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Improving the skills of forest harvester operators: Task analysis and empirical studies on learning to operate a simulated robotic crane with and without sensorimotor support systems

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"The noblest pleasure is the joy of understanding"

Leonardo da Vinci

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Abstract

Forestry suffers from a shortage of trained machine operators, which jeopardises efficient and productive operations. Extensive training is required to skilfully master the complex tasks of forest machine operators. Therefore, the digitisation of the industry envisages training and support systems on machines that provide real-time support to operators, both on-site and remotely. To improve training methods and pave the way for the development of future operator support systems, this thesis conducted a detailed analysis of harvester operators' work tasks, focussing on motor control skills and cognitive (work)load.

The aim of this thesis was to gain new insights into the efficiency of the operators' work practices and the challenges of operating a forestry machine such as a forest harvester and a forest forwarder. The work was guided by the following two general research questions that were systematically answered throughout the presented studies in this thesis. (1) How can training methods for robotic arm operators be improved by analysing performance limiting factors in the bimanual control of the robotic cranes and (2) How can the machine operators be effectively supported with different sensorimotor support systems to ensure high level performance?

To this end, a multi-pronged approach using qualitative and quantitative methods was adopted and five scientific studies were carried out. The initial qualitative analyses conducted as part of this thesis unveiled a lack of research on the execution of specific work tasks of the individual machine operator. Furthermore, the analysis indicated that it was necessary to examine work practices in more detail to refine current working methods and adapt them to future technological developments. These analyses, based on literature reviews, field research, and conceptual analyses, suggested that the main challenge for the operator in performing mechanised forestry work is the skilled and skilful use of the hydraulic crane. The following three empirical studies therefore specifically analysed the acquisition of skills related to motor and sensory support systems for crane control in a purpose-built simulation environment.

A multi-joint robotic manipulator was designed and programmed as a simulation environment for laboratory studies, which resembles the crane of forestry machines in terms of dimensions and can also be controlled with two joysticks, analogous to real machines. The basic kinematic chain of the robotic manipulator used in the simulation environment can be found in many industries such as construction, logistics, and forestry, therefore the research carried out in this thesis has far-reaching implications for various fields of work and is pivotal to the efficient operation of heavy machinery. Notably, learning the

bimanual control of robotic cranes is still under-researched, as most previous research has focussed on increasing productivity but not specifically on improving the skills of crane operators.

To identify the challenges in learning the motor control of such robotic cranes, this work focussed on the joystick control of the individual joints of the robotic cranes. The joystick movements as a direct behavioural output of the human operator were used to analyse and model the effects of adaptation and forgetting in learning motor control skills. Therefore, aiming movements were performed using the robotic crane with varying levels of difficulty. In addition, learning and performance constraints, such as joints that are more difficult to control than others, and how these contribute to overall performance measured in terms of movement time and accuracy were investigated.

Regarding motor control support, this work investigated the newly developed computer-controlled inverse end-effector control of robotic cranes, which is now possible on hydraulic cranes. The end-effector control allows only the tip of the robotic crane to be controlled in 3D cartesian space, while the required joint positions are calculated in real-time by advanced algorithms to facilitate the machine operators' task. Therefore, this work compared end-effector control with the widely used single joint control of robotic cranes in terms of skill acquisition and derived new performance indicators for support systems and training methods based on the trajectories of the robotic crane movement.

Two experimental studies on operating skill acquisition showed that in spite of a gain in mental workload reduction with end-effector control, movement accuracy remains difficult with both control schemes (joint and end-effector control). This refers with joint control to the challenging use of the joints involved in the fine control of the robotic crane and with end-effector control to movements that in the depths of 3D space as well as the general lack of accuracy. For this reason, sensory support was investigated in an additional study, that targeted the challenges of precise movement execution/control.

Visual and auditory support systems were implemented in the simulation environment and compared for increasing accuracy. Both support systems provided real-time operator assistance, thus information on performance, concurrently to the robotic crane movement. Auditory support was given by loudness as well as pitch feedback and visual support by a head-up display showing dynamic size and brightness feedback. Auditory support proved to be particularly suitable to support the movement accuracy of operators with low performance levels.

To conclude, this work has shown that behavioural analysis at the level of joystick movements as well as the analysis of crane movements can be very fruitful for studying the development of human control skills in more detail and deriving new performance indicators that can be used in operator training and the design of different operator support systems. From a technical point of view, the joystick signals can be captured very easily as a direct output of the crane operator, which can be of great importance especially for the technical implementation of the gained knowledge in the design of a new generation of future assistance systems. The development of machines with increasing technical operator support will also potentially lead to new challenges in real-world operation, where the management of cognitive workload and the detrimental effects, specifically of cognitive underload conditions, will require a rethinking and design of the operators' work.

Kurzfassung

Die Forstwirtschaft leidet unter einem Mangel an qualifizierten Maschinenführern, der einen effizienten und produktiven Betrieb gefährdet. Um die komplexen Aufgaben eines Forstmaschinenführers zu meistern, ist eine umfassende Ausbildung erforderlich. Daher sieht die Digitalisierung der Branche Trainings- und Unterstützungssysteme für Forstmaschinen vor, die den Forstmaschinenführer sowohl an Bord der Maschine in Echtzeit als auch aus der Ferne unterstützen können. Zur Verbesserung von Trainingsmethoden und um den Weg für die Entwicklung zukünftiger Assistenzsystem zu ebnen, wurde in dieser Dissertation eine detaillierte Analyse der Arbeitsaufgaben von Harvesterfahrern durchgeführt, wobei der Schwerpunkt auf den motorischen Bedienfähigkeiten und der kognitiven (Arbeits-)Belastung der Maschinenführer gelegt wurde.

Ziel dieser Dissertation war es, neue Erkenntnisse über die Effizienz der Arbeitspraktiken der Maschineführer und die Bedienherausforderungen und Schwierigkeiten eines Harvesters und eines Forwarders zu gewinnen. Die Arbeit wurde dabei von zwei Forschungsfragen geleitet, die durch die durchgeführten Studien systematisch beantwortet wurden. (1) Wie können Trainingsmethoden für Bediener von Roboterarmen verbessert werden, indem leistungsbegrenzende Faktoren bei der bimanuellen Steuerung von Roboterkränen analysiert werden? (2) Wie können die Maschinenführer mit verschiedenen sensomotorischen Unterstützungssystemen effektiv unterstützt werden, um ein hohes Leistungsniveau zu gewährleisten?

Zu diesem Zweck wurde ein mehrstufiger Ansatz mit qualitativen und quantitativen Methoden gewählt auf dessen Basis fünf wissenschaftliche Studien durchgeführt wurden. Die zunächst qualitativen Analysen haben gezeigt, dass die Ausführungen spezifischer Arbeitstätigkeiten durch den einzelnen Forstmaschinenführer nicht ausreichend erforscht sind. Darüber hinaus ergab sich aus der Analyse die Notwendigkeit, die derzeit angewandten Arbeitspraktiken zu verbessern und den Weg für Anpassungen an zukünftige technologische Entwicklungen zu ebnen. Diese Analysen, die sich auf Literaturauswertungen, Feldforschung und konzeptionellen Analysen stützen, legen nahe, dass die größte Herausforderung für den Maschinenführer bei der mechanisierter Holzernte der geschickte und gekonnte Einsatz des hydraulischen Krans ist. Die anschließenden drei empirischen Studien fokussierten sich daher speziell auf den Erwerb der Bedienfertigkeit im Zusammenhang mit motorischen und sensorischen Unterstützungssystemen für die Kransteuerung in einer eigens dafür geschaffenen Simulationsumgebung.

Ein mehrgelenkiger Robotermanipulator wurde als Simulationsumgebung für die experimentellen Laborstudien entworfen und programmiert. Dieser Robotermanipulator wurde an die Abmessungen eines Krans einer Forstmaschine angepasst und kann analog zu realen Maschinen mit zwei Joysticks gesteuert werden. Die grundlegende kinematische Kette der Gelenke des verwendeten Robotermanipulators findet sich in vielen Branchen z. B. dem Baugewerbe, der Logistik und der Forstwirtschaft wieder, weshalb die in dieser Arbeit durchgeführten Studien relevante Ergebnisse für verschiedene Industrien liefert und von zentraler Bedeutung für den effizienten Betrieb von Großmaschinen ist. Insbesondere das Erlernen der bimanuellen Steuerung dieser Roboterkräne ist bisweilen wenig erforscht. Die Mehrzahl bisheriger Forschungsarbeiten konzentrierte sich auf die Steigerung der Produktivität des Harvesters und nicht auf den Lernvorgang und die Verbesserung der Bedienung.

Zur Ermittlung der Herausforderungen beim Erlernen der motorischen Steuerung solcher Roboterkräne, konzentrierte sich diese Dissertation auf die joystickbasierte Steuerung der einzelnen Gelenke des Roboterkrans. Joystickbewegungen wurden als direktes Verhaltensmaß des menschlichen Bedieners zur Analyse und Modellierung der Bedienfertigkeit verwendet. Dadurch ließ sich der Verlust der Bedienkompetenz über die Zeit in Bezug auf Vergessen und Adaptation untersuchen. Hierzu wurden Zielbewegungen mit unterschiedlichen Schwierigkeitsgraden mit dem Robotermanipulator ausgeführt. Darüber hinaus wurden Lern- und Leistungseinschränkungen untersucht, wie z. B. Gelenke, die schwieriger zu erlernen und kontrollieren sind als andere, und wie diese mit Leistungsmerkmalen wie Bewegungszeit und der Genauigkeit zusammenhängen.

Im Hinblick auf die Unterstützung der motorischen Fertigkeiten des Bedieners wurde in dieser Dissertation die computergesteuerte inverse Endeffektorsteuerung von Roboterkränen untersucht, die seit kurzem bei Hydraulikkränen möglich ist. Mit der Endeffektorsteuerung wird allein die Spitze des Roboterkrans im kartesischen 3D-Raum gesteuert, während die erforderlichen Gelenkpositionen in Echtzeit durch fortschrittliche Algorithmen berechnet werden. Dadurch wird die Aufgabe der Maschinenführer erleichtert. In dieser Dissertation wurde die Endeffektorsteuerung mit der am weitesten verbreiteten Einzelgelenksteuerung von Roboterkränen in Bezug auf den Erwerb von Bedienfertigkeit verglichen. Dabei wurden neue Leistungsindikatoren für Unterstützungssysteme und Trainingsmethoden auf der Grundlage der Trajektorien der Roboterkranbewegung abgeleitet.

Zwei experimentelle Studien zum Erwerb der Bedienfertigkeiten zeigten, dass die Bewegungsgenauigkeit bei beiden Steuerungssystemen (Gelenk- und Endeffektorsteuerung) weiterhin schwierig bleibt, obwohl die kognitive Arbeitsbelastung durch die Endeffektorsteuerung verringert werden konnte. Bei der Gelenksteuerung bezieht sich dies auf die anspruchsvolle Kontrolle und den damit verbundenen Lernvorgang der Gelenke, die an der Feinsteuerung des Roboterkrans beteiligt sind. Bei der Endeffektorsteuerung ist die Kontrolle von Bewegungen, die in der Tiefe des 3D-Raums stattfinden schwierig, hier wurde ebenfalls eine verringerte Genauigkeit festgestellt. Aus diesem Grund wurden in einer weiteren Studie Möglichkeiten der sensorischen Unterstützung des Bedieners untersucht, die auf die Herausforderungen der präzisen Bewegungsausführung/-steuerung abzielten.

Visuelle und auditive Unterstützungssysteme wurden in der Simulationsumgebung implementiert und im Hinblick auf die Verbesserung der Genauigkeit verglichen. Beide Unterstützungssysteme boten dem Bediener Unterstützung in Echtzeit und somit Informationen über die Leistung parallel zur Bewegung des Robotermanipulators. Die auditive Unterstützung erfolgte durch Lautstärke- und Tonhöhen-Feedback, die visuelle Unterstützung durch ein Head-up-Display auf dem dynamisches Größen- und Helligkeits-Feedback gegeben wurde. Die Ergebnisse zeigten, dass sich das auditive Feedback über die Bewegungsgenauigkeit besonders eignet Bediener mit anfänglich niedrigen Bedienfertigkeiten zu unterstützen.

Insgesamt hat die vorliegende Dissertation gezeigt, dass die Verhaltensanalyse auf der Ebene der Joystick-Bewegungen sowie die Analyse der Kranbewegungen wertvolle Erkenntnisse über die Entwicklung menschlicher Bedienfertigkeiten liefert und somit neue Leistungsindikatoren abgeleitet werden können: Die neuen Beurteilungsindikatoren können sowohl im Training von Maschinenführern als auch bei der Gestaltung neuer innovativer Unterstützungssysteme verwendet werden. Aus technischer Sicht sind die Joystick-Signale als direkte Eingabe der Maschinenführer einfach zu erfassen und somit ist eine zügige technische Umsetzung der gewonnenen Erkenntnisse bei der Gestaltung einer neuen Generation zukünftiger Unterstützungssystemen an Bord von Großmaschinen möglich. Die Entwicklung von Großmaschinen hin zu immer technischeren und automatisierten Systemen bringt möglicherweise neue Herausforderungen für den realen Betrieb mit sich. Hierbei spielt die kognitive Arbeitsbelastung und deren nachteilige Auswirkungen eine immer größere Rolle, insbesondere bei geringer kognitiver Belastung durch den ansteigenden Automationsgrad wird die Gestaltung der Arbeit der Maschineführer in Zukunft eine zentrale Bedeutung einnehmen.

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Chapter 1
Introduction

Supplying the world with wood is becoming increasingly important as the need for renewable and sustainable resources grows. The European Union expects the demand to increase rapidly within the next decade driven by the shift from fossil fuels and less disposable construction materials to CO_2 neutral resources (Forest Europe, 2020). Furthermore, climate change has increased the frequency and severity of calamities and thus significantly aggravated the supply of wood. The forest-based industries in Europe have a net value added of 138.6 billion euros in manufacturing, production of paper products, wood products as well as printing services and employ 3.1 million people in the EU in some 400,000 enterprises. In the mere logging industry 511 000 people are employed. Employment in the forestry sector in Germany is decreasing and has almost halved over the last 20 years (Forest Europe, 2020). As a result, employment in logging operations remains one of the biggest issues facing the industry. Where a large demand meets a small number of available and trained workers. The mechanisation and digitisation of forestry is expected to reduce the effects of a shortage of labour on the industry (Müller et al., 2019), however, the available human resources remain scarce. Mechanisation also requires a generally higher skill level among workers (Axelsson & Pontén, 1990). Nonetheless, the need for trained specialists in mechanised forestry arises not only to meet the demands of a more technical environment but also to increase the added value of the use of forestry machines.

1.1 Problem Statement and Motivation for the Thesis

Skilled behaviour demonstrated by a harvester operator who can fell, delimb and cut a tree in less than 30 s shows an extraordinary control performance. These highly skilled operators took years to achieve their performance level (Purfürst, 2010). Therefore, all levels of human information processing from sensory processing, perception, decision, and response selection and execution (Wickens et al., 2021) need to be at a high level to show such performance. Generally, machine operators in forestry must be highly skilled to master the work task efficiently (Pagnussat et al., 2020). The task of the machine operators comprises navigation, driving the machine, and applying silvicultural methods (Gellerstedt, 2002). Knowledge about the forest work methods that are to be applied is crucial to operator performance (Tervo et al., 2009). Despite comprehensive training programmes, machine operators can vary in productivity by around 40% when working on the same forestry harvester in the same forest stand (Kärhä et al., 2004; Ovaskainen et al., 2004). Differences between machine operators in the way they drive the machines and the methods they use are assumed to be responsible for the varying productivity. For this reason, efforts have been made to improve the selection of harvester operators based on productivity tests in simulators (Pagnussat et al., 2020) and by using advanced simulators with high fidelity to train skills of harvester operators (Eliasson, 1999; Grönlund et al., n.d.; Lapointe et al., 1996; Ovaskainen, 2005; Ovaskainen et al., 2011; Ranta, 2009). However, these simulations do not always ensure long-lasting transfer to the real world. Also, the operational effects of an ageing workforce were targeted to keep the productivity of elderly workers high (Lopes & Pagnussat, 2018). Training programmes are commonly taught by experienced operators, but due to high costs, voluntary participation, and lack of decentralised training centres, more advanced support and training systems onboard forest machines are envisaged as part of the digitisation of the forestry industry (Müller et al., 2019). Furthermore, remote operation sites exacerbate the already present challenges in running training programmes. Large variances of productivity therefore persist and raise the need to improve and innovate training methods. Technical support systems that take over parts of the manual control task have been researched to increase the automation levels of the harvester to ease machine handling (Mettin et al., 2009; Ortiz Morales et al., 2011, 2014; Westerberg & Shiriaev, 2013). Furthermore, support systems were successfully tested that gave advice on, e.g. grapple load and feedback about productivity (Palmroth et al., 2009; Tervo et al., 2008) to aid forest machine operators in future operations. Newly introduced crane tip controls (controlling the XYZ position of the crane tip) have already achieved advantages in reducing training demands (Manner et al., 2017). However, the development of skill acquisition, the impact on long-term performance, productivity, and crane movement behaviour need to be clarified. Real-time onboard feedback systems that can enhance and support the acquisition of operating skills throughout the operation, independent of human instructors are under discussion but still to be designed. Pending questions are to identify the work practices that require support and how they can be supported in the best possible way. For this, determining what constitutes good work practises and insights into the most relevant challenges the machine operator is facing is necessary for efficient work practise application. In addition to the knowledge gap on work practises, these practices and the challenges faced by a harvester operator can vary from country to country due to the prevailing regulations, that determine the applied work methods and working practices used (targeted in Chapter 2). To gain an overview of the work of forest machine operators, a systematic analysis of the work task is required. A process-oriented view of productivity is often taken when analysing work tasks in forestry. However, in order to design training and support systems in a human-centred way, it would be more beneficial to focus on the human factors in terms of the task objectives that determine behaviour. This perspective is currently rarely taken in research on mechanised forestry operations and will be addressed in Chapter 3 of this thesis.

