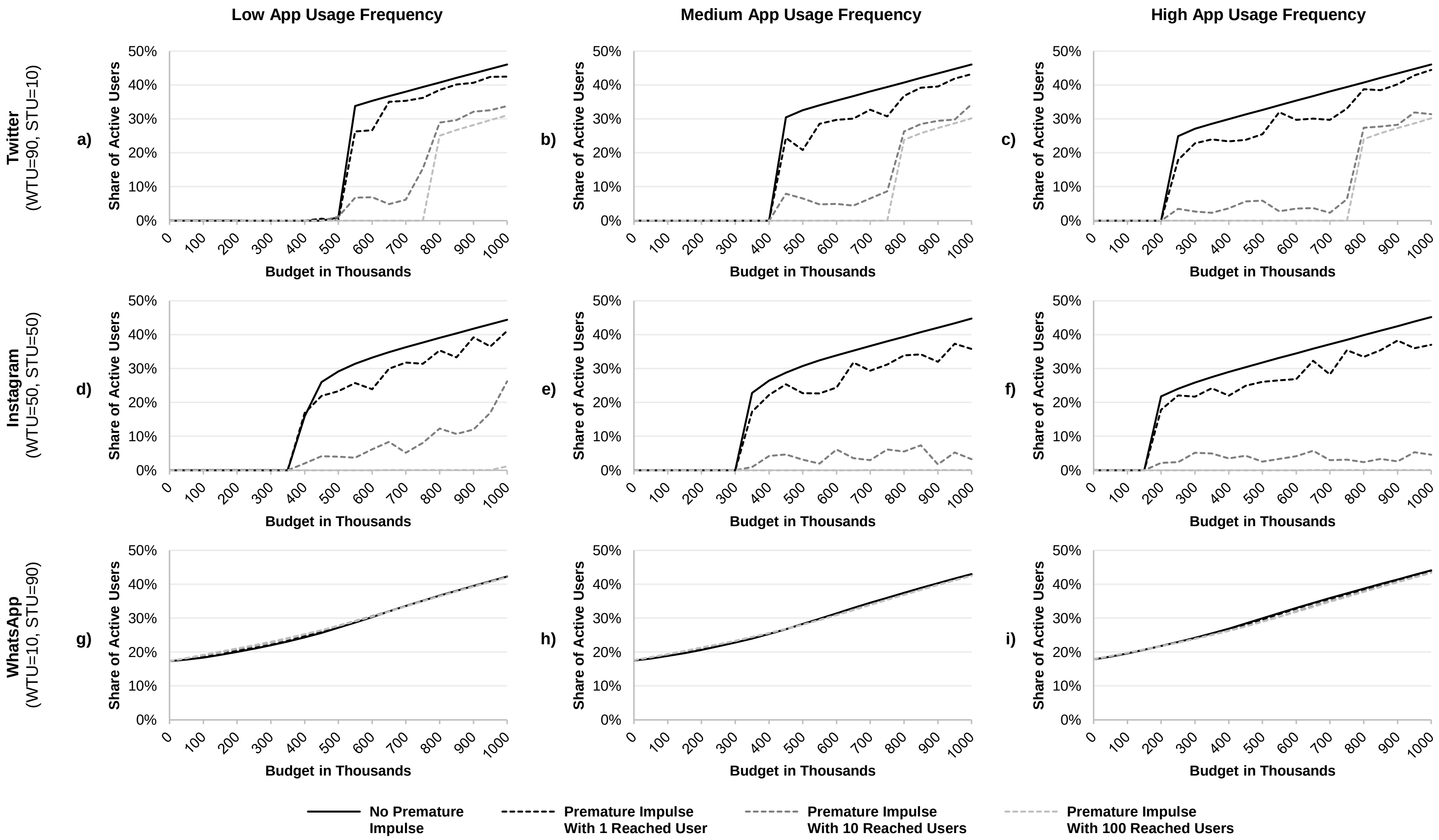

Figure 47. Influence of premature advertising impulses on the diffusion of different social media apps (medium excitement decay).

4.4.6 Targeting Strategies: Random, Influencer, and Cluster Marketing

An important aspect in the context of launching apps is the way they are initially presented in the OSN to potential adopters. In the previous subsections, we tested the effects of a random marketing strategy, where unique OSN members were randomly picked and presented the app for evaluation. In this subsection, we will compare the performance of the random marketing strategy to the effectiveness of influencer and cluster marketing. For deploying influencer marketing, at first members in the used Facebook sub-graph need to be identified who could qualify as influencers. We defined the top 1000 members with the most contacts in the OSN as influencers. In total, these influencers reached 439063 unique other members when the duplicates from their overlapping spheres of influence were removed. For testing cluster marketing, we wrote an algorithm that randomly picked clusters in the network where each cluster consisted of 400 unique members. In order to make the strategies comparable on a structural basis, new clusters were added until the total number of unique recipients of advertising reached 439063. These two strategies were compared to the random marketing strategy where likewise 439063 unique members were affected by advertising. Random and cluster marketing were characterised by the same click-through rate CTR^{AD} that determines the evaluation probability of the app by the targeted users. While recent empirical benchmarks based on online marketing campaigns show that the click-through rate for regular advertising on Facebook is $CTR^{AD} = 0.0125$, the evaluation probability of influencer marketing is comparatively higher with $CTR^{INF} = 0.02$ (Chen and Knisely 2016, p. 19). In order to reduce the computing time while keeping the ratio, we set the latter to $CTR^{INF} = 1.0$ and the former to $CTR^{AD} = 0.625$. We assume that the advertising channel (i.e. advertising directly in the OSN by random or cluster marketing versus advertising emitted by influencers) has no effect on the click-through rate for messages forwarded by EWOM, which was still set to $CTR^{EWOM} = 0.2$.

For these constellations, Figure 48 depicts the diffusion results, where both the app usage frequency and the excitement decay were varied. The SE was between 0.000004% and 0.429%. Figure 48a/b/c show the results for the low excitement decay scenario, where the app usage frequency is changed. If the usage frequency is low, influencer marketing dominates the other strategies, which notably perform worse in the Twitter and Instagram cases. If the usage frequency increases, the other strategies perform better but are not able to completely catch up with influencer marketing. As shown in Figure 48d/e/f, a medium excitement decay of users reduces the performance of random and cluster marketing, which particularly applies to the low and medium usage frequency scenarios. Influencer marketing, on the contrary, shows a higher robustness against the share-reducing effects of an increased excitement decay. The higher decay seems to be more harmful to apps with a predominating weak-tie utility like Twitter. It is less damaging to apps like WhatsApp, where the high strong-tie utility acts as a “safety net” as discussed before. The offered strong-tie utility prevents a decline in user activity and is thereby able to compensate for the consequences of a higher decay. This is underlined by the results of the high decay scenarios shown in Figure 48g/h/i, where all tested strategies are only able to show an effect in the WhatsApp case.

In sum, Figure 48 shows that influencer marketing performs best and should be used preferably. If influencer marketing is not an option and left out of consideration, for high weak-tie utility apps like Twitter, random marketing usually performs better than cluster marketing, which is the most suitable strategy for high strong-tie utility apps like WhatsApp. The greater the excitement decay is, the greater is the cluster marketing strategy’s advantage over the random marketing strategy.

Usually, vendors that offer and advertise apps in OSN also have some control over the click-through rate of EWOM messages. For instance, the app could provide easy-to-access functionalities for facilitating the invitation of peers. A higher click-through rate for these invitations could be reached by offering appealing pre-defined invitation messages that exhibit a higher level of attraction to receivers. For testing the effects of a higher EWOM activity level on the outcome of the targeting strategies, we doubled the EWOM click-through rate to $CTR^{EWOM} = 0.4$ and re-conducted the experiments, of which the results are depicted in Figure 49. The SE was similarly low and ranged from 0.000005% to 0.443%. The results show that all strategies considerably benefit from more EWOM among users by reaching a greater share of active users in the OSN. An increased level of EWOM activity also seems to be an effective countermeasure for a higher excitement decay. Interestingly, the results also indicate that EWOM has an empowering effect on the random marketing strategy, which in many cases performs as well as or even better than influencer marketing. In most cases, the random marketing strategy is also able to match the performance of cluster marketing, which used to have a strong lead in the advertising of WhatsApp. However, in the high excitement decay scenarios of WhatsApp, cluster marketing still shows a better performance than the random marketing strategy, particularly if a high app usage frequency exists.

In a further step, we again doubled the EWOM click-through rate to $CTR^{EWOM} = 0.8$. The results with a SE ranging from 0.000006% to 0.013% are shown in Figure 50. The random marketing strategy consolidates and further extends its lead in most scenarios. These performance differences between the random marketing strategy and the other strategies were tested for statistical significance and are given in Table 41. The cases where random marketing strategy performs worse are shaded grey. Most of the results are highly statistically significant confirming the observations.

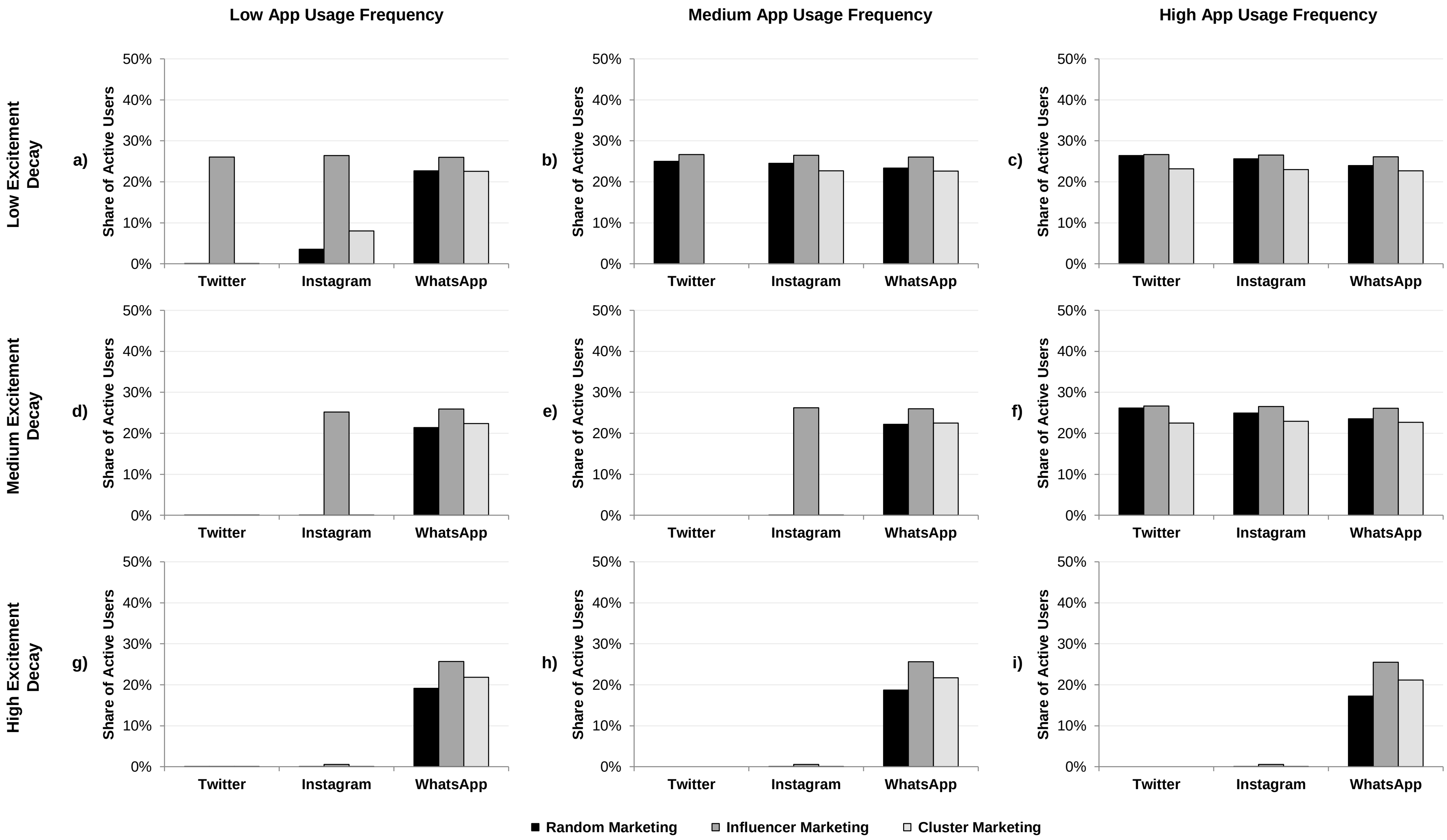

Figure 48. Benchmarking of targeting strategies (CTR^{EWOM}=0.2).