Improvement of operator performance in terms of productivity often tests modifications of the mechanical parts of the harvester crane (see above the grapple or aggregate design). In contrast, research on manual crane control is scarce and mainly conducted within the field of teleoperation of cranes, excavators, or robotic manipulators. The diverse fields always come with a specific control layout that are commonly tested for performance differences among input devices and control mapping and therefore cannot be used to infer learning of the harvester crane controls (for example see Dubey et al., 2001; Goldstain et al., 2011; Jung et al., 2013; Mattos et al., 2011; Morosi et al., 2019; Mower et al., 2019; Suzuki & Harashima, 2008; Won Kim et al., 1987). Despite the fact that the basic operation of the cranes is similar, these studies do not allow any conclusions to be drawn about learning due to the control layout. Therefore, this thesis aimed to study the learning process of the bimanual control of robotic arms.

1.2 Research Approach and Structure of the Research in this Thesis

The research in this thesis followed a multi-pronged methodological approach as shown in Figure 1, split between qualitative interviews, conceptual analysis, and quantitative experiments assessing objective behavioural and subjective measures. The qualitative studies in Chapter 2 (Work Practice study) and Chapter 3 (HTA study) provided the basis of the following research and were directed towards challenges in forest operations. The quantitative work builds on Chapter 2 and Chapter 3, aiming at analysing the use of the harvester crane inspired by principles of motor control transferred to applications in human factors research.

The first part of the thesis, Chapters 2 and 3, conducted a literature-based and qualitative analysis of a harvester operator's work task and related work practices, from which the precise scope of the experimental analyses was derived. In Chapter 2 work practices of forest machine operators and the training methods used were analysed with semi-structured interviews and a state-of-the-art literature review applying the established PRISMA approach. This allowed a structured classification and analysis of the beneficial work practices and challenges of the machine operators' task in terms of machine operator performance. For knowledge elicitation on training methods and challenges in the operation of the machine, interviews were conducted with experienced machine operators and instructors. The interviews were analysed based on an abductive and deductive approach aligned with the grounded theory and closely tied to the well-developed structure of the interviews. The results of the literature review were combined with the findings from the interviews to conduct a hierarchical task analysis of the operator's goals when operating a machine to fell a tree in Chapter 3. The HTA was used to analyse the challenges of driving a harvester and to infer specific training needs within the task-goal hierarchy. The identification of challenges in achieving the goal "grab a tree" provided the basis for the following experimental research that is at the heart of this dissertation in Chapters 5-7.

The experimental research focused on the control of the robotic arm movements. Therefore, the relevant concepts of motor control and motor learning, the role of feedback, and the measurement of motor behaviour are introduced in Chapter 4. The experimental research was conducted using a low-fidelity, fixed-based robotic arm simulator. This allowed full control over the training tasks, as well as the ability to vary the system specification between joint velocity and end-effector control of the robotic arm as well as the feedback provided. The simulation environment allowed insights into the joystick inputs and movements of the robotic arm. The recorded data were used to statistically analyse and model learning development with the two time scales power law of learning at individual session level as well as across sessions, including retention (Chapter 5, Learning study). The modelling enabled to infer the learning strategies and especially the learning difficulties of the participants. The study presented in Chapter 6 (Comparative study) investigated the benefits of end-effector control as a motor-cognitive support system in comparison to joint control. The focus of the analysis was next to general performance, the quality of the movement trajectories, and the perceived workload during control skill acquisition. The research in Chapter 7 (Concurrent Feedback study) used the conclusions drawn from the previous chapters, which unveiled control challenges in terms of accuracy. Auditory and visual concurrent feedback was designed to provide sensory-based information for the landing phase of the robotic arms' aiming movement. The feedback provided allowed recommendations to be made for future training methods and helped to design real-time operator support. Overall, the experiments conducted in this thesis provide insights into the acquisition of control skills of 4-degree-of-freedom robotic manipulators (which was based on a harvester crane) and how acquisition and performance can be analysed and supported.

Chapter 8 concludes the findings of this thesis and discusses the implications of the experimental research for the research questions derived in Chapter 4 with a focus on control skill limitations and performance enhancement (Chapters 5-7). Subsequently, recommendations for and relevance of the discussed findings for application in the forestry sector in terms of work practises and training are presented (Chapters 2-3).

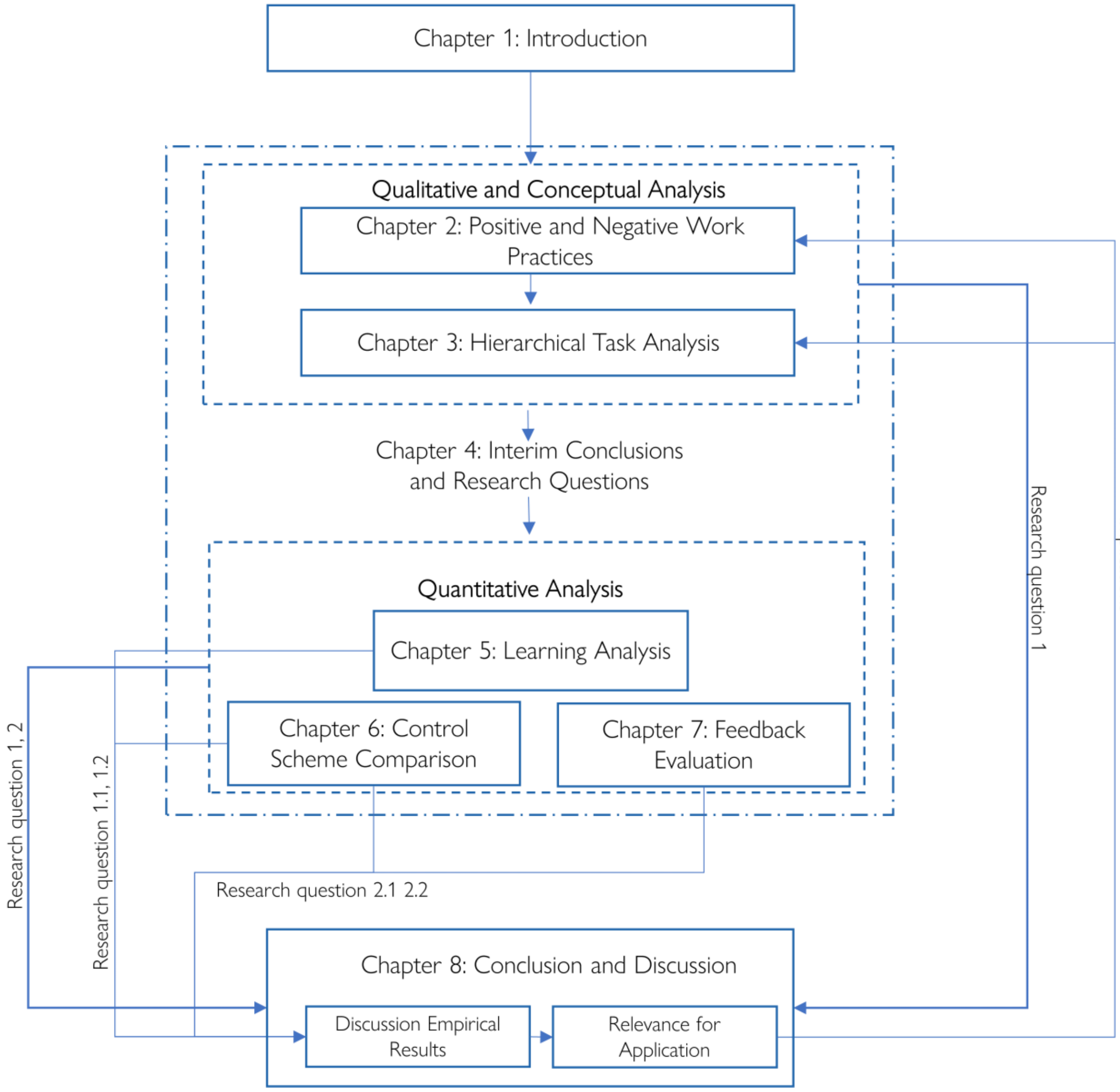

Figure 1. Outline of the dissertation structure including relations between chapters.

Chapter 2
Positive and Negative Work Practices of Forest Machine Operators: Interviews and Literature Analysis

Variance in productivity of fully mechanized timber harvesting under comparable stand and terrain conditions requires the investigation of the influence of work practices of machine operators. Work practices can vary among operators and may result in a wide range of productivity. Therefore, it is of great interest to identify positive and negative work practices of forest machine operators to improve forest work. For the qualitative analysis of work practices, 15 forest machine operator instructors were interviewed in Norway, Sweden, and Germany in semi-structured interviews. Additionally, a literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines was performed. The interviews brought up de-tailed positive work practices and showed negative examples of machine handling, specifically related to boom operation. The literature review retrieved 2482 articles of which 16 were examined in more detail. The review showed that work practice characteristics were only sparsely covered, however, still overlapped with the work practice recommendations from the operator instructor interviews. Further, the literature search unveiled a scientific knowledge gap related to the quantification of applied work practices. Generally, positive work practices can include using optimal working ranges from 4–6 m, frequent machine repositioning, a matched fit of operator skill and crane speed, and an assortment pile size that matches the maximum grapple loads. Training is recommended to focus on crane control in terms of movement precision and work range adherence whereby the speed-accuracy trade-off should be improved to meet productivity requirements and increase efficiency in forest machine operator work.

This chapter is an edited version of the following paper:

Hartsch, F.*; Dreger, F.A.*; Englund, M.; Hoffart, E.; Rinkenauer, G.; Wagner, T.; Jaeger, D. Positive and Negative Work Practices of Forest Machine Operators: Interviews and Literature Analysis. *Forests* 2022, *13*(12), 2153; https://doi.org/10.3390/f13122153. *Note. Joint first authorship.

2.1 Introduction

Highly mechanized timber harvesting systems account for the largest share of total logging, which is approximately 50% in Central Europe [1,2]. In Scandinavian countries, the share of highly mechanized timber harvesting is much higher [3]. Modern forest harvesters fell, process, and deposit full stems or assortments at the machine operating trail. Forwarders load and convey the assortments to the landing [4]. The control of these forest machines is highly complex [5] and work tasks in mechanized timber harvesting bear a high mental workload on the operator [6]. Therefore, operating forest machines requires lengthy training, continuous education, and supervision, throughout the operator's entire career. On average, up to three years of experience is required after training for a forest machine operator to reach full proficiency [7]. Work studies revealed that even experienced machine operators show productivity differences of up to 40% [8].

In recent years, operating forest machines has changed due to the introduction of new technologies. Sensor-based detection of the machine environment gained importance and opened new opportunities for forest companies [9,10]. Operator assistance systems, such as rotating cabins or boom tip control systems, were developed and are still being improved with the goal of increasing productivity and reducing the mental workload of machine operators [11,12]. More detailed analyses of operator as-assistance systems have shown that productivity can indeed be increased [13–15].

Generally, various factors affect the productivity of highly mechanized timber harvesting systems. These performance-determining factors are extensively studied and include operator-related parameters [16], stand-, timber- [17], and terrain-related characteristics [18], technical requirements [19], and organizational aspects [20]. Regarding the influence of forest machine operators on productivity, a number of studies have been conducted [7,17,21]. However, these studies focused mainly on productivity analyses of the main work elements.

Harvester and forwarder work can be categorized by these work elements. These work elements are divided into Driving/Crane use/Felling/Processing/Manipulation for the harvester [22] and Travel empty/Travel loaded/Loading/Unloading [23] for the forwarder, respectively. Studies suggest that the work method and the work practice of the forest machine operators are crucial for overall performance in highly mechanized timber harvesting systems [24–27]. Due to the interchangeable use in the literature of the terms work practice, work, and work method, it remains unclear how deeply work practices affect the productivity of forest machine operators.

Therefore, in the present study, a work practice is defined in accordance with the German REFA institute (REFA Verband für Arbeitsgestaltung, Betriebsorganisation und Unternehmensentwicklung e.V.) as part of the work process. A work practice considers the operator-related, individual way of carrying out the work process, based on the work method used. The term describes the personal scope of action within the work method, which serves as a basis for a higher performance and improved ergonomics can be achieved [28]. In some cases, the terms "work pattern" or "working behaviour" are used synonymously in the scientific forestry literature.

The definition highlights that the individual way of carrying out timber felling, -processing, and forwarding in highly mechanized harvesting systems depends largely on the skills of forest machine operators. In this context, even personal preferences can influence performance [29]. Individual work practices can be developed within all work elements and affect not only driving skills or operation planning, but also crane operation [26]. The literature on the evaluation of work practices is sparse although there is a need to identify favorable and efficient, and conversely, ineffective and mentally demanding work practices of forest machine operators to improve mechanized timber harvesting. Due to the interlaced task structure and multiple factors that can potentially affect the whole system's productivity, the role of these work practices remains unclear and in particular, to what extent personal work practices contribute to the execution and outcome of work. However, it is assumed that productivity differences between machine operators described in the literature are caused by work practices to a significant extent.

In a nutshell, it is essential to assess beneficial work practices that contribute to performance and lead to an increased productivity. Therefore, the present study aims to give an initial overview of the work practices of forwarder and harvester operators, that can have both an impact on productivity and mental strain, but also on the wear and tear of machines. Two methods, interviews with forest machine operator instructors and a scientific literature analysis will serve as the overview of work practices.

2.2 Material and Methods

For the evaluation of work practices, a multipronged approach was used to retrieve information on subject matter, expert interviews, and scientific literature. This allowed for coverage of a broad range of work practices and to compare the state-of-the-art in work practices, as reported on in the literature, to those work practices applied in service, as reported on in the expert interviews.

2.2.1 Qualitative Content Analysis of Expert Interviews

Step 1 – Preparation and conducting of interviews: A total of 15 expert subject matter interviews were conducted in Germany, Sweden, and Norway. To gain insights into details of instructed forest machine operator work practices, a semi-structured approach was used. Due to the complex content of interviews, the number of selected operator instructors was limited to a closed-question format survey. However, the semi-structured interview guideline revealed complex behavioral patterns that are rarely described in the work science literature. The experts in all contributing countries were selected by their expertise and their availability. All interviewees were experienced in operating forest machines and were currently working as instructors. This allowed for a high skill and proficiency level of the operators' analyses of work practices. The forest machine operator instructors interviewed work both with beginner- and experience-level operators. The interviews were conducted between June 2019 and May 2020. Participants consented to participate voluntarily. The interview guideline was developed by researchers from all partnering countries (see Appendix A). A major goal of the guideline was to ensure consistency, meaning that all interviewees were exposed to all relevant questions and thus comparability of answers could be ensured. The interviews were recorded and then transcribed, paraphrased, and anonymized. Next, the transcripts were assigned the first letter of the country and the interview number as a pseudonym (e.g., Germany = G1-7; Sweden = S1-5; Norway = N1-3). Demographic data and experience level of the forest machine operator instructors are shown in Table 1. The 15 experts satisfied the experience criteria in all three countries to have at least two instructors and thus perspectives with, similar experience, machine manufacturer collaboration, certification, and multiple instructed machines and operators.

Table 1. Demographic data of the operator instructor interviews conducted in Germany, Sweden, and Norway (number ranges only apply to present experience).