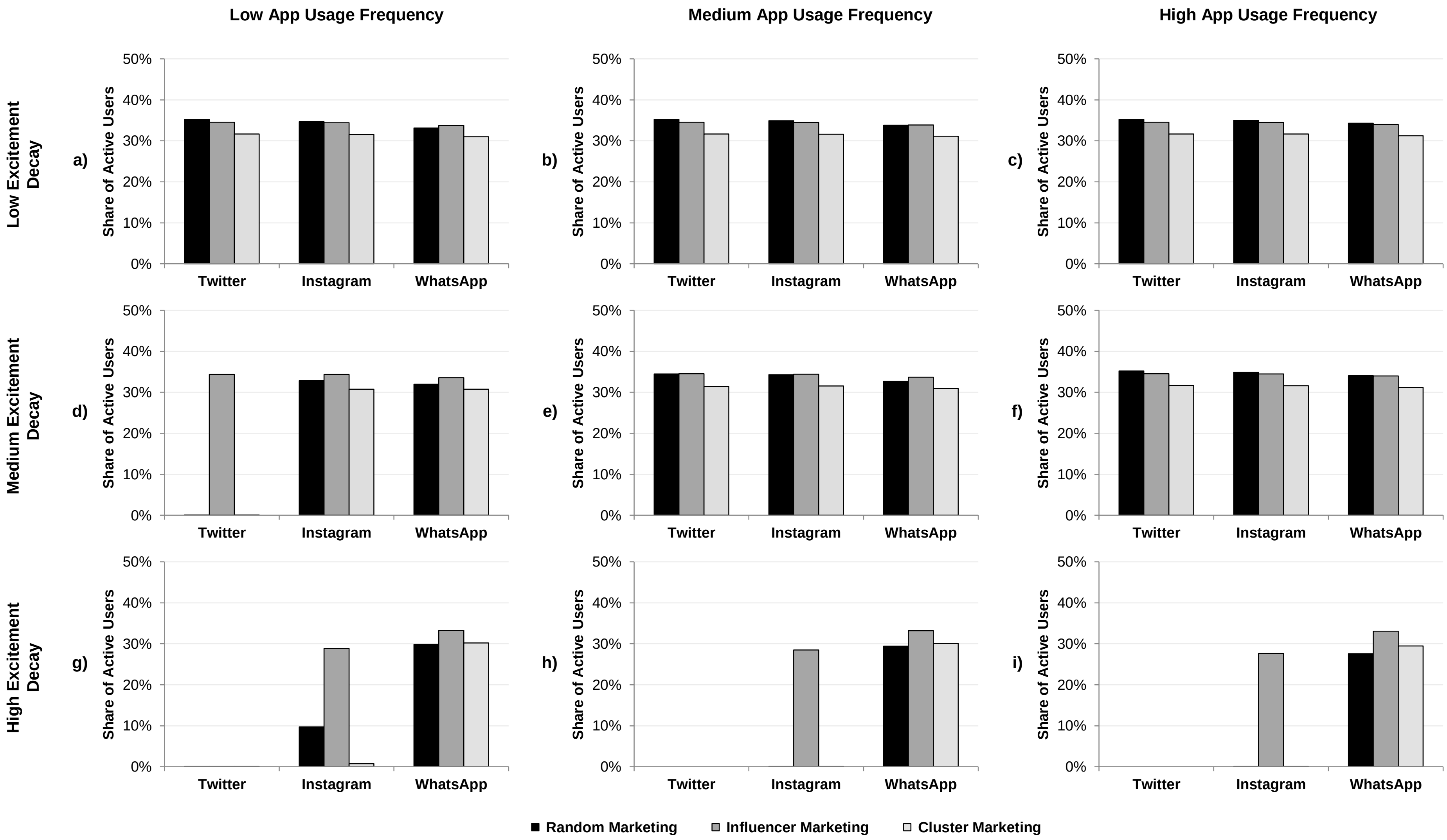

Figure 49. Benchmarking of targeting strategies (CTR^{EWOM}=0.4).

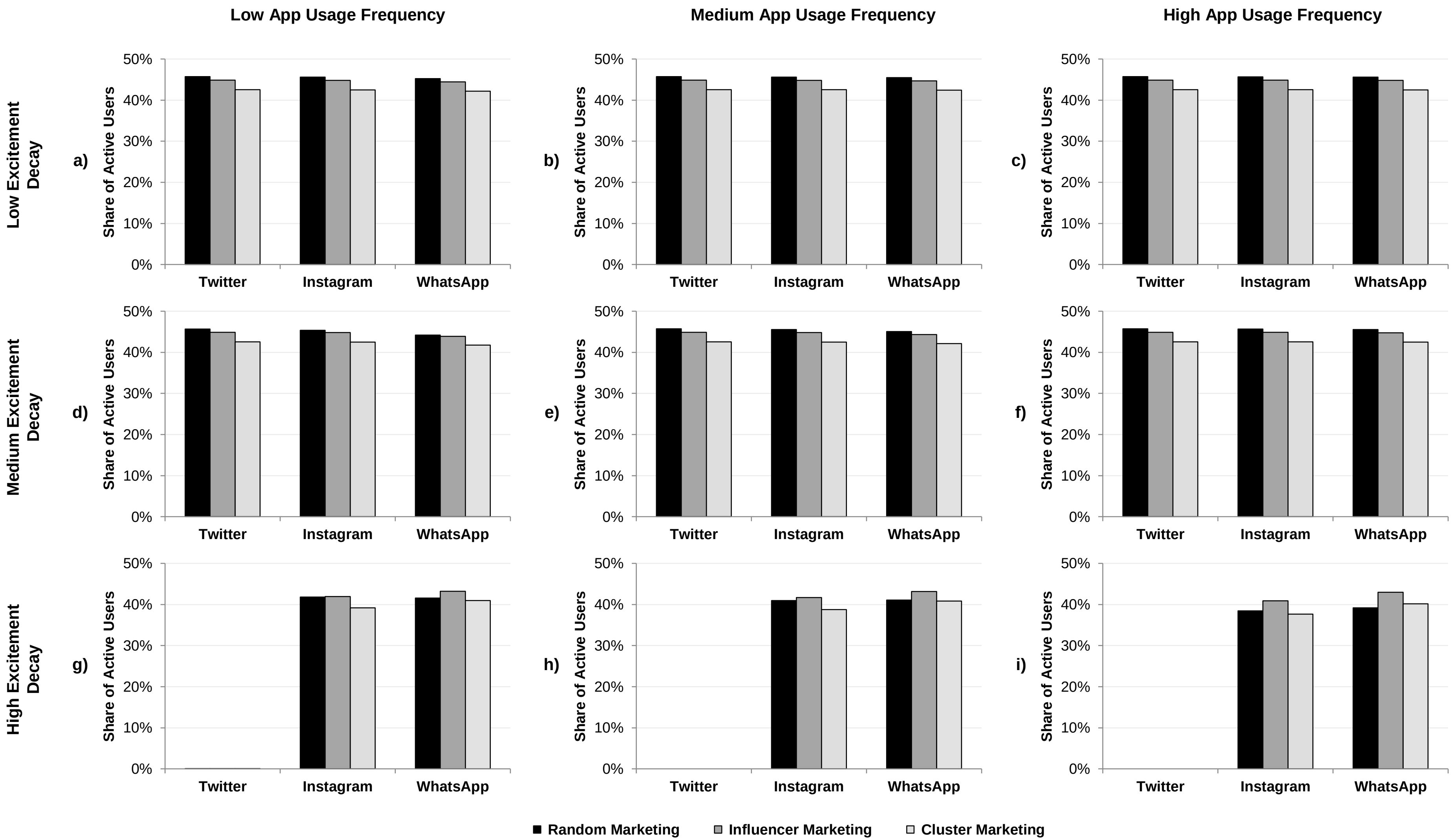

Figure 50. Benchmarking of targeting strategies (CTR^{EWOM}=0.8).

Table 41. Statistical analysis of the random marketing strategy's performance as compared to the influencer and cluster marketing strategies.

			Changes in the share of active users (the more, the better) evoked by the random marketing strategy in comparison to the influencer and cluster marketing strategies								
			Low App Usage Frequency			**Medium App Usage Frequency**			**High App Usage Frequency**		
EWOM Activity	**Decay**	**Marketing Strategy**	**Twitter**	**Instagram**	**WhatsApp**	**Twitter**	**Instagram**	**WhatsApp**	**Twitter**	**Instagram**	**WhatsApp**
Low (CTR^{EWOM}=0.2)	**Low**	**Influencer**	-26.031%***	-22.840%***	-3.343%***	-1.639%***	-2.010%***	-2.697%***	-0.216%***	-0.915%***	-2.169%***
		Cluster	+0.009%***	-4.492%***	+0.112%***	+25.000%***	+1.823%***	+0.723%***	+3.260%***	+2.615%***	+1.242%***
	Medium	**Influencer**	+0.007%***	-25.190%***	-4.481%***	-0.000%^{ns}	-26.254%***	-3.787%***	-0.443%***	-1.601%***	-2.564%***
		Cluster	+0.006%***	-0.017%***	-0.963%***	+0.000%^{ns}	-0.021%***	-0.312%***	+3.694%***	+2.011%***	+0.847%***
	High	**Influencer**	+0.005%***	-0.583%***	-6.540%***	-0.000%^{ns}	-0.541%***	-6.905%***	+0.000%^{ns}	-0.554%***	-8.292%***
		Cluster	+0.004%***	-0.011%***	-2.717%***	+0.000%^{ns}	-0.013%***	-2.998%***	+0.000%^{ns}	-0.014%***	-3.912%***
Medium (CTR^{EWOM}=0.4)	**Low**	**Influencer**	+0.679%***	+0.235%***	-0.623%***	+0.685%***	+0.435%***	-0.085%***	+0.683%***	+0.518%***	+0.251%***
		Cluster	+3.553%***	+3.101%***	+2.146%***	+3.545%***	+3.288%***	+2.673%***	+3.541%***	+3.371%***	+3.014%***
	Medium	**Influencer**	-34.334%***	-1.497%***	-1.598%***	-0.091%***	-0.141%***	-0.973%***	+0.689%***	+0.458%***	+0.048%***
		Cluster	+0.001%***	+2.106%***	+1.202%***	+3.009%***	+2.757%***	+1.801%***	+3.539%***	+3.304%***	+2.814%***
	High	**Influencer**	+0.001%***	-19.105%***	-3.413%***	-0.000%^{ns}	-28.480%***	-3.829%***	-0.000%^{ns}	-27.646%***	-5.479%***
		Cluster	+0.001%***	+9.004%***	-0.375%***	-0.000%^{ns}	-0.023%***	-0.715%***	+0.000%^{ns}	-0.022%***	-1.886%***
High (CTR^{EWOM}=0.8)	**Low**	**Influencer**	+0.870%***	+0.770%***	+0.804%***	+0.867%***	+0.796%***	+0.777%***	+0.866%***	+0.820%***	+0.780%***
		Cluster	+3.191%***	+3.088%***	+3.048%***	+3.189%***	+3.108%***	+3.075%***	+3.188%***	+3.140%***	+3.103%***
	Medium	**Influencer**	+0.794%***	+0.593%***	+0.283%***	+0.865%***	+0.737%***	+0.724%***	+0.862%***	+0.804%***	+0.750%***
		Cluster	+3.110%***	+2.905%***	+2.442%***	+3.187%***	+3.045%***	+2.935%***	+3.185%***	+3.124%***	+3.063%***
	High	**Influencer**	-0.000%^{ns}	-0.129%***	-1.668%***	+0.000%^{ns}	-0.729%***	-2.090%***	-0.000%^{ns}	-2.463%***	-3.823%***
		Cluster	-0.000%***	+2.653%***	+0.579%***	+0.000%^{ns}	+2.207%***	+0.229%***	+0.000%^{ns}	+0.778%***	-0.962%***

*, **, *** = $p < 0.05$, $p < 0.01$, $p < 0.001$ respectively, ^{ns} = not significant