Demographic Data	Germany (G1-7)	Sweden (S1-5)	Norway (N1-3)
Sex [numeral; male, female]	7 m	5 m	3 m
Age [numeral; years; range]	40–57	51–61	29–55
Formal certificate as forest machine operator? [numeral; yes, no]	3 yes, 4 no	3 yes, 2 no	3 yes
Formal certificate as forest machine operator instructor? [numeral; yes, no]	4 yes, 3 no	5 no	2 yes, 1 no

Training cooperation with machine manufacturer? [numeral; yes, no]	6 yes, 1 no	2 yes, 3 no	2 yes, 1 no
In contact with other operator instructors? [numeral; yes, no]	6 yes, 1 no	5 yes	3 yes
Experience on harvesters? [numeral; yes, no]	3 yes, 4 no	5 yes	3 yes
Experience on harvesters? [numeral; years; range]	6–10	10–40	5–26
Experience on forwarders? [numeral; Yes, No]	7 yes	5 yes	3 yes
Experience on forwarders? [numeral; years; range]	1–25	1–40	5–13
At the moment operating any forest machine? [yes; no]	6 yes, 1 no	5 yes	2 yes, 1 no
Years as forest machine operator instructor? [numeral; years; range]	5–25	4–25	1–14
How many forest machine operators get trained per year? [numeral; years; range]	8–20	20–90	20–40
How many forest machine operators were trained in career in total? [numeral; range]	40–300	100–3500	25–400

<u>Step 2 – Interview analysis:</u> The interview analysis was performed by using MAXQDA v. 12.3.5 software. Following the transcription and anonymization of the data, a coding system was developed to analyze the interviewees' opinion on positive and negative work practices of forest machine operators and also to guarantee that all relevant comments on the objectives of the study could be included in the analysis.

The coding system can be described as follows: Firstly, categories were roughly clustered deductively using literature prior to analysis. Before and during the analysis, comments of forest machine operator instructors related to the study objectives were then abductively selected first by type [Forwarder, Harvester, Value, Teamwork, Teaching and communication skills], and secondly based on a category itself [Forwarder: crane settings, crane skill, loading, unloading; Harvester: Positioning and reaching for trees, felling, crane settings, crane use, other; Value: value; Teamwork: teamwork and Psychology: psychology]. The categories developed are not exclusively based on work elements, but also on other aspects that are essential for the daily work of a machine operator. While analyzing the material, a brief written summary for every interviewee's verbal comment on a specific category should guarantee a detailed description of a work practice. It formed the basis for evaluating the operator behavior as either positive or negative, in connection to certain work aspects affected by the work practice (productivity, fuel efficiency, mental strain, machine wear and tear, occupational safety, timber value, hydraulic load). While reviewing the categories of behavior, the importance with respect to the severity in affecting the work outcome was reviewed. In addition, strategies for changing negative work practices were integrated to give advice for productivity improvements in modern cut-to-length systems. In the results section, statements were cited by using the interview number as a pseudonym (e.g., G1, S2). In the discussion of results, an integrative cross-sphere discussion approach was used with the goal of summarizing the categories to extract aspects which are important for practitioners.

2.2.2 Methods of the Literature Analysis

Step 1—Scientific literature database search: The guidelines recommended by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach were selected as the framework for the literature analysis [30]. As no previous review on forest machine work practices was available, the focus was set on the scientific databases Scopus, PsychInfo, GreenFile, Engineering Science, and Web of Science. The following search terms and syntax were used: ('forestry' OR 'forest' OR 'harvester' OR 'forest machine' OR 'forest harvester' OR 'forwarder') AND operator AND ('performance' OR 'workload' OR 'behaviour' OR 'work practice' OR 'work method' OR 'productivity' OR 'Skill'). Next to the online literature search, senior scientists were consulted to obtain literature recommendations (cf. Figure 2 grey column).

Step 2—Initial screening criteria of search results: The literature search resulted in 2480 journal articles and reports. Duplicates were removed from the results. The literature search showed low coherence of the retrieved studies of interest. Then, the journal article titles were reviewed. Articles related to other fields such as machine learning or algorithmic behavior, non-forestry harvesters (i.e., agricultural crops), or the analysis of technical properties of the machine while neglecting the operator, were excluded (see Figure 2). In addition, two recommended journal articles were included at this stage to review the procedure.

Step 3—Final inclusion criteria: The inclusion criteria for the literature retrieved from the databases were the following: (1) the article needed to undergo a peer-revision procedure and needed to be published in English. (2) The article was not a review, but rather an empirical study or structured interview. (3) The study concerned forest harvester, forest forwarder, or harwarder. (4) The study reported the behavior of the operator, a work practice or method that relates to operator behavior, and (5) the study reported an outcome variable or recommendation for the given work method or practice used. Full-text articles retrieved from the databases which did not adhere to these criteria were subsequently excluded from the study.

Step 4—Data and result extraction: The data/information of the remaining studies was extracted by (1) determination of the work practice or work method applied, (2) the measured outcome variable that was either workload, performance, skill, or work behavior, (3) the used system/machine (4), and further (5) the setting in which the study was conducted, e.g., a field test or simulator-based study.

Step 5—Results and Analysis approach: All relevant journal articles with the extracted results were listed. Then, the skill/work behavior was classified as either positive or negative with respect to the specific result. This approach resembled the method from the above-described interview analysis (for more details see Chapter 3.2.2).

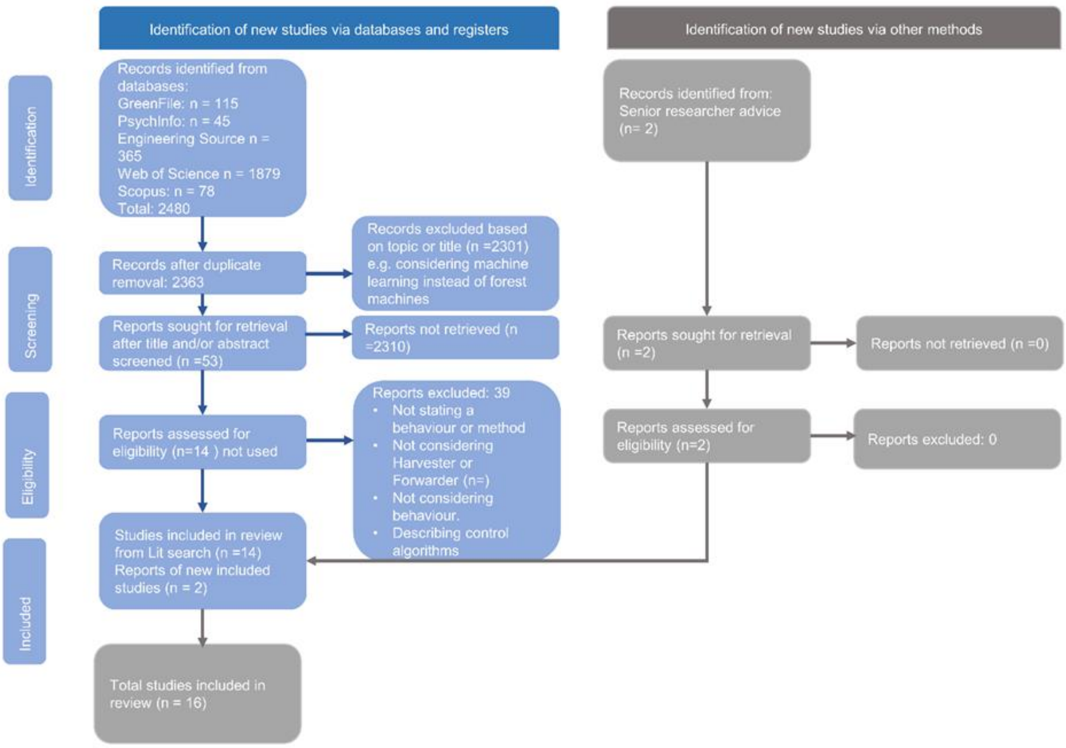

Figure 2. The PRISMA flow diagram shows the process of searching for and identifying relevant literature for this review [30].

2.3 Results

2.3.1 Results of Operator Instructor Interviews—Overview of Beneficial and Negative Work Practices of Forest Machine Operators

2.3.1.1 Harvester

Positioning and reaching for trees: Operator instructors describe that excessive crane reach (between crane origin and harvester head) is often a problem during both felling and processing, as crane speed and precision decreases, and machine wear and tear increases (S1, S2, S4, N2, N3). As a consequence of this, wood piles become too large and assortments get mixed (S1, S2, S4, S5). When trees are felled in a wide operating range, the stems need to be moved closer to the machine for processing. This affects not only time consumption and mental workload for the operators negatively (N2, N3), but also occupational safety (G1, G3, S1, S5). Another problem is that forest machine operators reposition the machine too infrequently, so that crane paths increase and productivity decreases (N2, N3), which is especially a problem for beginner operators. However, if harvesters are moved or relocated too frequently, this is not optimal, and also affects time consumption (S1, S4, S5). Systematic moving of felled trees from one side of the machine to the other for processing is also frequently observed (S3, S4).

Felling: Forest machine operators often seem to lack a plan in which order to fell trees (S1). Several operator instructors observe that failing to achieve the intended felling direction is a problem too (S2, S3, S4). Based on the interviewees' comments, the first tree to be felled from a harvester's position decides where the pile is placed. Trees are sometimes felled leaning slightly backwards instead of forwards, which means that the operators' view is hidden from the trees' cross-section, hiding potential rot, which negatively influences wood value aspects (S1, S3, N1, N3). While processing, assortment piles should be laid out in a fan pattern. Different assortment piles processed within one harvested stem should touch each other at the machine operating trail facing end but have a separation distance of around 1.5 m at the opposite side (S5) to simplify the consecutive forwarder work.

Crane settings: Forest machine operator instructors notice poorly adjusted cranes (G1, G2, G6). In this context, crane speed is often too high (S2, S5, N1, N2, N3) or too low (N1), which affects productivity, workload, and fuel efficiency.

Crane use: While reaching the tree with the crane, it is sometimes observed that too much tension is put into the tree during felling, which affects timber value, as it induces more cracks in the stem. Furthermore, it is noticed that operators use the extension too late when reaching for a tree. A frequent, unplanned use of the extension is also observed (S1). Forest machine operators also sometimes seem to hold the harvester head too high when processing, which leads to oscillating cranes (N4, S3). After processing trees, harvester operators unnecessarily elevate the harvester head several meters, which negatively corresponds with productivity, workload, fuel consumption, and machine wear and tear (S1, S3). Moreover, if the harvester head grabs the tree too high at the stem to be harvested and not on the stem basis, this leads to correction movements with the harvester head at the stem and can negatively impact the wear and tear of the crane (S1).

Other: Forest machine operator instructors mention that weather conditions are sometimes not considered when planning the operation. For example, consideration of wind and felling direction is insufficient (S3). In thinning operations, single crane elements are not observed frequently enough. Too much focus on the head can lead to the crane causing damage to the remaining trees (G1, G2). In addition, it is observed that saw chains are often too blunt, which leads to higher fuel consumption and lower productivity (S2, S4).

2.3.1.2 Forwarder

Positioning: Operator instructors from Germany and Sweden confirm that forwarder positioning is a problem while operating the machine. Many operators reach too far with the crane to grab logs instead of moving the machine (G1, G3, S1, S4).

Crane settings: Interviewed operator instructors mention that a disharmony between crane and grapple settings often appears. When closing the grapple, the down-ward motion of the grapple sometimes does not match the upwards motion of the boom tip from lifting (S1). Operator instructors acknowledge that crane speed should harmonize to “typical” movements. The extension should be used immediately to lift a load and be fully retracted by the time the grapple passes the load space supports. If not, productivity and workload are negatively affected (S2). Full joystick signal to ex-tension in, main boom and slewing should have the logs at an appropriate height over the ground (S4), otherwise this would negatively affect operator workload and productivity. It is observed that operators often operate cranes with too high crane speed (G3, N1, N2, N3, S2, S4), too low crane speed (S2), or that crane settings generally do not fit to the operator (G1, G3).

Crane skill: Especially when beginner forest machine operators work with the crane, they partly perform the movements of the single crane elements non-simultaneously (G1), which affects productivity and fuel efficiency. In addition, crane or joystick movements are mixed up (G4-7). Operator instructors observe that the crane extension is often not used enough or only when a pile cannot be reached without the extension (S2, S3, S4, N3). Operators sometimes forget to pull the extension in and bottoming out the main lift boom instead (G2). Even if intelligent boom control (IBC) is activated, some operators unnecessarily use the extension manually (N3). Continuously holding down "grapple close" while carrying logs is observed as well (S1). After releasing the logs in the load space, the grapple is sometimes closed, which is unnecessary (S1).

Unloading: While unloading, some operators position the grapple too low when opening to release the logs onto the pile, resulting in the grapple pushing on and spreading the logs in the pile. The height at which they open the grapple should account for the space the grapple needs to open (S1, S3). While building a pile, operators should make a succession of peaks and valleys to facilitate the logs falling into place (S4). An incorrect layout of the roadside piles can be observed. The main assortment should be the closest to point (S2, S3, S4, N2, N4). Sometimes, an incorrect buildup of piles at the roadside makes the operators lift over the top of the pile. Placing the logs is then more difficult (S1, S2, S4). Some operators do not fill the grapple as much as possible while unloading (S2). While unloading (or loading), operators unnecessarily lift the empty grapple over the supports of the load space, instead of moving through or between the supports, which negatively influences productivity, workload, and fuel consumption (G1, G2, S2, S3, S4, N3). A clumsy release of the logs is also observed. The operators also seem to forget to adjust the height of the boom tip (S2). Mixing assortments is a problem in practice as well. Operators sometimes do not communicate on which assortments to mix in loads (S1, S4) filling the grapple from the load space, the grapple is often opened too wide. Reaching too wide makes the logs roll over one another, making the load potentially unsafe and disordered. The operators should aim to fill the grapple by reaching deeper into the load (S4).

Loading: Some operators move the machine while having logs in the grapple. This is risky as sudden machine movements can cause the grapple to lose hold of the logs (S2). To ensure flush ends of the grappled logs, some also bump the logs' ends against the ground. This is usually not necessary while loading (S2, S3) and negatively affects productivity. It is observed that forest machine operators start filling the load space against the "cradle". Based on the instructor´s view, it is more productive to start loading against the supports to later allow the logs to fall into the central space (S2, S3). Moreover, sometimes the grapple is not sufficiently filled while loading (G4, S2, S4). Some operators do not want to mix assortments in the load space, which leads to increasing forwarding distances and loading time (N2, N3, S1, S2, S4). Logs are also sometimes gripped at the "wrong" point, which leads to increasing wear and tear and decreasing productivity (S1). A good organization throughout the loading process is often missed. The highest value assortment should be loaded firstly (S1) to keep the option to downgrade logs.

Other: Operator instructors observe that operators do not follow curves in the machine operating trails correctly (G3).

2.3.1.3 Value Recovery of Harvester and Forwarder

Value: Regarding the added value of harvesting or forwarding, the influence of various factors is mentioned. Firstly, unbeknownst to the operator, the saw motor could be worn out and not reach suitable rpm, leading to longer cutting times and consequently more cracks in the logs (S2). Secondly, not sharpening the knives of the harvester head (S2, S4) and poor measurements of control logs (calibration) (S2) negatively affect value creation. A blunt chain or not changing a worn-out chain on the harvester head on time is observed as well (S2, S4). Using worn-out feed rollers and compensating for this by pulsing the knives following along the stem with the crane tip can also occur (S4). Aggression with the crane tip while following along the stem is observed (S4), which leads to timber damage.

2.3.1.4 Teamwork of Harvester and Forwarder Operators

Teamwork: According to the interviewees, in the context of teamwork, there is often a lack of agreement on a system for how the harvester should stack the assortments. This deeply affects the productivity of the forwarder (S2, S3, N1, N2, N3). Sometimes, harvester operators pile assortments in places with poor ground conditions (wet, sloping), which also negatively affects forwarder productivity (S1, N1). Operator instructors mention that some harvester operators do not understand highly mechanized harvesting systems as teamwork between harvester and forwarder (S2). Additionally, some harvester operators seem to believe that bigger piles are better for forwarder operators. Based on the instructors´ comments, one full grapple per pile is optimal (S1). In contrast, forwarding productivity is negatively affected by the harvester spreading out the logs too much (S3).

2.3.1.5 Teaching and Communication Skills (Harvester and Forwarder)

The relationship between operator instructor and operator is considered to be highly important to the success of the coaching process. Operator instructors frequently mentioned that the first contact with the operators is important. Firstly, to get the initial impressions of the applied work practices and secondly, of the operators' attitude towards training (i.e., receptiveness). If the opinion of operators on how the machine ought to be operated is considered, they can come up with ideas on which aspects they need to work on, also on a long-term basis (follow-up meetings) (S2). It seems to be important to praise operators when they work well or improve, not only remark on things they should do differently (S2). Recording operators on video is an appropriate way to improve their working behavior (S2, N3). Motivation of operators in exercises is important to improve their productivity in the long-term, since their performance might decrease in the early stages of testing a new work method (S1).

To improve productivity, feedback such as that which is available in simulator training, is beneficial (S1). Additionally, testing other crane settings can improve skills while reducing mental workload. This is especially important while teaching younger operators. Setting up the machine and crane correctly so that it fits to the operator is mentioned as a central requirement for a successful training session (N2, N3). When asking operators to try new settings, it is important to give operators the possibility to revert to the original crane settings (S3). Furthermore, when teaching new operators, the most difficult task for the instructors seems to be adapting them to different circumstances (S4). Setting goals and objectives for the operators, which are achievable, are mentioned as well (S5).