4.5 Conclusion

4.5.1 Summary

In today's world, OSN like Facebook and Instagram need to continuously adapt their offered social media apps and services to the changing needs and preferences of their users (Arango 2011; Mui 2011). In this study, we proposed a classification scheme for social media apps and services that can be differentiated in regard to the offered personal and social utility. We divided the latter into a strong- and weak-tie utility. For answering our first research question (RQ3.1: *How do social media apps and services that are varied in terms of strong- and weak-tie utility differ in their diffusion behaviour?*), we developed a diffusion model for investigating how different kinds of apps diffuse in a sub-graph of Facebook with more than 3 million vertices. Our results demonstrate that apps that offer a social utility generally reach higher levels of diffusion in OSN. The constitution of the social utility, namely the relation between the offered strong- and weak-tie utility, plays a pivotal role in the diffusion process. Apps with a predominating weak-tie utility show signs of a critical advertising budget that needs to be at least invested in order to reach and maintain an active user base. Otherwise, there is a high risk that the share of active users decreases to zero after reaching an unmaintainable peak in activity. The critical budget is less of an issue for apps where the strong-tie utility predominates. Although such apps diffuse easier with limited advertising budgets, for higher investments they are overtaken by apps with a predominating weak-tie utility that reach higher shares of active users. We addressed the second research question (RQ3.2: *How important is the advertising schedule structure?*) by testing various types of advertising schedule structures where the available budget was split into multiple advertising impulses with temporal distances between them. We evaluated the structures in regard to the reached diffusion and compared them to the "invest all at once" strategy, which served as a benchmark. Our results demonstrate that, except for some particular cases, a one impulse strategy performs best and should be preferably applied by the app or service vendor. We answered the third research question (RQ3.3: *How effective are influencer and cluster marketing as compared to random marketing in launching social media apps and services?*) by benchmarking random marketing against the targeting of followers of influencers and clusters in the OSN. Our results suggest that influencer marketing generally shows a good performance, closely followed by random marketing. Cluster marketing is suitable for apps with a high strong-tie utility if influencer marketing is not an option. Our results also show that EWOM has a moderating effect on the performance of the tested targeting strategies. If the social media app or service vendor is able to induce high levels of EWOM activity among users, the random marketing strategy mostly overtakes the other strategies and becomes the solution of choice.

4.5.2 Managerial Implications

The results of this study allow the deduction of several managerial implications for OSN vendors and start-ups that are interested in advertising a social media app or service in an OSN. An important finding of our study is that a critical advertising budget exists for apps with a predominating weak-tie utility. If the invested budget is less than the critical budget, an active user base cannot be maintained rendering the investment worthless. When a new social media app or service is introduced to the market, its vendor has, to a certain extent, control over the app usage frequency, e.g. by sending out push notifications to users for reminding them of the newly installed app. If the target group or audience of the app is characterised by a certain level of patience, i.e. there is a low excitement decay, vendors should apply such methods as it can help to reduce the critical budget in size. However, if the excitement decay is high, meaning that users are impatient and quickly lose interest in the app because it does not provide the promised social utility, a higher usage frequency has no effects at best and negative effects at worst. Therefore, vendors should be cautious about sending out push notifications for promotional purposes or with the aim of stimulating social activity in the app. If they are not able to keep the excitement of their users at a high level over a longer period of time, push notifications could amplify the disappointment of users about insufficient levels of social activity and thereby endanger the steady state and enduring success of the app.

If the OSN vendor itself is the provider of the new social media app or service, it theoretically has an unlimited advertising budget and could continuously expose its members to the innovation. But as our results demonstrate, the timing and intensity of the advertising campaign, which is represented by the advertising schedule structure, is crucial to the success of social media apps and services. In order to build and keep an active user base, an adequate scheduling of the available advertising budget is required, which, in turn, depends on the social utility characteristics of the social media app or service.

If the weak-tie utility predominates or is balanced out with the strong-tie utility, a one impulse advertising strategy should be deployed, where the whole budget is spent at once. A splitting of the budget into multiple impulses is counterproductive and should be avoided. For this kind of apps, our experiments could further demonstrate that premature advertising can have adverse effects on reaching a high level of diffusion in the OSN. Even if only a few users are reached, a prematurely set advertising impulse can have severe consequences for subsequent advertising campaigns as it considerably reduces their impact. Premature advertising increases the critical budget that would have been significantly smaller if it had not been deployed. This is because the few reached users disseminate EWOM in the OSN that depletes the excitement of a multitude of potential adopters before sufficient social activity is built up within the app. The vendor of the social media app or service should therefore carefully consider whether to launch small promotional campaigns for testing purposes before the main advertising budget is invested. For reducing the risks posed by EWOM in this case, vendors should try to assess the user response to such apps in closed beta tests where users are technically prevented from inviting others. From a strategical point of view, this could bring additional benefits because it would lead to an increased level of excitement about the app or service among OSN members who are not able to try it out yet. As soon as the app is released, the increased excitement could be harnessed as a catalyst during the main advertising campaign and enhance the diffusion in the OSN as it fosters EWOM activity.

If an app with a predominating strong-tie utility is to be released, the "invest all at once" strategy is not always the optimal solution. Its effectiveness depends on the available advertising budget and the behavioural characteristics of the targeted user base. If only a limited advertising budget is available and users quickly lose their excitement, an "invest all at once" strategy should be avoided as it performs worse than multiple impulse strategies. The performance of the former is further worsened if a high usage frequency exists. This stresses the role of push notifications, which need to be handled cautiously by the vendor of the social media app or service. Not only do push notifications reduce the diffusion in cases with high excitement decay, but they also influence the optimal advertising scheduling. The greater the app usage frequency is, the more impulses the advertising schedule should have. The splitting of the budget into multiple impulses helps to mitigate the harmful effects of a high app usage frequency in the presence of a high user excitement decay. The "invest all at once" strategy is suitable and worthwhile only if a sufficiently large advertising budget is available. A larger budget leads to the generation of more EWOM in the OSN, which empowers the "invest all at once" strategy and enables it to overtake the multiple impulse strategies irrespective of the usage frequency.

The EWOM activity level in the OSN also plays an important role in picking the correct targeting strategy. Our findings indicate that for lower levels of EWOM activity, influencer marketing outperforms random and cluster marketing. As a runner-up, random marketing shows the second-best performance in most of the conducted experiments. If the vendor is able to increase the level of EWOM, e.g. by incentivising adopters to invite their peers or by providing more appealing pre-defined invitation messages, random marketing gains the upper hand in most scenarios and performs better than influencer and cluster marketing. As hypothesised in the introduction section, the deployment of cluster marketing could be particularly beneficial for apps that offer a high strong-tie utility. Even though our results suggest for such apps that cluster marketing performs worse than influencer marketing, it may still perform better than random marketing. This mostly applies to scenarios where users quickly lose their excitement due to impatience and the frequent opening of the app. In such cases, even a high level of EWOM activity is not able to empower the random strategy to the extent that it outperforms cluster marketing. These results illustrate the importance of picking the appropriate advertising strategy that may differ from app to app and highly depends on the achievable level of EWOM in the OSN.

4.5.3 Limitations and Future Research Directions

There are several ways of how our work could be extended by future research. First of all, our model should be applied to other sub-graphs of real-world OSN for determining the changes that occur with different network sizes and structures. It was discussed that the "invest all at once" strategy performs best in most examined scenarios because the initiated EWOM waves are able to overlap and reinforce each other. A larger network dataset could alter this finding as the probability of overlapping decreases with the network's size. Secondly, we distinguished between directly and indirectly connected peers for determining the strong- and weak-tie utility respectively. Similar to the approach of Choi and Lee (2012), indirectly connected peers and the resulting weak-tie utility could be further differentiated in regard to the distance to a focal OSN member. The greater the distance is, the weaker is the relationship to indirectly connected OSN members. Such an extension to the model would enable a more realistic examination of apps and services for which the adoption in the extended social neighbourhood plays an important role in the decision-making process. Examples for these are video chat or conferencing apps where a potential user might attach importance to the network adoption both on a micro- and meso-level, e.g. for granting compatibility with friends of friends. The degree of adoption on a macro-level could play only a subordinate role for such apps. Thirdly, some of our assumptions require empirical validation. We assumed, for instance, that the forwarding probability is the same for all kinds of apps. In reality, however, the probability could be higher for apps with a high strong-tie utility, which could directly incentivise users to use EWOM for inviting their peers for an imminent increase of the perceived utility. This would be similar to the peer effect mentioned by Henkel and Block (2008). In the present study, we deliberately chose not to implement the peer effect because it would have given diffusion advantages to apps with a high strong-tie utility and thereby hampered the comparability of different apps on a structural level. Future research should analyse the impact of the peer effect in the context of the proposed diffusion model and investigate to which extent it alters this study's results. Fourthly, the developed model should be used for examining more market constellations. For instance, a duopolistic market setting would enable the testing of the diffusion of a new social media app that competes against an already existing app in the OSN. Different advertising strategies could be analysed in regard to their effectiveness for coping with the impact of the lock-in effect caused by an existing app. Finally, targeting strategies like influencer and cluster marketing were compared to each other on a structural level to examine the diffusion differences when the number of reached OSN members is the same. In future investigations, the tested marketing strategies should also undergo a comparison in terms of administrative and activation costs.

Chapter 5:

Conclusion

5 Conclusion

5.1 Key Findings

The purpose of this dissertation was to investigate and derive strategies for coping with the opportunities and challenges of EWOM that emerged with the widespread success of social media and OSN (Chang et al. 2015, p. 49; Kim et al. 2016, pp. 511-512; van Noort and Willemsen 2012, p. 132). EWOM has significantly facilitated the exchange of product-related experiences and opinions among customers (Balaji et al. 2016, p. 528; Cheung et al. 2008, pp. 230-231; Hussain et al. 2016, p. 493) and thereby induced substantial changes in e-commerce (Ho and Rezaei 2018, p. 205; Huang and Benyoucef 2013, p. 246; Zhou et al. 2013, pp. 61-62). Three related subject areas were outlined, and for each of them an overall research question was formulated. These were addressed in the three main Chapters 2 to 4 that comprised different published and working papers in the corresponding research fields.

Chapter 2 addressed the challenges evoked by NWOM messages that are disseminated by dissatisfied customers in OSN. For answering the first overall research question (RQ1: *How should NWOM be countered in OSN?*), a diffusion model was introduced for testing various reaction strategies by simulation. A reaction strategy consisted of multiple decision variables such as counter-message strength, response delay, seed quantity, and seed quality. For examining their effectiveness and efficiency in different NWOM scenarios, the diffusion of messages was simulated in artificially generated networks and sub-graphs extracted from Facebook. The impact of NWOM and its countering by PWOM were analysed in different markets where customers behaved differently regarding the credibility evaluation of received messages. In individualistic markets, customers paid more attention to the content and persuasiveness of the conveyed information, whereas in collectivistic markets the behaviour of the social surrounding was more important for assessing the credibility of the transmitted information.

The results of Chapter 2 suggest that, in general, the message strength is the most important factor in countering NWOM. In most cases, a delayed but highly convincing counter-message is able to outperform quick reactions with weaker counter-messages. To some extent, this also holds if the weaker counter-message is launched by multiple seeds. The results further show that a reaction is not always mandatory because in some cases the negative impact of NWOM on sales is small. This applies to cases where weak NWOM messages are authored by weak or medium NWOM seeds and disseminated in collectivistic markets. A reaction, however, is required if weak NWOM messages are launched by strong NWOM seeds, which significantly increases their impact on sales. In individualistic markets, weak NWOM messages are more challenging because medium NWOM seeds are already sufficient to cause considerable economic damage. Only if they are launched by weak NWOM seeds, their impact in individualistic markets is negligible, and the firm may opt for the no-response strategy.

In this regard, it is important to note that a reaction is a double-sided sword. Although the published PWOM message may reduce the prevalence of NWOM in the OSN by inducing sales-promotional effects, it can unintentionally initiate new waves of NWOM. As the findings of Chapter 2 indicate, in some scenarios the negative effect outweighs the positive one, which brings the economic appropriateness of carrying out a reaction into question even if NWOM severely harms sales. In particular, this applies to strong NWOM messages in individualistic markets and strong NWOM seeds in collectivistic markets, where the financial consequences of NWOM can hardly be reversed with the tested reaction strategies. In these cases, firms should try to maximise the strategy parameters by designing a well-founded and persuasive counter-message that is both quickly published and disseminated by multiple, potentially strong, PWOM seeds. These findings clearly show that a countermeasure is not always able to undo the damages caused by NWOM. Firms are therefore strongly advised not to neglect proactive strategies. The customer relationship management should put emphasis on working out strategies that increase the trust of customers in the firm’s customer support services. In cases of product or service failure, this should motivate dissatisfied customers to first contact the firm in anticipation of well-grounded assistance instead of spreading NWOM. If the customer support faces a complaint that is only partly justified, it should still take financial compensation for the customer into consideration as it may prevent much greater damage that could result from NWOM in OSN.

Chapter 3’s subject of research was the development of pricing strategies for offering individualised prices in e-commerce in the presence of EWOM in OSN. Many online retailers are hesitant to deploy individualised pricing because of the apprehension of customer rejection (Matsumura and Matsushima 2015, p. 887; Vulkan and Shem-Tov 2015, p. 182). In order to answer the second overall research question (RQ2: *How should individualised pricing be deployed in the age of EWOM and OSN?*), a pricing decision model was developed for deriving pricing strategies that allow profitable price individualisation in online stores. The model considered an online store that sold a durable good to customers who were interconnected in an OSN and could share price information via EWOM. Customers visiting the online store were assigned to customer groups for which pre-defined sets of prices existed that resembled the decision variables of the seller in the developed model. Depending on the number of previous visits and their group membership, customers were offered different prices in the online store. Customers were characterised by various behavioural effects like lowering their willingness-to-pay if they got aware of other customers paying less for the offered product. The decision model was solved numerically by applying different AI solution methods including an evolution strategy and particle swarm optimisation. In order to make individualised pricing profitable, the profit-increasing benefit of its deployment needs to outweigh the potential losses caused by dissatisfied customers, who could either lower their willingness-to-pay or decide against making a purchase. In this context, EWOM also acts as a double-sided sword. Low prices shared by customers via EWOM entice more customers to visit the online store but also cause them to lower their willingness-to-pay. High prices have an opposite effect: although they might initiate an increase of the willingness-to-pay, they can frighten off customers from (re-)-visiting the online store.