2.3.2 Results of Literature Review

2.3.2.1 Overview of Study Layout

Sixteen studies were examined in total [4,8,24,27,31-42]. Three out of these studies [24,31,36] were simulator-based studies, and 13 studies were conducted in-field [4,8,27,32–35,37–42]. Simulator studies assessed more participants, whereas field studies range from 1–6 participants. Commonly, field studies depend on specific machines and operators driving on-site. That is why the analyzed studies considered the operators related to a specific machine (e.g., two operators for one machine, working in shifts), as participants. Generally, when reported, the operators that served as participants were experienced and had more than 10 years of experience. Four [4,27,33,36] out of the sixteen studies were assessing forwarder work whereas ten [24,31,32,34,37–42] were concerned with harvester operations, a single study was concerned with a harwarder [35], which is a combined machine of harvester and forwarder. Both thinning and clear-felling operations were the focus of the research. The variables of interest were predominantly productivity and time, but operator workload and tree damage were also assessed.

2.3.2.2 Synthesis and Evaluation

To identify work practices, behaviors, or skills that were beneficial to the productivity, well-being, or general performance of the system of forest machine and operator, the study outcome was filtered with respect to recommendations or results that can be used to advise and inform machine operators. Then, the results were compiled within the evaluation column of Table 2, which shows that there is a vast range of applicable situations that can benefit from informed operator behavior. The results of Table 2 will be briefly summarized here. As the machines and methods are highly complex only specific situations, methods, or single work elements were addressed within the analyzed studies. The eleven studies investigating work methods with harvester operators provided the basis of recommendations. Generally, recommendations are found independent of the type of operation (thinning or clear felling).

Only one study for piling was found that researched the difference between these general operations in forestry. In thinning operations, beneficial work practices are "right angle piling" and "under the boom piling", whereas in clear felling (forward felling), "two-sided piling" is applied by the operators [11]. Efficient work practices for both methods that were identified included: Reducing the number of times the machine drove in reverse, moving the machine frequently and realizing short tree-handling distances to avoid unnecessary boom movements, keeping movements of the stem to a minimum after felling [8], placing edge trees at 1.2 m rear distance to the boom base [34], using automated bucking while processing (in particular in spruce stands), employing a high feeding speed and processing the tree as close to the machine as possible [8], and piling the logs according to the assortments [4]. Furthermore, long-term productivity was found to be negligible if the forest manager or an experienced operator decided on the tree selection [38,39]. With respect to operator workload and fatigue, we found a study that showed increased tree damage at dawn and at the end of the shift [32]. In addition, workload was found to increase with increased slope and working in mixed stands, compared to monoculture stands [31,37]. A single study researched the work method of a harwarder and found driving along the cut edge and processing the tree directly into the load space as the most efficient method [35]. The literature search on forwarder operators showed that loading is the primary interest of the retrieved studies. [27] found log and loading angles of 45° as most beneficial within a work range of 4–6 m for a certain machine type. Moreover, the grapple load was analyzed in another study, and the assortment pile size should match the maximum grapple load, to ensure efficient handling [4]. As a new tool, a multi-assortment grapple would improve loading efficiency if the remaining trees do not obstruct the trajectory between assortments [36]. Furthermore, to mitigate the impact of vibrations on the operator while keeping a high efficiency, a driving speed of 8 kph was found to balance well-being and efficiency [33]. Overall, the recommendations on work practices are given within all work cycle elements of forwarder, harwarder, and harvester.

Table 2. Data extracted from the PRISMA literature review.

Online Databases						
Study Title	*N*	Skill, Work Method, Behaviour, Work Practice	Outcome Variable, Performance	Machine	Setting	Evaluation
Hartsch et al. (2022). Influence of Loading Distance, Loading Angle and Log Orientation on Time Consumption of Forwarder Loading Cycles: A Pilot Case Study. [27]	1	Loading logs with forwarder	Loading distance Loading angle Log orientation angle	Forwarder	Field	Beneficial for productivity: • 45° Log angle • 45° Loading angle • 4–6m range
Vasiliauskas et al. (2021). Driving Speed influence on operator vibration exposure in forwarding operations. [33]	1	Control of driving speed	Driving speed Vibration exposure	Forwarder	Field	Optimal vibration/productivity ratio at 8km/h

Bembenek et al. (2020). Effect of Day or Night and Cumulative Shift Time on the Frequency of Tree Damage during CTL Harvesting in Various Stand Conditions. [32]	2	Shift-dependent boom control	Tree damage	Harvester	Field	Increased tree damage: • Dawn • End of shift
Spinelli et al. (2020). The Effect of New Silvicultural Trends on Mental Workload of Harvester Operators. [31]	13	Mental control demand of boom in mixed vs. mono cultivation	Workload/ NASA TLX	Harvester	Simulator	Higher workload in mixed stands compared to mono cultivation
Ovaskainen et al. (2011). Productivity of Different Working Techniques in Thinning and Clear Cutting in a Harvester Simulator. [24]	5	Piling methods in thinning and clear-felling	Productivity	Harvester	Simulator	Beneficial work method Thinning: • right angle piling • under the boom piling Clear felling: • forward felling • two-sided piling
Ovaskainen et al. (2006). Effect of Edge Trees on Harvester Positioning in Thinning. [34]	6	Decision of where to leave edge trees and position harvester	Productivity and distance of Edge tree to boom base	Harvester	Field	Edge trees are best at the roadside 1.2 m from boom base to the rear
Andersson and Eliasson (2004). Effects of Three Harvesting Work Methods on Harwarder Productivity in Final Felling. [35]	1	Three methods of tree cutting and loading	Productivity	Harwarder	Field	Most efficient: Driving forward along cut edge and process directly in loading area
Manner et al. (2020). Innovative productivity improvements in forest operations: a comparative study of the Assortment Grapple using a machine simulator. [36]	4	Assortment grapple tested in loading task	Productivity m^3 Time (s)	Forwarder	Simulator	Assortment grapple is more productive (if movement is not blocked by young stand)
Szewczyk et al. (2020). The mental workload of harvester operators working in steep terrain conditions. [37]	1	Felling at varying slopes 9%, 23%, 47% assessed	Workload measured by eye tracking: fixations and saccades	Harvester	Field	The steeper the slope the greater the workload
Eberhard and Hasenauer (2021). Tree marking versus tree selection by harvester operator: are there any differences in the development of thinned Norway spruce forests? [38]	4	Fell decision making trees in advance vs. operator while operating	Productivity Forest development	Harvester	Field	• 70% concurrency of forest manager vs. operator tree selection. • After 50 years sylvicultural differences neglectable
Holzleitner et al. (2019). Effect of prior tree marking, thinning method and topping diameter on harvester performance in a first thinning operation—a field experiment. [39]	1	Fell decision making trees in advance vs. operator while operating	Productivity	Harvester	Field	Tree marking is not relevant factor in tree selection of productivity
Labelle et al. (2017). The effect of quality bucking and automatic bucking on harvesting productivity and product recovery in a pine dominated stand under Bavarian conditions. *[40]*	1	Operator manual cuts or automatic, system defined cuts	Productivity/ value	Harvester	Field	Automatic bucking beneficial in spruce but not in pine trees compared to manual logging
Labelle and Huß (2018). Creation of value through a harvester on-board bucking optimization system operated in a spruce stand. [41]	1	Operator manual cuts or automatic, system defined cuts	Productivity/ value	Harvester	Field	When thinning in spruce dominated stands, automated bucking is more productive than in pine in stands
Uusitalo et al. (2004). The effect of two bucking methods on Scots pine lumber quality. [42]	2	Operator manual cuts or automatic, system defined cuts	Productivity/ value	Harvester	Field	Automated bucking does not reduce productivity
Articles from recommendations						

Väätäinen et al. (2006). The effect of single grip harvester`s log bunching on forwarder efficiency. **[4]**	6	Pile size/ bunching	Productivity	Harvester Forwarder	Field	• Piles = max. grapple load. • Single pile is to be avoided • Adapt method to machine size used • Small and Large diameters are to bunch precisely
Ovaskainen et al. 2004. Characteristics and Significance of a Harvester Operators' Working Technique in Thinnings. **[8]**	6	Observation of entire work cycle	Productivity m^3	Harvester	Field	• No reversing • Move the machine frequently to adjust work location • Short distance to cut –reducing unnecessary boom movements • Unnecessary stem movement while felling should be avoided • Processing close to stump • High feeding speed in processing

2.4 Discussion

The goal of this study was to identify positive and negative work practices of forest machine operators using two different approaches. One approach used interviews with machine operator instructors in Norway, Sweden, and Germany. The second approach used a literature review of forest machine operator work practices, in accordance with the PRISMA guidelines [30].

2.4.1 Discussion: Interviews

The interviews aimed to get a detailed description and informed analysis of the work practices of forest machine operators for both harvesters and forwarders. An integrative cross-sphere discussion approach for both harvester- and forwarder-related comments was followed to extract the relevant work practices.

The main results of the interview unveiled five key elements that contribute to work practice performance that are discussed below for both harvesters and forwarders.

Positioning the machine: Negative work practices often become evident while positioning the machine. "Negative" positioning, i.e., too far a distance between the machine and the tree to be harvested (harvester), or the wood pile to be loaded (forwarder), leads to increased wear and tear of the crane elements and also to decreased productivity due to longer crane paths. This is in line with other studies which revealed that increasing loading distances can have a negative impact on time consumption per loading cycle [27], and therefore productivity. Since the loading element is the most important [23] to productivity, adequate positioning towards reducing time consumption during loading is worth striving for.

Crane use: A second important aspect is the use of the crane. Both the sequential use of single crane elements and the lack of using the boom extension were identified as problematic ways of working. Based on the instructors´ statements, it can be assumed that these work practices occur particularly with beginners. Accordingly, it could be important to apply training programs such as RECO (economical driving and fuel consumption) [43] or state-certified forest machine operator training (Germany). When novice operators control the crane, productivity can be increased by using intelligent crane controls [14].

Value: Regarding value-added timber production, forest machine operator instructors highlighted the continuous maintenance of the harvester head and saw chain as a decisive factor. Based on the interviewees´ comments, respondents cited that dull chains increase the machine's fuel consumption and decrease the value of the produced timber. Furthermore, worn-out feed rollers and the actions operators take to compensate for this introduce errors in the length measurement. There is no literature investigating feed rollers specifically, but forest machine operator instructors report that feed roller maintenance does not receive enough attention in forest operations.

Teamwork: Forest machine operators often do not seem to understand the collaboration between harvester and forwarder as a crucial aspect of overall system productivity. Based on the comments of the forest machine operator instructors interviewed, harvester operators sometimes do not know that the quality of log processing and depositing deeply affects forwarder productivity. When depositing the logs at the edge of the machine operating trail, a pile size corresponding to one full grapple seems to be optimal based on the instructors´ comments. In practice, this likely depends on stand and terrain conditions. Studies have shown that a higher degree of timber concentration along the skid trail generally increases the productivity of the forwarder [4]. Further, the assortment-related log concentration affects forwarding efficiency [44]. This shows that the optimal placement of logs by the harvester can mitigate the tedious sorting of different assortments by the forwarder during subsequent loading.

Teaching and communication skills: Operator instructors mention the significance of adaptive teaching and training activities to achieve compliance with the training to increase productivity. In this regard, scientific studies underline that the skills and the aptitude of the forest machine operator affect productivity significantly [21]. However, task complexity during crane operations can be simplified by using intelligent crane controls [13]. This suggests that future studies on training should focus on how to cope with the complexity and increase training motivation to support the mental well-being of forest machine operators. Based on the interviewees' comments, the effectiveness of the harvester and forwarder work seems to be related to the freedom and autonomy given to the operator in the design of training and the work task while achieving clear performance goals (see Section 3.1.5).

In summary, the interviews provided detailed insights into challenges in machine operation in terms of specific work practices that are to be avoided and others which should be favored by the operators. Forest machine instructors highlighted negative work practices that they encounter in their daily work. In contrast, "beneficial" work practices were partly inferred from non-negative behavior. Interviewees could hardly determine quantitatively the general impact of the work practices on productivity or machine wear since work practices need to be assessed within their context. Thus, the impact on system productivity must be seen within the interaction of the individual machine operator and other performance-determining factors (i.e., environmental). Compared to interviews, large-scale surveys with sufficient sample size could produce statistically more accurate and representative results [45]. However, because neither the number of forest machine operators in Germany, Norway, and Sweden is known nor the research field of forest machine operator work practices has been researched in detail, it was decided to conduct subject matter expert interviews. It can be assumed, despite the limited number of interviewees, that the results have practical relevance, precisely because of the years of experience and the number of trained operators.

2.4.2 Discussion: Literature Search

The literature search was aimed to allow for a comparison with the actual applied practices and enrich and validate reported work practices from the interviews. Research studies on operator work practices unveiled room for improvement of productivity in all work elements. According to the studies analyzed, Forwarder operators ought to focus on diligent execution of the loading cycle, raising efficiency, and should be meticulous in assortment handling, namely the separation and size of piles. Harvester operators need to realize short tree handling distances and therefore improve on machine driving and efficient boom trajectories to ensure a short work range (see Table 2 above).

The studies included in the review are a glimpse into the diverse range of work practices that are applied by the operators in the field (see also Section 3.1). The number of studies included in the review was surprisingly limited, despite having a broad range of search terms. Only a few studies investigated a specific work practice independent of new technical systems. This may lie in the research foci of the field of forestry work science, where the effect of operators' work patterns or method execution on productivity is less researched than equipment and machine advancements. The studies that were excluded from the review research timber harvesting on a broader scale than on the level of the work practice of the individual operator. The small number of studies found on optimal boom control, driving, and positioning of the harvester is showing that there is still a huge potential for analyzing the efficiency of specific work practices. In general, the included studies suffered from small sample sizes, which is common in the forestry sector due to limitations in access to machine operators. Therefore, some of the recommendations within the research are based on expert opinions. Still, the review unveils efficient work practices that can be used to inform operator support, training, and further increase the resource efficiency in timber harvesting.

2.4.3 Literature Review and Interview Result Synthesis and Limitations

The interviews and the literature review showed overlapping results with respect to crane control, assortment piling, and assortment handling of harvesters and forwarders. For instance, keeping tree-handling distances short, within a range of 4 to 6 m, is good practice, as well as piling assortments in sizes matching the capacity of the grapple. Notably, there is a large difference in the number of work practices described by the operator instructors and the ones found in the literature. Within the interviews, instructors elaborated in fine detail on many work practices they observe in the field and instruct. Specifically, the forest machine operator instructors made detailed statements on the relation between working ranges, optimal machine (re)positioning, appropriate crane settings, best practice training concepts, and adequate machine maintenance. This information cannot or only rarely be found in the literature. The literature review results revealed a vast knowledge gap on the detailed description and specifically, the quantification of work practices. In line, the literature covered a small range of practices; not many studies covered each element of the work task and thus lacked in-depth analyses. The shortage of evidence needs to be enriched to bolster the statements of operator instructors with quantitative data.

In this regard, the interviews shed light on a large amount of advantageous and disadvantageous work practices that are not or insufficiently described in the scientific literature, such as the effect of the felling direction on processing and log piling. Herein, the interplay of reaching distance and repositioning of the machine or the advantages of fan patterns of piles, pile sizes, locations, or loading angles on forwarding efficiency or operator strain (see Section 3.1.1.) remain to be supported by scientific evidence. Furthermore, the negative effect of improper crane settings on wear and tear, fuel efficiency, value recovery, and the operators' mental load needs to be determined. In line, the effects of the consequences such as additional stem relocation or failure to control for rot while bucking due to visual obstruction cannot be found in the scientific literature, although play an important role in practice according to the instructors. The future challenges of forest research lay in the interaction of work practices such as the above example of the felling direction and the processing location on the operator task level, but also in the demand imposed by the triad of task, machine, and work environment. Altogether is known to reduce efficiency, where the extent of each of the work practices requires thorough quantification.

For system design, we encourage next to the recent automation advances such as boom-tip controls to ease the precision motion of the crane including operator recommendations, e.g., on stem handling. Operator training can be improved with a focus on the interaction of the work phases whereby enhanced crane efficiency needs to be trained considering the advantages of proper positioning, but also on a higher goal level with the focus on low-wear handling of forestry machines. Currently, machine operator training is based on the experience of the instructors, which contributes to the present study by giving a detailed view on work practices which potentially optimize the work system. The complex and diverse emerging picture of advantageous and dis-advantageous work practices goes beyond conventional training (and the above-cited scientific literature), which is often based on national education curricula that may diverge for countries, vary in the applied methods, and is inaccessible to the broader scientific community. Nonetheless, the link between the interview results to real-world operations can be considered accurate and relevant since instructor recommendations come directly from application and show overlap with scientific studies [8,27]. Despite the individual instructor views in three different countries, coherent statements on work practices across Norway, Sweden, and Germany were found. However, a full representative coverage despite a thorough conduct cannot fully be ensured with 15 interviews. That is why a few groups or categories are built on a few coherent statements.