The findings of Chapter 3 illustrate that despite the sharing of price information via EWOM, individualised pricing can be feasible in the age of social media and OSN. Even if EWOM leads to full price transparency in the market and OSN members are aware of all paid prices, the deployment of individualised pricing can still be profitable. This, however, requires the application of pricing strategies with complex pricing schemes that are capable of dealing with the requirements of different customer groups. It has been shown that AI solution methods are able to find profit-increasing solutions to such complex pricing decisions that make use of EWOM's positive effects and mitigate its negative effects. For instance, the found pricing schemes suggest that under price transparency it is more profitable to successively lower prices on subsequent online store visits for customers with a high willingness-to-pay. Customers who are characterised by a low willingness-to-pay should be offered higher prices on their first visits for pulling up their willingness-to-pay. If the price is set too high, there is a risk that visitors will not return to the online store and potentially purchase somewhere else. The tested AI solution methods can be used for determining the optimal prices that will help to prevent deterrent effects on visitors. However, the deployment of such strategies is not always possible. If, for instance, the number of available prices per group is limited like in traditional group pricing, it is not possible to derive complex pricing strategies for balancing out the divergent influences of EWOM in favour of the positive effects. This is reinforced if customers exhibit a high loss aversion, i.e. quickly adapt their willingness-to-pay to lower prices that they receive via EWOM.

Another problem regarding the deployment of individualised pricing concerns the correct identification and assessment of customer characteristics. Even though the recognition accuracy increases with larger amounts of available data (Bourreau et al. 2017, p. 40), the true willingness-to-pay of customers is difficult to assess correctly without misjudgements (Bar-Gill 2019, pp. 228-229; Hennig-Thurau and Houston 2019, pp. 760-761). This poses the risk of offering inadequate prices to customers, which can harm the profit of the firm. The findings of Chapter 3 demonstrate that even under uncertainty, the deployment of individualised pricing can be financially worthwhile.

Chapter 4 dealt with the diffusion of social media apps and services in OSN and addressed the third overall research question (RQ3: *How should social media apps and services be launched in OSN?*). For this, a diffusion model was developed that considered the social utility of social media apps and services that emerges from the number of existing adopters in the OSN. The social utility was differentiated into a strong- and weak-tie utility that refer to the utility derived from the adoption among a user's strong and weak ties respectively. The diffusion model was numerically analysed by simulation, where a sub-graph of Facebook with more than 3 million vertices and 23 million edges was used. With this setup, the diffusion of three characteristic social media apps was examined in greater depth. These apps offered a social utility where either the strong- and weak-tie utilities were balanced out or one of them predominated. Each app was advertised in the OSN, where the reached users evaluated the app's offered utility for deciding on whether to adopt it. When users opened the app for the first time, their adoption decision was mainly influenced by an initial excitement about the app. After adoption, a user would use the app regularly depending on a defined usage frequency. Each time the app was used, a user would re-evaluate the app's offered utility in order to determine if it still was sufficient for staying active. When a user eventually lost his initial excitement about the app, the decision for continuing the active usage of the app solely depended on the number of actual active users among his strong and weak ties. If the encountered social activity in the app diverged significantly from his expectations, a user would discard the app, possibly causing a cascade that could induce other users to also leave the app. For reaching a high diffusion in the OSN and preventing this kind of decline in activity, various advertising schedule structures were tested that determined how much of the available advertising budget was spent during a discrete period of time. Different targeting strategies for advertising the app were examined and compared to each other regarding their ability to reach a high share of active users in the OSN. In the random marketing strategy, randomly chosen members who were scattered throughout the OSN were presented the advertisement. The random marketing strategy served as a benchmark and was compared to influencer and cluster marketing. In the latter, whole clusters of users were shown the advertisement at once, whereas in the former the most influential users in the OSN were selected to share sponsored posts about the app in the OSN.

The findings of Chapter 4 provide important implications regarding the deployment of launch strategies for successfully releasing social media apps and services in OSN. These are not only relevant for start-ups that want to advertise social media apps in an OSN but can also serve as decision-making aids for OSN vendors that aim to introduce a new social media app or service for their existing user base. The findings demonstrate that social media apps and services with a predominating weak-tie utility are prone to the emergence of a critical advertising budget. If less than the critical budget is invested, the aforementioned decline in user activity cannot be prevented. For this kind of apps, the deployment of a rather simple advertising schedule structure was proven to be the best solution where the whole budget is spent at once. A splitting of the budget into multiple advertising impulses increases the risk of not being able to reach a steady state where the activity of a large number of users is ensured. In this context, the effects of premature advertising were investigated where a few users were prematurely shown the advertisement before the actual budget was invested later on. It turned out that premature advertising poses a severe risk to the sustainability of the steady state, which can hardly be reached and maintained by the follow-up advertising campaign. Because of EWOM, a multitude of OSN members get aware of the app and lose their excitement too early, which afterwards cannot act as a catalyst for the diffusion during the main advertising campaign. If vendors are not able to reduce the level of EWOM in such cases, they should waive any small-scale advertising tests even if only a few OSN members are affected.

Chapter 4's results further indicate that these findings must not necessarily hold for apps that offer a high strong-tie utility. Although in most of the examined cases the "invest all at once" strategy is also applicable and performs best, there are scenarios where the continuous spending of the available budget by splitting it into multiple advertising impulses is better suited for reaching a high share of active users. This applies to scenarios where the budget is rather limited and users quickly lose their excitement about the app if they frequently open the app and encounter insufficient social activity. The "invest all at once" strategy performs worse under such circumstances because it initiates multiple EWOM waves in the OSN that come to an early standstill before being able to overlap and reinforce each other. If the budget is spent continuously, a "breeding ground" is generated from which potentials emerge for subsequent impulses. If an EWOM wave is initiated in an area or cluster of the OSN that already exhibits a certain activity, it might be able to expand its reach. This phenomenon only occurs for apps with a high strong-tie utility, which acts as a "safety net" for advertising expenses. Unlike apps with a predominating weak-tie utility, smaller advertising impulses do not trickle away but still reach a certain degree of adoption because the users attach more weight to the activity in their social neighbourhood and are less dependent on a large user base.