2.4.4 Conclusions

Work practices can be described as the machine operators' implementation style of a given work method, that affects system productivity and machine wear and tear. However, the instructors´ descriptions of work practices are based on subjective observations of forest machine operators. When setting goals for work practice optimization, the instructors usually refer to machine positioning, crane work, value creation, teamwork between harvester and forwarder, as well as motivation and stress.

Due to the high level of experience of the interviewed forest machine operator instructors and overlap with the scientific literature, a practical relevance can be assumed.

Although work practices can also be defined by means of the literature, the number of studies found was rather small and touched upon few but distinct task domains of machine operator work. Although there are extensive studies on the influence of the machine operator on system productivity, a large proportion of the studies reviewed examined the effects of a specific factor on productivity. Few studies considered also forest development or mental strain.

This study combined a thorough literature review and the analysis of 15 exploratory interviews to investigate an almost untouched field of forest research—the forest machine operator work practices and their potential effect on system productivity, fuel consumption of forest machines, and machine wear and tear. There is a plethora of factors that potentially affect harvester and forwarder productivity, with the human operator at the heart of the operation. Due to the extensive challenges associated with establishing both ecologically considerate and scientifically valid laboratory conditions in forest operations research, the evidence of the actual effect of specific work practices still needs to be investigated further. However, previous studies including exploratory interviews suggest that work practices may have a strong impact on productivity and machine wear and tear. Technical developments that ease machine control, the shortage of labor, and new silvicultural requirements due to climate change urge to set an increasing focus on operator performance in work systems, despite the introduction of automation. Efficient work practices are essential for future mechanized timber harvesting and ought to be addressed in research to raise the quality of operator training and support system design. By that, the research line of work practice performance may unlock new productivity potential of mechanized timber harvesting.

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Chapter 3
Hierarchical Task Analysis (HTA) for Application Research on Operator Work Practices and the Design of Training and Support Systems for Forestry Harvester

Highly mechanized forestry operations are essential for efficient timber harvesting. Therefore, the skills of harvester operators appear to be key to productive and sustainable use of the machines. Recent research has revealed a knowledge deficit regarding the work practices of forest machine operators. This urges systematic research into forestry machine handling and a corresponding refinement of analytical methods. Current analyses of operator tasks in forestry are less formalized and focus predominantly on machine efficiency and overall performance, but not so much on the human-related conditions of work performance and workload. Therefore, the objective of this paper is to introduce hierarchical task analysis (HTA) into forestry science. HTA is a versatile, formalized human-factors method that can be used to describe the work objectives of forest machine operators. HTA is suitable, for example, for describing (in)efficient work practices and thus as a basis for de-signing machine operator training and for systematically evaluating assistive technologies. The task analyses in this paper draw on a recently published empirical approach to analyzing work practices, workflows, and machine operator behavior for optimal human–machine collaboration in forestry application research. Specifically, the main work methods of clearcutting and thinning stand in European forestry were considered, with examples from Scandinavian and German method application. The process of HTA is described and a prototypical approach to HTA for both working methods provided. As a result, this work could show that a single work practice affects operator goals within different work elements and sets out how inefficient work practices can be described in terms of operator goals. With the introduction and exemplary application of HTA, a structured task definition in human-centered approaches is encouraged to analyze work practices, workflows, and machine operator behavior for optimal human–machine collaboration in forestry application research.

This chapter is an edited version of the following paper:

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3.1 Introduction

Forest harvester operators are faced with a complex machine-control task that is determining the productivity in logging operations. Studies investigating operator work therefore focus on assessing the human operators' performance to increase harvesting productivity [1–4] and further reduce performance variance by motor-skill analysis and targeted training in operator recruitment [5]. Within a previous empirical study, the authors found that the variance of operator performance lies, among other causes, within the individual method application of the machine operators that is called work practice. Work practices are commonly identified and trained by experienced machine operators and instructors that are involved in operator training. So far, only a few scientific studies deal with the investigation of operator work practices; for example, it was shown that loading angles of 45° to the machine trail and working ranges of 4–6 m are advantageous when loading logs in transport operation [6]. Notably, however, there are knowledge gaps related to efficiency and, in particular, the lack of quantification of forest machine operators' work practices [7] that suggest that a systematic analysis could be useful to more accurately describe and analyze work practices. For this purpose, the following section will introduce the concept of hierarchical task analysis (HTA), which, interestingly, has not been used in forestry yet.

3.1.1 The Concept of Hierarchical Task Analysis

Hierarchical task analysis is a widely used human-factors research method to structurally analyze a work or control task [6]. HTA was developed by John Annett [7] to represent human information processing aspects that are necessary to fulfil a task (operation). It makes it possible to represent goal-directed human behavior. Within HTA, a main task goal (goal of operation) is hierarchically organized into subgoals. Subgoals represent operations and thus inherently comprise actions to achieve the (higher-level) goal. Moreover, subgoals are determined by the information of whether they are active or not, the actions that need to be carried out to achieve the subgoal, and the presence of feedback that indicates goal fulfilment [8,9]. This structure allows the analysis of why a subgoal could not be activated and therefore the sub-operation not be completed. Initially HTA was used to identify training needs for specific control tasks (e.g., chemical industry and power plant control room; [7]). HTA is mostly applied to system control where one operator is controlling one system; however, it is now also applied to team operations in fields such as driving, piloting, or excavator operations [10–12]. HTA was further detailed over the years and refined [13]. With the introduction of plans as method extension, HTA provides the opportunity to account for aspects of time, sequence, and relevance of actions to achieve a goal. Subgoals of a specific higher-level goal do not necessarily need to be achieved (activated) in all respective instances of operation variants. The order and the necessity of the action can be specified within such a plan. The success of HTA lies in its versatility to adapt and extend the analysis as needed while adhering to some fundamental rules [9,14]. Dissecting a task into subgoals that lead to a hierarchical goal structure serves the idea that a fine grain analysis of the task identifies actions that may ease erroneous behavior in the human–machine system interaction. Moreover, HTA allows to recognize training needs for the entire task [8]. Notably, goals are inherently representing knowledge, actions, and skill that are required to fulfil a specific subgoal. The descriptive nature, however, allows to simplify the complexity and reduces the focus on cognitive and motor prerequisites of the work task by still outlining challenges for the operator and task dependencies. Therefore, HTA provides the possibility to identify tasks and subtasks that bear high demand for the operator. The level of detail of an HTA is a major challenge to the practitioner and shall depend on the PxC criterion (the probability of an error associated with the consequence of the error) [7]. The PxC criterion, however, is not trivial to validly determine, so [6] recommends leaving the level of de-tail up to the practitioner. As a guide for choosing the hierarchical depth of the HTA, [15] recommends high probabilities and low consequences of errors for the goal achievement on the job training. This would not require a deep revision of the task structure, whereas high consequences of errors require analyzing a task or system entirely by considering all behavioral and procedural aspects of goal achievement. An HTA can be both performed as graphical notation and in a table format to outline the human–machine interaction. One strength of HTA that should be emphasized is that the analyses are based on goals instead of the mere observation of operator behavior.

In summary, HTA can be applied to different human–machine systems and different workflows. The formalized description of the task can form the basis for both the design and improvement of technical support and individual operator training. These approaches include testing subtask performance, designing operator workflows for training, and specifying feedback requirements. In addition, HTA helps define evaluation criteria of support systems with respect to workload and the allocation of cognitive resources while achieving a task goal by interacting with a system.

3.1.2 HTA in the Context of Highly Mechanized Forestry Work

The current study aims to conduct a human-centered hierarchical task analysis (HTA) applied to the task of a forest harvester operator. The study objective is to demonstrate the use of HTA by specifying the forest harvester operators' task within two different forestry work methods and by that provide the basis for research on the quantification of work practices. Thereby, the current work wants to shed light on (in)efficient work practices in a structured manner and derive implications to inform targeted machine operator training. Moreover, the goal is to systematically point out challenges a machine operator faces while enriching the methods used for work task and cycle analyses in the forestry domain. The analyzed forestry work methods represent the predominant operations stand thinning and clear felling in highly mechanized forestry [16,17], applied to German and Scandinavian operations. The detailed description of an HTA shall encourage forest scientists to apply human-factors methods to complement current machine operator analyses.

3.2 Materials and Methods

3.2.1 Approach to HTA in Forestry Timber Harvesting

This HTA followed the conceptual outline as described in [9,12]. First, the overall goal was defined, namely, to analyze the task of a harvester operator in mechanized timber harvesting within clear felling and thinning operation in Germany and Scandinavia to contrast inefficient and efficient work practices. The goal was agreed upon by forestry experts and human factors scientist from Sweden and Germany in the context of the EU co-funded project AVATAR.

First, information on the task of the harvester operator was collected. For this, (a) a literature search on positive and negative work practices was carried out and (b) expert opinions were obtained. The results are published in [18]. In [15], task analysis is understood as a process that entails three elements: (1) "break task content down into elements", (2) "determine relationship among elements", (3) "restructure in accordance".

The literature review in [18] was used to extract descriptions of the forestry harvester operators task that states at least three work elements. The task descriptions varied substantially. Eighteen journal articles served as the basis to derive the first set of operational goals. To analyze the structure of task goals, work task descriptions were extracted. In most cases, irrespective of the field of forest research, the journal article stated a sequence of tasks or work elements, either as a table, list, or enumerated sequence. The identified sequences were analyzed with respect to communalities in count and sequence of the work elements (see Table 3). In spite of the different details of the task descriptions, a first draft of the task hierarchy was derived from the extracted sequences, which served as the starting point for further iterations of the HTA.

Table 3. Counts of work elements across all journal articles. The sequence is based on the predominant occurrence within articles where at least three of the elements were mentioned.

Sequence	Count	Work Element
1	12	moving
2	8	boom out
3	18	cut tree
4	18	process tree
5	6	non-productive time
6	3	piling logs

Subsequently, subject matter experts (SME) were contacted and queried about the task, i.e., harvester operator instructors [18] (c.f. Table 4). Five forestry scientists were asked to review the task structure. All scientists reviewed drafts for both work methods. Respective SMEs were asked about the goals, e.g., on the positioning of the machine and how to grab trees. Then, a forestry scientist reviewed the first draft of the complete HTA. In the next phase, the analysis was re-described; therefore, the comments of the SMEs were adapted to the formal rules of the HTA, and the draft was further iterated. After completing the HTA for clear felling, the HTA was extended and iterated with the SMEs for felling a tree in thinning forest operations, in German felling operations. The latter is the standard method in mechanized timber harvesting in German forestry.

Table 4. Demographic data of the contacted operator instructors (SMEs) that served as sources for information about the operators' task.

Demographic Data	Germany	Scandinavia
Sex (*all male*)	7	8
Age (*years*)	40–57	29–61
Years of experience on harvesters	6–10	5–40
Years of experience on forwarders	1–25	1–40
Currently operating forest machines [*yes/no*]	6/1	7/1
Years as forest machine operator instructor	5–25	1–25
Trained machine operators (*count*)	40–300	25–3500

3.2.2 HTA—Level of Detail

The advantage of HTA is the versatility and thus various application domains (e.g., control rooms, piloting, driving). However, this versatility led to a plethora of different implementations of HTA. Therefore, the task analysis within the example of clear felling and stand thinning was based on the recommendations in [9,12,14]. As the goal was to have an instrument that is conducive to further research in domains such as motor control and training design, the required level of detail of the analysis is high. The following rules constitute the design of the HTA.

Subgoals must be mutually exclusive, and goals have between two and ten sub-goals on the next lower level of abstraction [12]. Plans are used to describe relations, activation status, and aspects of time within the analysis [9]. The notation in accordance with [8,9,19] is detailed in Table 5.

Table 5. Notation of plans in HTA.

+	dual/parallel operation
>	sequential activation, i.e., first subgoal 1, then 2;
/	either or subgoal is active
:	any subgoal is active; order and time are not critical
?	subgoal is active if necessary/condition applies

3.3 Results and Analysis of the HTA of Forest Operations

The HTA can be outlined within a graphical and within a table notation. The entire HTA was depicted in graphical notation of which excerpts are shown as an example within the text. The complete HTA can be found in Appendix A (see Figure A1, A2, A3). Additionally for demonstration, the first hierarchy level of the HTA of clear felling is shown in table notation (Table 6).

Table 6. Example of table notation of Figure 3a.

Superordinate Task	Components and Description	Execution Plan	Cues (Enter/Exit Rules)	Notes and Remarks
1. Position harvester	1.1 Plan route 1.2 Drive harvester to target position 1.3 Decide trees to be kept	Plan 1: 1.3 > 1.1 > 1.2 1.2 > 1.2	Upon start of the felling operation/End of felling operation	Route planning may depend on weather conditions
2. Fell tree	2.1 Grab tree 2.2 Fell-cut 2.3 Pre-strain stem	Plan 2: 1.? > 2.3? > 2.2	Start felling/tree is felled	Pre-straining and grabbing depend on tree and terrain properties
3. Process tree	3.1 Decide pile position 3.2 Change species in board computer 3.3 Check tree damage/rot 3.4 Position/adjust harvester head for delimbing/feeding 3.5 Monitor automated head travel/cross-cut	Plan3: 3.1 > 3.2? + 3.3 > 3.4? > 3.5 > 3.6 > 3.7? > 3.8	Start after tree is felled/tree is processed and aggregate is free of branches	The pile positions, depend on terrain and number of assortments

	3.6 Sort logs 3.7 Correct measurement baseline 3.8 Clear tree	

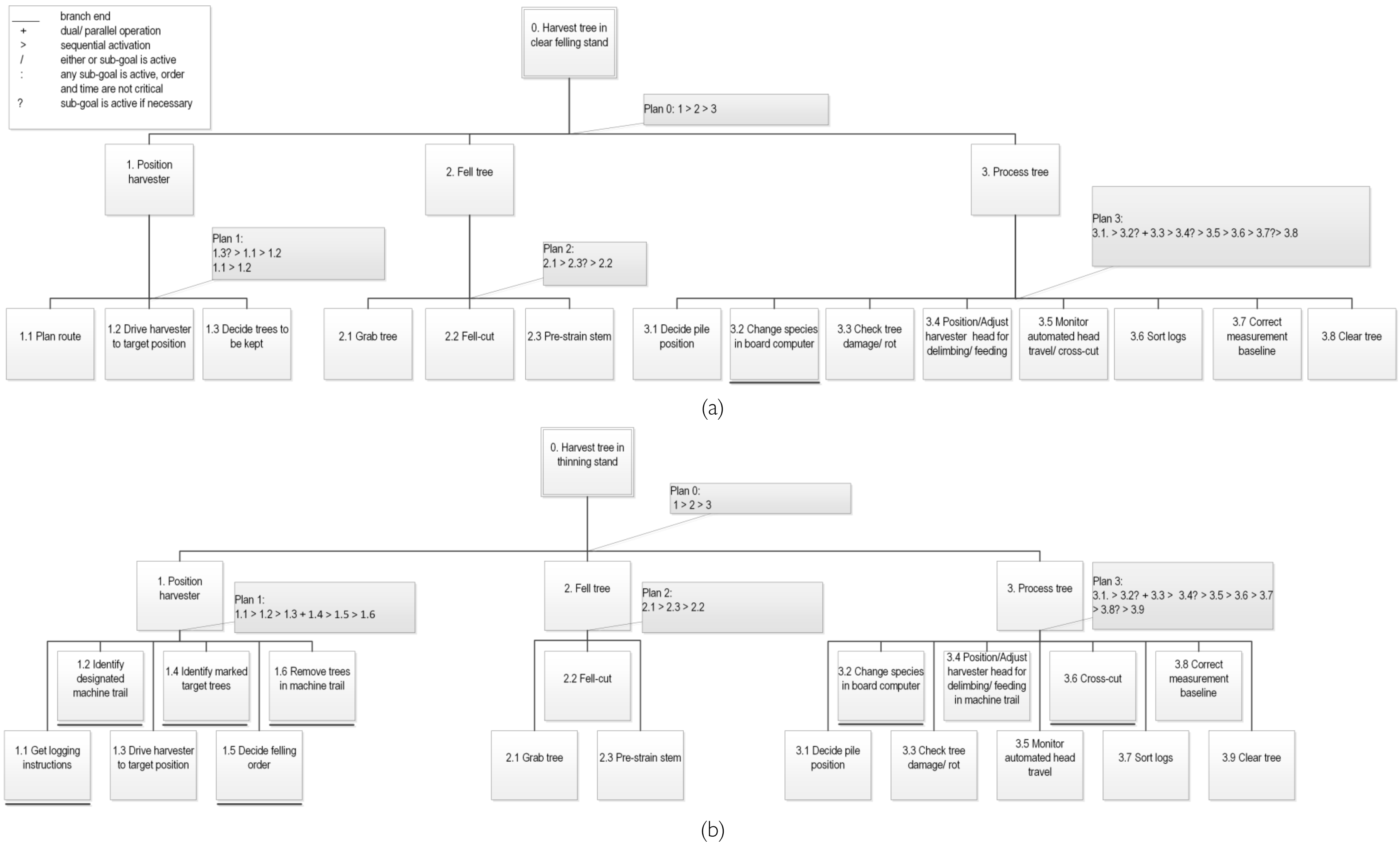


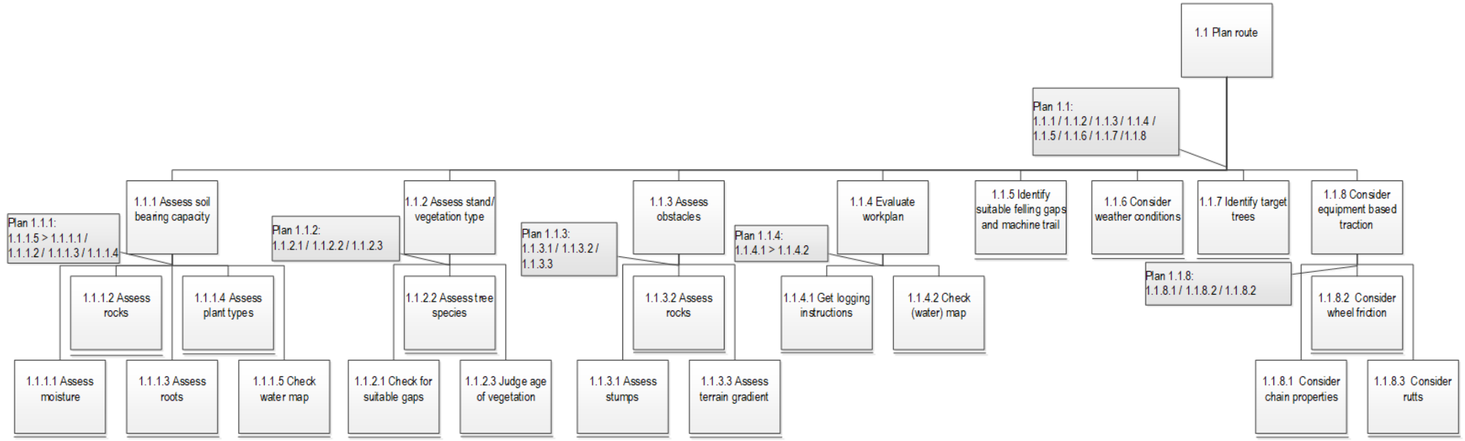
Figure 3. Level 0–2 of the hierarchical task analyses of the harvester operators' task in (a) clear felling and (b) thinning stand operations.

3.3.1 Higher-Level Goals of Clear Felling and Stand Thinning

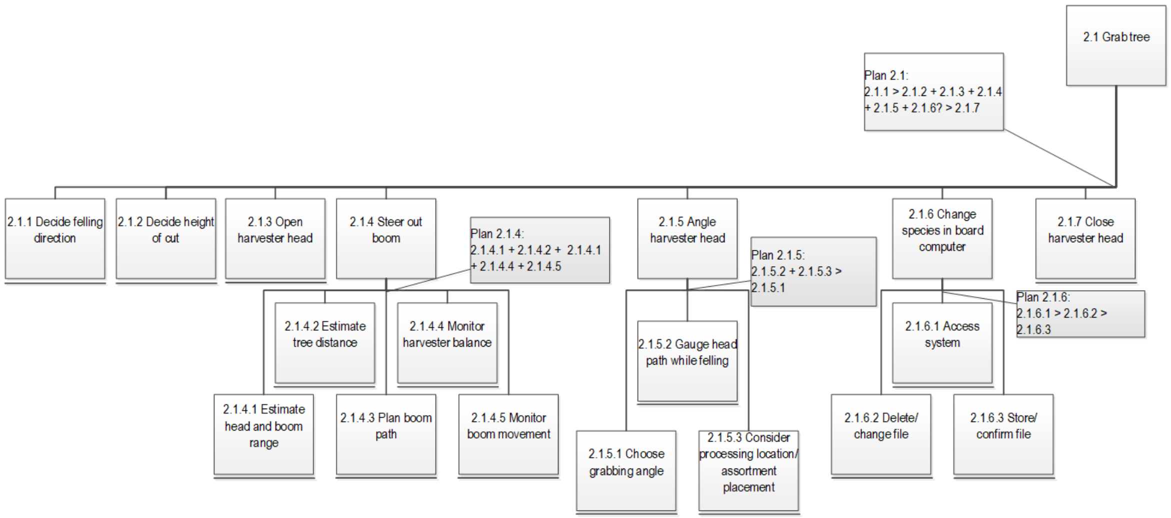
Figure 3 shows the highest level of the two task analyses of Scandinavian clear felling (Figure 3a) and German stand thinning (Figure 3b) operations. The main difference between the above working techniques lies in the processing and the planning of the felling operation, where the harvester needs to be positioned to the trees. In clear felling, the route is not pre-planned and thus the planning (if necessary) lies with the operator. Moreover, the decision of which trees may be kept or not is on behalf of the operator in clear felling and stand thinning in Scandinavia. In comparison, in German stand-thinning operations, the decision of which trees are to be kept is accomplished by planning in advance of the operation. The planning is commonly carried out by the forest manager. The machine operator needs to identify the marked trees for felling and the designated machine operating trail. While processing the tree, the main difference between thinning and clear fell operations for the operator is that the processing and the pile location are more confined in stand thinning by other trees that are preserved. Furthermore, delimbing needs to take place within the machine trail, and the saw actuation of cross-cutting of the logs is not automated. The cross-cut while processing in German stand thinning is initiated manually, whereas in Scandinavia it is the operators choice to use automation.

3.3.2 Detailing HTA Subgoals

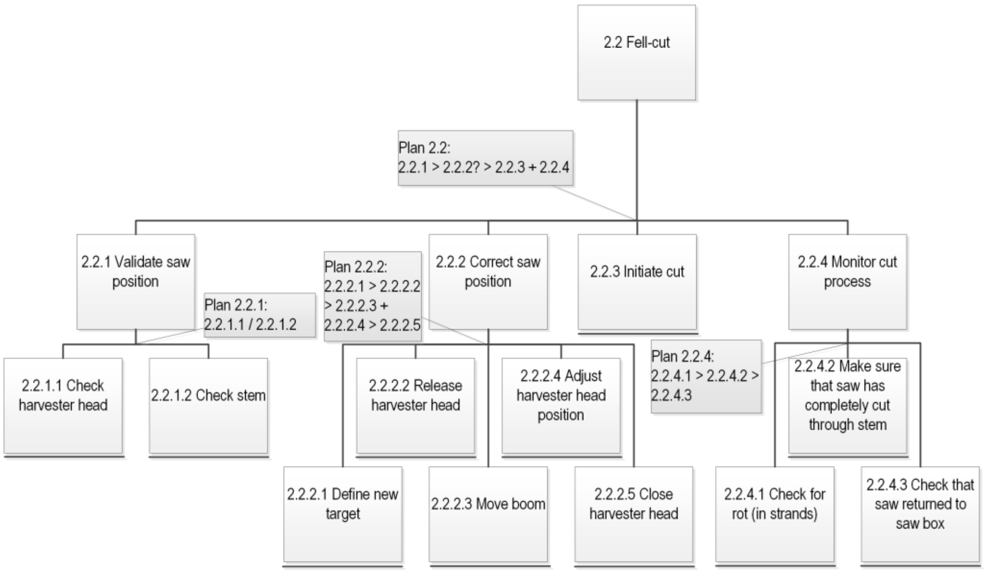
HTA can further be detailed to identify operator goals that are of interest within a specific work element and thus work practice. Examples of further defined subgoals are shown in Figure 4. Goals that comprise many actions and decisions were chosen for contrasting inefficient and efficient work practices. The HTA levels 4–6 give an impression of the goals in the route planning and tree grabbing phase. Here the hierarchy shows the high number of subgoals that is necessary to describe the operators' actions and considerations while planning the route and aiming for the tree. To plan a route, the analysis of the silvicultural conditions and terrain constrains is essential to successfully drive the machine. HTA visualizes the requirements of goal achievement, including the plans that are describing choices, routines, and sequences of the operators' actions. The parallelization of goal achievement can be used as a marker for expertise in a given task [20]. The completion of the entire HTA can be found in Appendix A.


1.1 Plan route
Plan 1.1:
1.1.1 / 1.1.2 / 1.1.3 / 1.1.4 /
1.1.5 / 1.1.6 / 1.1.7 /1.1.8
1.1.1 Assess soil bearing capacity
1.1.2 Assess stand/ vegetation type
1.1.3 Assess obstacles
1.1.4 Evaluate workplan
1.1.5 Identify suitable felling gaps and machine trail
1.1.6 Consider weather conditions
1.1.7 Identify target trees
1.1.8 Consider equipment based traction
Plan 1.1.1:
1.1.5 > 1.1.1 /
1.1.2 / 1.1.3 / 1.1.4
Plan 1.1.2:
1.1.2.1 / 1.1.2.2 / 1.1.2.3
Plan 1.1.3:
1.1.3.1 / 1.1.3.2 /
1.1.3.3
Plan 1.1.4:
1.1.4.1 > 1.1.4.2
Plan 1.1.8:
1.1.8.1 / 1.1.8.2 / 1.1.8.2
1.1.1.2 Assess rocks
1.1.1.4 Assess plant types
1.1.2.2 Assess tree species
1.1.3.2 Assess rocks
1.1.4.1 Get logging instructions
1.1.4.2 Check (water) map
1.1.8.2 Consider wheel friction
1.1.1.1 Assess moisture
1.1.1.3 Assess roots
1.1.1.5 Check water map
1.1.2.1 Check for suitable gaps
1.1.2.3 Judge age of vegetation
1.1.3.1 Assess stumps
1.1.3.3 Assess terrain gradient
1.1.8.1 Consider chain properties
1.1.8.3 Consider rutts

(a)


2.1 Grab tree
Plan 2.1:
2.1.1 > 2.1.2 + 2.1.3 + 2.1.4
+ 2.1.5 + 2.1.6? > 2.1.7
2.1.1 Decide felling direction
2.1.2 Decide height of cut
2.1.3 Open harvester head
2.1.4 Steer out boom
Plan 2.1.4:
2.1.4.1 + 2.1.4.2 + 2.1.4.1
+ 2.1.4.4 + 2.1.4.5
2.1.5 Angle harvester head
Plan 2.1.5:
2.1.5.2 + 2.1.5.3 >
2.1.5.1
2.1.6 Change species in board computer
2.1.7 Close harvester head
Plan 2.1.6:
2.1.6.1 > 2.1.6.2 >
2.1.6.3
2.1.4.2 Estimate tree distance
2.1.4.4 Monitor harvester balance
2.1.5.2 Gauge head path while felling
2.1.6.1 Access system
2.1.4.1 Estimate head and boom range
2.1.4.3 Plan boom path
2.1.4.5 Monitor boom movement
2.1.5.1 Choose grabbing angle
2.1.5.3 Consider processing location/ assortment placement
2.1.6.2 Delete/ change file
2.1.6.3 Store/ confirm file

(b)

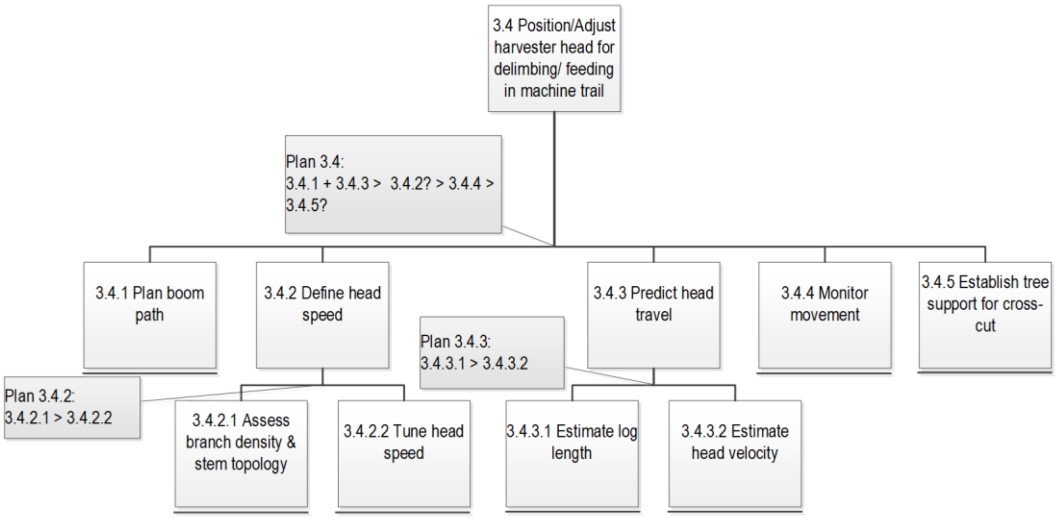


(c)

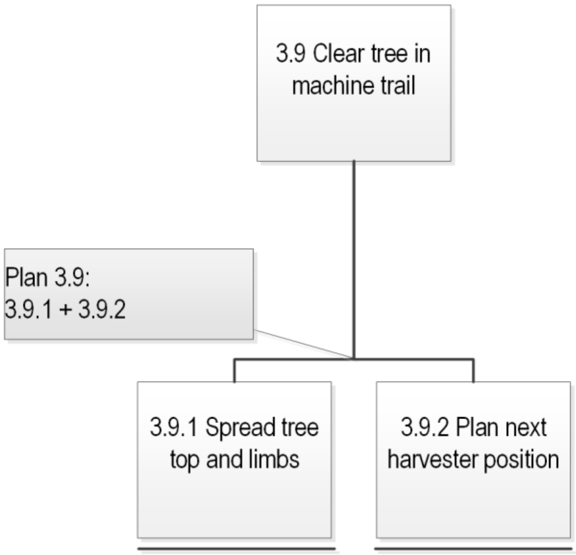
Figure 4. Displayed subgoals: (a) goal 1.1: Plan route of goal 1.1, position harvester, (b) goal 2.1: Grab tree, and (c) goal 2.2: Fell-cut of harvester operators in *clear-felling* operation.

3.3.3 Differences between Work Methods

Figure 5 shows the subgoals that are different in German stand thinning and Scandinavian clear felling. The route planning outlined in Figure 3 appears to be the major difference between the work methods as the initial planning is not carried out by the operator in stand thinning. However, while on the machine operating trail, the operator has still the task of planning the next suitable harvester position and for that needs to assess the silvicultural conditions to navigate to the next felling position. In addition, in German operations, the degree of head travel automation is reduced com-pared to that in Scandinavia, where automatic cuts are allowed. Thus, the delimbing and handling of the treetops diverge from that of clear-felling operations due to, e.g., the use of brush mats.



(a)



(b)

Figure 5. Displayed subgoals: (a) 3.4: Position/adjust harvester head for delimbing/feeding in machine trail, (b) 3.9: Clear trees in machine trail that are different in stand thinning compared to clear felling of the goal 3: Process tree in *stand-thinning* operations.

3.3.4 HTA to Contrast Efficient and Inefficient Work Methods for Training Design

The usefulness of HTA to reveal inefficient and efficient work practices will be demonstrated by the examples below. Moreover, implications for training design were drawn.

3.3.4.1 Efficient and Inefficient Work Practices

The need for a task analysis is commonly associated with a task that may be im-proved in terms of productivity or resilience of execution. The former was considered to contrast inefficient against efficient work practices for demonstration in clear felling. The relevant goal identified (i.e., by SMEs) was aiming for the stem at cut height within a working range of 4–6 m. This work practice includes crane control, which is a major challenge for the machine operator according to [18].

To demonstrate efficient and inefficient work practices with the example of the working range, goal 2.1 was identified: "Grab tree". Goal 2.1 "Grab tree" is attained by seven subgoals (see Figure 4a) of which not all are completed to successfully enclose the tree with the harvester aggregate (see Plan 2.1). Plan 2.1 provides the subgoal sequence and indicates where the operator has autonomy in decision making. Thus, the felling direction and the cut height need to be decided; meanwhile, the boom is steered out towards the stem, and the aggregate is oriented in the desired direction. The change of the species in the on-board computer is only active if needed. That means that if the correct species and assortment is the current default, no action is required. Tree grabbing is completed with the closed aggregate. Efficient behavior would attain all the subgoals in one go in the desired order. The obvious inefficient behaviors that arise are failures described on the third level of the HTA. For instance, the decision for the wrong cut height. This would reduce efficiency either by reduced value recovery because a high stump is left or by the time spent that is needed to correct the harvester aggregate position at the stem (see also goal 2.2: Fell-cut). The severe mistake of missing to open or close the harvester aggregate can potentially damage the machine and thus prevent the tree from being felled. The finer, more nuanced behaviors affecting efficient and inefficient work practices such as maintaining a specific work range are described by the lower levels of the HTA. In the specific case of goal 2.1, on HTA level 4. Goal 2.1.4 "Steer out boom", in which the work range is controlled, requires five subgoals to be attained. The machine operator must monitor and plan the boom movement in parallel and thus control the boom speed while balancing the harvester at the same time. More efficient behavior would enclose a precise notion of the crane reach and of the distance to the felled tree. This would allow for high crane speed while an efficient boom path could be implemented that ends between 4 and 6 m from the harvester crane base. In contrast, inefficient behavior arises if the distance to the tree is misperceived and thus over- or underestimated. This would lead to an inefficient and, due to required corrective movements, jerky path out of bounds of the desired work range.