Chapter 4 also led to important insights regarding the use of targeting strategies and their suitability for launching different types of social media apps and services. The level of EWOM activity plays a crucial role in the effectiveness of the tested strategies. If the EWOM activity level among the adopters of the app is rather low, influencer marketing performs best and should be preferably deployed by vendors. The higher the EWOM activity level is, the better is the performance of the random marketing strategy in comparison to the other strategies. Due to the empowerment by EWOM, the random marketing strategy is able to overtake the other strategies in most scenarios. Exceptions are, for instance, scenarios where an app with a high strong-tie utility is to be launched among users who are prone to quick disappointment because of impatience and frequent app re-evaluations. In these scenarios, the cluster marketing strategy shows the best performance and should be deployed for launching the app. Irrespective of the deployed targeting strategy, more EWOM activity also means a significantly higher level of diffusion in the OSN, which could lower the overall advertising expenses. These findings demonstrate the importance of app functionalities that facilitate EWOM, e.g. by providing assistance in inviting new users, which vendors of a social media app or service should pay particular attention to.

5.2 Limitations and Future Research Directions

Some limitations need to be considered in the context of this dissertation that could be addressed by future research. In Chapter 2, the diffusion of two opposing messages was tested. These messages were not varied in their characteristics during the diffusion. In reality, OSN users can comment on and discuss messages and news that get forwarded. The discussion could change the persuasiveness of the information conveyed by the initial message, e.g. by providing more arguments. However, it should be investigated to which degree supplementary comments are actually read by OSN members. In order to get a quick impression of the relevance and general tenor, it is conceivable that members rely more heavily on peripheral stimuli such as the number of comments or the reactions to the message by emoticons (e.g. smiley or angry faces), which is, for instance, supported by Facebook. Future research needs to examine how these kinds of interaction with the shared message influence the credibility perception of the conveyed information.

In Chapter 3, the optimisation of individualised prices was carried out in a market setting where the demand was fixed at one purchase per customer. It needs to be investigated how the optimal pricing schemes suggested by the AI solution methods change if repetitive purchases are allowed or the inventory of the offered product is limited. Furthermore, Chapter 3 only examined a monopolistic market setting. Even though duo- and oligopoly effects were incorporated into the model (e.g. customers leaving the store without buying and not approaching the seller again), the model should also be tested with competitive market structures where two or more online stores co-exist. This would allow deriving implications for optimising prices under competition where either none, some, or all other competitors deploy individualised pricing.

It was outlined in the introduction of Chapter 3 that individualised pricing suffers from customer rejection, which is the main reason for its scarce deployment in e-commerce today. As discussed before, under certain circumstances price individualisation is not rejected but accepted by customers. This applies, for instance, to scenarios where differences in product quality exist or social norms prevail (Garbarino and Lee 2003, p. 498). However, these cannot always be influenced by an online store. The optimisation of individualised prices as carried out in Chapter 3 does not solve the acceptance problem but adequately utilises EWOM's positive effects on customer behaviour to outweigh customer rejection resulting from EWOM's negative effects. Research shows that, in general, the acceptance of individualised prices is higher if these are presented to customers in the form of individualised discounts (Aydin and Ziya 2009, p. 1530; Bourreau et al. 2017, p. 41). In order to incorporate personalised discounting effects, future research could extend the developed optimisation model where two decisions need to be made: (1) which uniform price should be initially shown to all online store visitors and (2) which discount should be offered to each visitor? Its outcome should be benchmarked against the model presented in Chapter 3.

In Chapter 4, various launch strategies for social media apps and services in OSN were examined regarding their effectiveness of maximising the share of active users. These included different advertising schedule structures where the available budget was uniformly split into multiple advertising impulses. More schedule structures should be tested in future where the budget is not uniformly distributed but, for instance, exponentially increasing or decreasing within the advertising time horizon. Another approach could be to optimise the structure, e.g. by AI solution methods, for analysing how the optimal structure changes depending on the relation between the strong- and weak-tie utility of an app or service. Furthermore, the advertising schedule structure and targeting strategies were analysed separately. The effectiveness of different combinations of multiple targeting strategies and their optimal scheduling could also be investigated in future.

Another aspect that deserves closer inspection is the lock-in effect. Chapter 4 provides a basis for future research that could examine this more closely. The lock-in effect is relevant for both OSN vendors and start-ups that want to release an app in a market where already similar apps or services prevail. This applies, for instance, to the case of WhatsApp, where multiple competitors emerged over time that challenge the predominating position it has in several countries (Hootsuite 2020, p. 96; Kim 2018). In such situations, it needs to be taken into account that the role of EWOM could be altered for the users in the OSN who are affected by the lock-in effect. Since they already actively use an app due to the perception of sufficient social utility, the incentive of forwarding an invitation to join a competitor's app would be smaller. The receiver of the invitation might also tend to reject it if he is a user of the prevailing app. It is important to consider that users who have adopted the new app do not necessarily have to discard the former app but can be active in both apps simultaneously. To reflect this in the proposed diffusion model of Chapter 4, the activity status of users should not be modelled as a binary state but as a continuum. Because not every user is equally active in social media apps and services, users could be characterised by an “activity volume” that is split and distributed among the apps they actively use depending on the amount of provided social utility.

Last but not least, the role of influencers and opinion leaders in the perceived utility of social media apps and services should be investigated in greater depth. Influencers can exert a considerable impact on the perception of such apps and create added value for their followers. In a directed OSN, influencers could be treated as hubs who have a large number of followers and a small number of people whom they follow. While they are most likely seen by their followers as strong ties due to fandom and emotional bonding, they would regard the vast majority of their followers as weak ties. This requires an extension of the current model presented in this dissertation to enable applicability to directed graphs. The differentiation between influencers and regular OSN members could serve as a basis for additional experiments regarding the lock-in effect. Suppose, for example, that a famous social media app like Instagram is challenged by a newly released competitor app. As a market entry strategy, the vendors of this new app could consider incentivising prominent influencers on Instagram with a multitude of followers to exclusively use and be active in the new app. Would the potential social activity created by these influencers and their entourage justify the financial expenses needed for incentivising them to move? Or would it be more worthwhile to aim for so-called micro-influencers with a significantly smaller number of followers, who would probably accept lower financial compensation? These and similar questions should be in the focus of future research.

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