Another frequently mentioned work practice in [18] is the appropriate positioning of the machine that is goal 1 "Position harvester" on level one of the HTA. This goal is preceding the goals of "Fell tree" and "Process tree" (see Plan 0). In clear felling, the subgoals "Plan route", "Drive harvester to target position", and "Decide tree to be kept" determine the harvester position. Therefore, the route or drive planning as well as the drive to the felling position require thorough assessment of the stand conditions. Inefficient work practices are identified by missing a subgoal such as appropriate route planning or changing the proposed sequence within "Plan 1". A clearer picture is provided on the lower levels of the HTA such as subgoal 1.1 "Plan route" (see Figure 3). Herein, the goal of the operator is the correct assessment of the soil, terrain, vegetation, and weather conditions as well as the identification of obstacles and trees that are to be felled. Inefficient work practices would be, for example, to misjudge the vegetation age or to accept a too-small felling gap (subgoals 1.1.2.1–1.1.2.3), which negatively affects work ranges, boom movements, and the following task goals.

Next to the work practices identified already in [18], efficient (and inefficient) work practices in other work elements can also be identified with the use of HTA. For instance, while felling the tree (goal 2.2 "Fell-cut"). Here, failing to monitor the fell-cut of a rotten tree would affect the subsequent processing such that the assortment needs to be changed, or the cut logs repositioned. Moreover, if the machine operator fails to ensure that the stem is cut completely, then a damaged cut surface/log and a time-consuming re-initiation of the fell-cut would be needed. In contrast, efficient felling would be characterized by thorough monitoring of the cut process to plan for rot and to make sure that the fell-cut is completed in one go.

Such efficiency analysis could be conducted for each respective subgoal to describe positive and negative work practices.

3.3.4.2 Training Concepts and Exercise Design

HTA can help structure training for operators. Training needs arise because of in-efficient work practices and high operator workload. For example, within subgoals that require simultaneous control, such as keyboard and joystick control. To successfully fell a tree (goal 0), all subgoals need to be attained by the machine operator. This argues for whole-task training by including HTA goals altogether. However, work practices may comprise a single goal or clusters of goals within a work task. Therefore, training should be focused on subgoals where inefficient work practices are likely to have a high impact on the operational success and challenge the machine operator. Recent research [18] reveals that important work practices require precise crane control. Here, a clear differentiation is necessary between the lack of knowledge of methods, i.e., the booms' desired path and the lack of motor control, i.e., the ability to follow the path. Both the required knowledge and the required motor skills can be represent-ed within a single subgoal (see Section 1.2). Thus, work-practice training may both focus on efficient motor control of the crane and foster knowledge on efficient movements. HTA can provide training goals that are relevant to the respective work practice. For demonstration purposes, the same example as above was used, and the work practice to keep a work range of 4–6 m (knowing that this does not apply to all work conditions) was chosen. This work practice involves all three first level subgoals: “Position harvester”, “Fell tree”, and “Process tree”. Within the respective subgoals, training can focus on the subgoals that decide a position, location, or involve crane movements. Within subgoal 1 “Position harvester”, this applies to subgoals 1.1 “Plan route” and 1.2 “Drive harvester to target position”. Within subgoal 2 “Fell tree”, the involved subgoal is 2.1 “Grab tree” and within subgoal 3 “Processing tree”, the relevant subgoals are 3.1 “Decide pile position” and 3.4 “Position harvester head for de-limbing”. The focused training session thus must consider multiple first-level goals where the above subgoals are to be accomplished while maintaining the desired work range of 4–6 m. The lower levels of the HTA could be used to further detail the task.

For instance, if the goal is to train aiming for the tree (subgoal 2.1), the work ranges/distances of target trees to the harvester, the grabbing angles, and cut height can be varied systematically. In addition, task difficulty may be mediated by the slope or tree size to address the balance of the harvester. HTA shows that a trainee needs to be exposed to a vast range of situations to master felling a tree. Generally, HTA can be used to structure training and set training goals. Within existing training programs, HTA can be used as a basis for scaling complexity systematically, e.g., by combining different branches of the hierarchy for part-task training on specific hierarchical levels. Nonetheless, the need for training of a specific task for a specific machine operator cannot be deducted from HTA and must be defined by an SME.

The above exemplary application of HTA is only a prototypical insight of the use of HTA for application research. Demonstrating the full potential of HTA would be out of the scope of the current paper. For comprehensive discussions on HTA, see [9,12,14,21–24].

3.4 Discussion

The purpose of the current study was to introduce HTA as a method and basis for research on forest machine operator work practices. It should be shown that HTA can significantly complement current approaches to task analysis such as time studies [25,26] in the field of forestry work science by emphasis on machine operator goals that drive work behavior. HTA outlines a formalized task description and helps de-scribe and analyze complex patterns of operator behavior. Evidently, complexity is mainly indicated in HTA by the amount and combination of subgoals at a time, e.g., the demands of the positioning of the machine, boom control, and a plethora of decisions while processing a tree. Here, efficient work practices are key to productive operations. Extending work from [2,27,28], HTA allows to visualize crucial work elements such as positioning the machine, cutting a tree, and processing a tree in an operator-centered view. To add to the above studies, the current work aimed to further detail and unveil those elements and the subgoals that need to be accomplished for a successful operation. By that, HTA showed large differences in route planning between German stand-thinning and Scandinavian clear-felling operations. The in-advance planning and the selective manner in taking out trees in stand-thinning operations re-duces the number of operator decisions for navigation. Contrastingly, a machine operator needs to assess target trees and suitable felling gaps more thoroughly in stand thinning compared to clear felling to preserve a younger stand. This also implies adapting work practices to different work methods to fulfill the respective task requirements. In this regard, HTA can be used to derive meaningful criteria to assess operator behavior in relation to work practices that could also inform machine-based detection of skills such as in [29]. HTA plans can be used to assess how effectively an operator's goals can be achieved and to what extent an operator adheres to the appropriate implementation of subgoals. It also makes it possible to uncover errors that lead to conflicts in the achievement of goals and thus to inefficient work processes.

In particular, HTA helps identify parallel requirements, for example in tree control. In [27], the complexity of tree control and the role of efficient work practices have already been pointed out. In the analyses carried out above with HTA, the high number of parallel requirements in the safe and efficient control of the boom, e.g., for grabbing the tree, was discussed, and it was shown that especially the lower hierarchical levels are important for the execution of efficient processes. Here, HTA can be used as a basis for designing appropriate operating plans and verifying their execution in working practice. In this context, efficient and inefficient operator actions, as outlined above, can then also be compared.

Regarding the design of training plans, the examples in Section 3.4.2. highlight that a single work practice can span multiple subgoals and thus require training different work elements at a time. Therefore, it is recommended that subgoals relevant to a work practice be trained simultaneously. In addition, HTA shows possibilities for subtask training, in which subgoals that build on each other can be trained systematically to build up complex work practices. The description of complex goal structures is simplified by hierarchical design. This advantage of task description can be of use to scaling difficulty of the tasks for incremental training. Especially the lower levels of HTA can help determine isolate skills such as the positioning of the harvester aggregate at the stem, whereas the higher levels can help determine how to train broader skills such as the processing of the stem.

Taken together, HTA can be used to highlight the challenges faced by a machine operator in more detail. HTA reinforces the notion that goal-directed work practices are crucial to improve a machine operators' performance. The described examples illustrate the versatile use of HTA. The authors believe that HTA could also inform the design and development of support systems that aid positive work practices and learning. For example, in the design of support systems, HTA allows to identify relevant intervention points for guidance and feedback in the work process and thereby helps to optimally embed the necessary assistive functions into the work patterns to support the goals of the machine operator. Depending on the design of assistance systems, it should be possible to adapt support interventions individually to the skills and performance level of the operators in order to compensate for skill-related productivity losses [30]

3.4.1 Limitations

Although HTA is a widely used tool for decades [8,12] and is characterized by the focused description of a complex task as a simplification, the HTA performed provides only limited insights into the underlying cognitive processes that drive behavior. To go further into the core of cognition, for example, to describe the cognitive processes required for a particular task, HTA would need to be extended [31]. Nonetheless, this study was able to provide new insight into the forest machine operator's information processing required to achieve the main goals and subgoals in work tasks. Another limitation of HTA is the rules for establishing "plans" of subgoals when considering serial and parallel task requirements in all situations encountered by a harvester operator. The plan generally describes the task as it might occur in real-world situations. However, the dynamics within the operation are difficult to capture because they are taken at the cost of formalization of the task description. However, goals can change dynamically. Therefore, additional conceptualizations of the HTA are needed to better describe the dynamics at least within subgoals. This is the objective of future research.

3.5 Conclusions and Future Perspectives

HTA offers a wide range of uses for the structured analysis of work tasks, both for practice and for applied research. The goal of this paper was to illustrate its importance for practitioners with respect to work practices. For applied research, HTA can generally serve to generate research hypotheses, e.g., for a study of operator performance, motor learning, workload, and safety analyses in a forestry context. In addition, HTA can be used to investigate perceptual and attentional issues, like to derive operator feedback requirements for specific subtasks. The formal structure of HTA also lends itself as a basis for algorithmic and software-based monitoring as well as for feedback of work performance and work practices, for example, in the context of real-time operator support and training systems. Furthermore, in the various development and evaluation phases of work and support systems, HTA can be of use to establish relevant performance evaluation criteria. In summary, HTA provides a promising foundation for advancing the development of future human–machine interaction in forestry operations' research.

Using HTA as a basis for knowledge representation may also facilitate future operator education. Innovative training settings are needed that bring the classic approaches of theoretical knowledge transfer in the classroom bolstered by simulators in forestry schools to the field and into practice, that is, integrating digital operator support and aptitude training in real-time on the harvesting machines. This would make operator training more affordable and may reduce observed performance differences among harvester operators.

With this HTA, fruitful access to the machine operators' task for digital assistance system design was provided. Well-educated and supported machine operators will benefit the demands of renewable energy produced in a nature-preserving manner.

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Chapter 4
Interim Conclusions and Focus of Experimental Studies

The beneficial work practises and challenges of training the operators in machine control have been described in Chapter 2. The following structured analysis of the forest machine operators' task in Chapter 3 revealed several aspects that can be addressed to improve harvester operator skills, among the most challenging is addressed within this thesis, which is crane control. Therefore, the focus of the experiments in Chapters 5-7 was to analyse and support the control skill of harvester operators. The movements performed with the harvester crane are aiming movements to, e.g. grip the stem of a tree and place the cut logs (cf. Chapter 3). Therefore, aiming movements with a harvester crane were investigated in this thesis to analyse skill acquisition for support systems and training design. Aiming movements are discrete movements, i.e., have a clear beginning and end (Wallace & Newell, 1983). Controlling the aiming movements with the control sticks requires learning the sensory transformation (also called mapping) from the joysticks to the harvester crane. Sensory transformation takes place using two control loops, of which (1) the proximal loop controls the body movement and (2) the distal loop controls the tool (Müsseler & Sutter, 2012). In the case of forest harvesters, the movements of the hands at the joysticks would be controlled by the proximal loop and the movement of the crane via the distal loop. Feedback from the distal control loop was found to be more important for complex transformation learning than feedback from the proximal control loop (Sutter et al., 2011). Applied to harvester control, this means that the feedback of the harvester crane movements is more relevant than the hands' movements. Consistent with the above study, an eye-tracking analysis showed that the harvester operator attends the largest share of the operating time fixating the harvester aggregate and thus the end effector of the controlled movement (Häggström et al., 2015). More evidence was found in neuroscience studies on motor control where hand-held tools were shown to be integrated in the control of body movement (Baugh et al., 2012). These findings suggest that the movement of the harvester crane is integrated in the operators' motor control and may be seen as an extension of the body (i.e., a limb). The completed integration would then be found in the highest skill levels of robotic arm control, which underlines the notion of effortless control and automaticity in highly skilled movements. In conclusion, the research in this thesis assumes that the control of the harvester crane underlies human motor control principles. The most relevant principles and theories of motor control and their implications on learning are outlined in the following.

4.1 Theories of Motor Control and Motor Learning

Early work by Fitts and Posner (1967) describes three stages of acquiring a motor task in terms of the required attentional demand. The first stage is the cognitive stage, the second stage is the associative stage, and the third stage is the autonomous stage. Progressing continuously through the stages reallocates attentional resources from acquisition to other tasks or demands not necessarily related to acquisition. Meanwhile, the time invested in practising increases. Applying the stages to the motor control of joysticks first, the mapping of joystick control is learned in the cognitive phase, second, the learner translates this information into procedural skills in the associative phase and third, transfers through practise to the autonomous phase. The greatest improvements in terms of motor control gain are made in the associative phase according to Fitts and Posner (1967). This model is a simplification as transitions of skill in control performance also require revisiting cognition and knowledge throughout the process of motor control learning, as described by motor control theories in the following section. Before describing the motor control theories relevant to learning bimanual joystick movements, it is worth mentioning that the motor control theories that are the basis of the following research stem from two different on the first glance contradictory perspectives. That is on the one hand the predominant explanation of motor control from a cognitive perspective in which the information processing of a central unit is the essential part of what is relevant to enable prescribed motor movements. Conversely, the notion that the environment and properties of the human body are viewed as a dynamic system that is self-organising, guided by biomechanical properties, external constraints, and relying on feedback from interaction with the environment is described as dynamic systems theory. Both theories influenced the research on motor control and learning throughout decades and both bear worthful thought that serve the investigation of learning a bimanual control skill of a robotic arm. Here, this thesis was not aimed at positioning at one or the other but following the evidence that is produced in both fields that explain motor behaviour. Therefore, both lines of research are considered to explain motor behaviour in the context of bimanual robotic arm control and effective operator support system design. To this end, the general idea of information processing and its inner meaning of the schema theory of motor learning will be outlined as well as the relevant theoretical assumptions of constraints in the framework of dynamic systems theory in the light of coordination, control, and skill development on different time scales.

4.1.1 Schema Theory of Motor learning — Generalised Motor Programs

Schema theory by Richard A. Schimdt aimed to address the problems of Adams closed loop theory of motor learning (Schmidt, 1975). Foremost Adams theory could not explain storage problems due to scarce memory in movement information processing. According to Adams theory, every movement requires a unique motor program to be stored (Adams, 1971). In addition, the generation of novel movements could not be explained, and the closed-loop theory expected negative effects of movement variability on the acquisition of motor movements and thus on learning. Schmidts' schema theory of motor learning transfers the idea of a single motor program for every action to a generalized motor program (GMP) that can be used for a class of similar but still different movements. Schmidt put forward the idea that these GMPs are organised and memorised in schemas (Schmidt, 1975; Schmidt et al., 2019).

4.1.1.1 Generalised Motor Programs — GMP

The GMP is a general structure of muscle commands that comprises all necessary parameters of a movement (Keele, 1968). Fundamental to the concept of the GMP is the notion of invariance, which refers to the observation that features such as relative timing (also named impulse timing hypothesis) of e.g., force peaks are constant across the same movements. By this Schmidt (1975) regards the production of fast or slow movements and accounted for the observation that in skilled movements these actions occur in a specific order at specific points in time that are relative to each other invariant and independent of the execution speed. Thus, the movement features are unchangeable by high or low forces. These invariant features define the movement and are stored within the GMP. The GMPs' generic structure is instantiated by adding parameters that determine the execution of the produced movement. The selection of the GMP and parametrization takes place before movement execution. After the selection, parametrisation, and execution of the GMP, thus movement completion, four information types are stored in short-term memory. First, the starting condition of the movement, e.g. the posture, joint positions, and visual input. Second, the parameters used in the GMP. Third, feedback about the movement result; and fourth, the sensation of the movement, i.e. feeling while execution, visual movement characteristics (Schmidt et al., 2019). This information is used to find meaningful interrelations between the information types used to refine the movement and update the GMP. The interrelations between information types are abstracted and stored as rules that constitute two schema types, the recall and recognition schema. The stored information is only available for a short time after movement. Therefore, updates of the schemas based on transient information can only be made immediately after the movement.

4.1.1.2 Schemas

The *recall schema* contains information that relates the parametrisation of the GMP to the outcome of the movement and is therefore concerned with the programming of the movement. Repetitive movement execution produces new parameters that are incorporated and update the relationship between movement parameters and movement outcome. The actual magnitude of parameters of the movement are shortly stored in working memory and the refined relationship between outcome and parametrisation is transferred to the long-term memory as abstraction (Magill & Anderson, 2014).

The *recognition schema* relates the environmental movement outcome to the initial conditions of the movement and the sensation of the movement (more generically called: sensory consequences). This means that the expected outcome based on the initial conditions of the movement is associated with the expected proprioception and sensation that comes along with the movement produced. After movement execution, the expected sensory consequences (based on the initial condition) are compared to the actual sensory consequences. The relation between initial conditions and the expected sensory outcome is stored within the recognition schema and refined with repetitive movement execution. The evaluation is used to answer the question of how well the GMP parameters worked for the given movement (Schmidt, 2003).

Both schemas can therefore explain motor skill acquisition by updating the relationships of information sources within the schemas. The update is based on new movement parameters that are generated if movements are varied.

4.1.1.3 Learning, Variability of Practice, and Motor Movement

Schema theory uses two types of schemas to explain motor learning, which occurs by forming both schema types with practice. In the recall schema, learning is the update of the relation of movement outcome and GMP to define the correct magnitude of parameters. Likewise, motor control learning in the recognition schema means that a specific expected sensory consequence is learned over time and linked to the GMP parameters and starting conditions. Skilled motor control would then require schemes that hold optimised structures, which include correct parameters for the respective movements. Novel movements can be learnt if there is a somewhat similar schema available as schemas hold only rules and relations. Novel movement can be produced and thus learned by update processes. Variability in movement practices is beneficial for skill acquisition because the rules for schema formation are extended (Wulf & Schmidt, 1997). The schema theory of motor learning applies solely to rapid, discrete movements that have a clear beginning and end. Due to the motor program that is selected prior to the movement as core concept of schema theory, the theory is referred to as prescribing or preprogramming movement (Johnson & Proctor, 2017). Along with this notion, feedback cannot be used during the movement execution due to time constraints. According to the schema theory, slow movements cannot be explained. During slow movements, the error-based corrections are used to guide the movement and thus, according to schema theory, resources are not available for post movement evaluation (Magill & Anderson, 2014).

Analogues to human movements, movements with a human-operated robotic arm are likely to be a mixture of preprogrammed fast movements for movement initiation and slower movements in the landing phase, comparably to human aiming movements (Elliott et al., 2010; Meyer et al., 1988). The resulting end effector movement of a robotic arm can thus be a result of feed forward and feedback control in e.g., discrete aiming movements such as grasping with the robotic arm and therefore partly explained in the realm of schema theory. Feed forward control refers to defining a movement in advance (or action sequence) that is executed and cannot be altered until completion. In contrast feedback control allows the movement to be adjusted to new sensory input throughout execution. The shift from feedback control, which demands high attentional resources, to feed forward control with a higher share of preprogramed skills throughout learning (see above Fitts & Posner, 1967 and Logan, 2018) affects how much and which feedback is used to perform and control robotic arm movements (Magill & Anderson, 2014). More recent research in human aiming movements suggests that feedback is also used in rapid movements and changes throughout goal-directed reaching (Elliott et al., 2017) as with higher skill levels (Johnson & Proctor, 2017).

In a nutshell schema theory is finding the right parameters for movement production using the two schema types. Discussions about the details of the schema theory are still ongoing, however, the major contribution in motor skill acquisition of the theory is understanding the effects of knowledge of results (see also Section 4.2) and movement variability on skill acquisition.

Theoretical shortcomings of schema theory in explaining coordination and adaption to sensory input (e.g., feedback from complex movement tasks), during motor movements in prescribed movements can be overcome by dynamic systems theory and its assumption of constraints. Dynamic systems theory emphasises the dependencies and constraints of the motor movement by the task and the context of the movement. In addition, motor control is seen as resulting from context conditions. In contrast to schema theory, dynamic systems theory assumes that the capacities of the central nervous system are insufficient to actively control the multitude of degrees of freedom that human movement encompasses, and therefore mechanisms of self-organization play an important role in the learning and execution of movement. Another criticism of schema theory was the assumption that short and long movements could be achieved simply by scaling the time axis. However, faster movements also change the dynamics, which would require different motor programs e.g., the difference between walking and running, making the assumption of simple time scaling untenable.

4.1.2 Dynamic Systems Theory—Self-organisation, Coordination, and Constraints

The coordination of movement and the use of feedback from the environment is the focus of dynamic systems theory. Grounded in the research (from the 1926s to 1966s) of Nikolai Bernstein aimed at explaining "physiology of activity", he explored the question of how humans organize movement (Bernstein, Nikolai A., 1967). The focus of Bernsteins' studies was the self-organisation of movements that enable humans and animals to move and act in a controlled manner and develop skilled motor movement. His research tried to explain movement by neurological activity and biomechanics. The basic assumption of Bernstein was that the organisation of movements cannot only rely on efferent motor commands such as in schema theory but instead need afferent sensory input to organise. This means that humans require feedback to coordinate motor movement. In Bernstein words "feedback is necessary to resolve the problems of context conditioned variability and the problem of degrees of freedom" (Bernstein, Nikolai A., 1967). Context conditioned variability occurs because of different behavioural demands of the movement context and comes from anatomical, biomechanical, and physiological sources (Turvey, Michael T. et al., 1982). With different behavioural demands of the movement context Bernstein referred to the vast amount of highly non-linear relationships that need to be accounted for in movement. For example, a contraction of a muscle depending on the joint angle can lead to an inverted movement direction. Similarly, exerted forces can, in combination with other muscles, make the difference between isotonic or isometric contractions. Next to muscles, this non-linearity in movement is also caused by physiological properties where states of cells, noise in signal transmission, and lower level reflex control circles cause variability and thus introduce changing movement conditions (Magill & Anderson, 2014).

4.1.2.1 Degree of Freedom Problem

The above-described problems of context conditioned variability in movement identified by Bernstein complement the well-known degree of freedom problem that Bernstein first described. The degree of freedom problem refers to the question of how the individual can control the many degrees of freedom in movement production, despite the large number of variation possibilities of movement, where his research focussed mostly on biomechanics. The human arm, for example, has seven degrees of freedom by its joints alone (Turvey, Michael T. et al., 1982). However, humans do not control their joints directly but by scaling the muscle activity, which raises the complexity of the motor control problem. The entire body can assume an unimaginable number of states and produces a vast range of movements (cf. gymnastics, walking, throwing). Bernstein identified the "degrees of freedom" problem as the core challenge to targeted motor movement and motor learning. The idea refers to the problem that the brain—if at all involved in movement production such as in schema theory—needs to regulate all muscle activity to get hold of the degrees of freedom to produce coordinated movement that allows for skilled actions. According to (Bernstein, Nikolai A., 1967), the coordination of the degrees of freedom is necessary to create movement that is homogenous and integrates the respective involved entities (e.g., joints, muscles (motor units), limbs) to form a "structural unity" later referred to as coordinative structure or subsystem. To state with Bernstein (1967): "The co-ordination of a movement is the process of mastering redundant degrees of freedom of the moving organ, in other words its conversion to a controllable system". By that, Bernstein aimed to challenge the concepts of open loop control and points to the fact that it is hard to imagine that the number of variables for motor movement can be controlled by the brain directly in a feed forward manner. From the degree of freedom problem Bernstein derived that motor learning is the coordination of activity. The coordination pattern is a higher-level structure that confines the degrees of freedom and has inherent information that determines the general movement. The coordinative pattern is guided by a cost minimal optimisation to provide efficient coordination of the entities (structures). Bernstein (1967) postulates a three-stage process leading to coordination: (1) freezing degrees of freedom leading to coordination (2) gradually releasing degrees of freedom with learning, and (3) utilising and exploiting the control. The question of how the coordination evolves and what influences the outcome of the coordinative process was addressed by Kugler (1980). Coordination is achieved by synergies of the coordinative structures (see above e.g., motor units, limbs, muscles) that form an autonomous subsystem that controls and executes movements. The regulation of the subsystem and the synergies between structures can be described by non-linear equations. The process of coordination leads to a stable coordinative pattern of the subsystem(s), which is reflected in skilled movement (Magill & Anderson, 2017).

4.1.2.2 Stability and Variability

The coordinative pattern and thus the behavioural system has the property of either being stable or unstable. Stable states refer to coordination where intrinsic dynamics that are determined by individual properties (e.g., body structure and neuronal properties) are mapping the behavioural information of the context, i.e., the task demands. If the behavioural demands do not map the intrinsic dynamics, the system is unstable. The organization of the movement is thus largely dependent on the internal properties and the current external conditions, which together determine the stability of the coordination. Generally, the system is gearing towards an efficient, stable state that allows to fulfil the respective movement goal. Familiar, constant, and easy conditions, in which movement is produced, are characteristics that lead to stable states. For example, riding a bicycle on a familiar street with a flat surface has a specific learned pattern of coordination that can be performed appropriately. In contrast, riding the bicycle in unknown, challenging rocky terrain requires a constant adaptation of the coordination pattern. By adapting the initial coordination pattern over time unstable states can become stable states (learning) and allow the rider to master rocky terrain. Once a coordination pattern creates a stable regulatory subsystem, changes of external information or changes in the internal properties of that subsystem can affect the stability. For example, hands-free riding would change the internal properties of the subsystem, and thus the system becomes unstable. On the other hand, riding over a sandy beach would change external/behavioural demands and destabilise the system. In both examples, the coordinative subsystem needs to adapt to the new demands and develop and maintain an appropriate coordination pattern. In general stable system states are preferred and thus the system is attracted to resume to such states, which are therefore called attractor states (Johnson & Proctor, 2017; Magill & Anderson, 2017).

High movement variability is associated with less stable coordination and thus is often observed at the boundaries of the prevailing coordination. Unstable system dynamics can cause transitions between different coordination patterns. Here, instability is not necessarily negative for skilled movement as it may simply be required for rapid transitions between skilled and coherent movement coordination for task performance (for example a change in execution speed of the movement) or finding the most stable (attractor) state (Stergiou, 2020). The strength of dynamics systems theory is the notion that variability in movement is not detrimental to performance and thus allows the co-existence of similarly efficient coordination patterns that can meet the task demands and external constraints. Furthermore, these different coordination patterns allow flexible adaptation to external demands and cope in real-time with real-world conditions. In line with the idea of a flexible adaptation of subsystems, coordination occurs on multiple interacting time scales, which are the basis for the flexibility and complexity of adaptation. The challenge in skilled movement is to balance both stability and variability. Variability should remain coordinable, whereas stability must not cause inflexibility due to rigidity in coordination.

To specify the stability of a coordinative pattern in terms of observable parameters in (experimentally observed, derived) equations, collective variables need to be identified. Collective variables can describe the overall behaviour of the system, and thus, these variables are of interest in characterising a movement pattern. One such overarching variable identified was relative phase. With the help of collective variables different movement patterns can be described and thus distinguished. (Magill & Anderson, 2017).

4.1.2.3 Movement Context and Constraints

The above-mentioned aspect of self-organization of the system coined by Bernstein and the notion of system stability and variability is crucial to understand the relevance of the movement context in which a coordination pattern emerges. In the systems dynamics view, the coordinative pattern is passively determined by the conditions and external characteristics of the situation in which the resulting pattern occurs. These conditions limit the possible stable states and thus emerging synergies. Newell (1986) describes situational characteristics named constraints that act as the boundaries of coordination leading towards a stable pattern of optimality. Constraints on the emerging self-organisation occur from three different categories, (1) the organismic, (2) the task, (3) and the environment. Organismic constrains come from structural and functional properties on different levels of the organism. For example, weight and size are common organismic constraints on the structural level, whereas frequently mentioned functional constraints are e.g., the neural connections (see also context conditioned variability of Bernstein). The environmental constraints are external to the individual/the system and can for instance be temperature, air pressure, light, or gravity. For example, if there is a change in gravity, the coordinative pattern will need to adapt as dynamics are different and thus are the synergies between coordinative structures (organisation of movement) (Magill & Anderson, 2017). The third constraint is the task that is completed with the movement, and the task goals act as movement constraints. Newell (1986) subdivides three categories of constraints of the task. First, the task goal, secondly, rules that guide or constrain "response dynamics", and thirdly, machines that constrain the "response dynamics". Newell (1986) highlights that the coordinative pattern can be prescribed for instance in gymnastics (not referring to (Schmidt, 1975) prescription) where the constraints are rather strict on response dynamics or act as boundaries of the response dynamics such as in swimming techniques.

4.1.2.4 Perception-Action Coupling

The relevance of the context is also important to explain how perceptions will lead to specific actions. The emerging coordinative pattern and the underlying parameters occur only while interacting in a specific context/environment. The perception that occurs in this context extracts relevant invariant features often referred to as psychophysical properties such as the time to contact and is linked to the emerging coordinative pattern and structure (Magill & Anderson, 2017). This is referred to as perception-action coupling. Also, objects can be coupled to a coordinative pattern that is called affordances leading to target behaviour (see Gibson, 2014).

4.1.3 Implications from Motor Control Theories on Robotic Arm Operating Skill Acquisition

The dynamics systems theory underlines that motor learning takes place in terms of adaptation to external constraints (Newell, Karl M., 1991). Here, convergence of the system to a stable state (attractor state) in oscillatory behaviour (Kelso, 1984) and coordination in control behaviour is achieved and referred to as learning. This occurs from a global perspective in terms of freezing degree of freedom and stepwise releasing them as described above but as well as the tuning of the motor system to the constraints (Bernstein, Nikolai A., 1967). The emergence of coordination through self-organisation has the benefit of explaining fast adaptation to different contexts and allows flexibly tuning motor movements by changing the coordinative structure and respective parameters. Therefore, changes of tools used in motor movement or adaptations to changes in the coordinative structure, for example, when one's foot gets impaired by stepping on a sharp object, are possible (Magill & Anderson, 2017). The strength of this idea is that context plays a major role in determining behaviour, and each behaviour is directly related to the context in which it occurs, relying heavily on feedback from multiple sensory sources.

However, dynamic systems theory also has relevant limitations. The emergence of skilled behaviour and how the perception-action coupling leads to higher skill levels is hardly explained. Learning is seen as a passive process of adaptation over time, but how practice of complex movements makes skilled behaviour remains to be stated. Truly there is remarkable explanatory power of oscillatory movements and how they emerge, however, robotic arm control is highly non-linear and not a cyclic or oscillatory movement. Finally, passive adaptation to the context in which learning occurs would be described in dynamics systems theory as learning to control a robotic arm. This would also provide a hard time explaining the transfer from simulators to the real world that is possible, as shown by Ranta (2009). Learning can be seen as setting parameters for the equations that create synergies of the coordinative structure leading to an optimal coordinative pattern. However, there is no real explanation of how these parameters are set or extracted, as they emerge through self-organisation. Although researchers see this as a possible link between the system dynamics perspective and the schema theory of motor learning, where the parameters of the GMP are to be defined, the exact mechanics of learning remain to be determined (Walter et al., 1998).

Schema theory has a clear focus on the active involvement of the CNS in the development of skill. Although the scaling of the motion parameters is difficult to explain, because scaling would also change the dynamic features, empirical evidence shows that the development of skill follows a traceable explanation that produced most of the evidence on this topic within the last five decades (Magill & Anderson, 2017). Furthermore, the active role of how feedback can benefit performance in terms of either knowledge of results or knowledge of performance was based on research of schema theory (Schmidt, 2003; Wulf & Schmidt, 1997). The applicability of both theories to control-learning of a robotic arm has its limitations. Due to the transformation and closed-loop control required during operation, the robot arm control is not entirely feed-forward and thus allowing feedback throughout the process is more in line with explanations referring to the importance of context. Conversely, as robot arm movements are made up of multiple sub-movements using the joysticks, it is not clear how much of the movement requires feedback and which sub-movements are feed-forward. In addition, highly skilled movements and thus fast movements are assumed to be feed-forward, which would be consistent with the strong evidence found for schema theory's assumptions about these movements. Therefore, schema theory has the potential to explain robotic arm control in terms of finding the parameters for the GMP and storing the corresponding schema. In addition, there is a large body of research on the effects of feedback on skill acquisition (Johnson & Proctor, 2017; Oppici et al., 2021; Schmidt et al., 1989; Sharma et al., 2016; Wallace & Hagler, 1979), therefore, this thesis will build predominantly on the assumptions that can be drawn from schema theory on skill acquisition and feedback in robotic arm control.

4.2 The Role of Feedback and Time Scales in Motor Skill Acquisition

In spite of the theoretical considerations of motor control and learning, a large body of research has focussed on the use of feedback to support motor skill acquisition. Feedback can be divided into inherent feedback, which is information from the body and its perceptions that is accessible to the learner, and augmented feedback, which is information from sources external to the learner that is difficult or impossible to access. (Schmidt et al., 2019). Inherent feedback can always be used by the learner to enhance skill acquisition, for example, proprioception. Augmented feedback is provided from outside observation either in the form of knowledge of results (KR) or knowledge of performance (KP). KR is feedback about the movement outcome and thus the movement must be completed to have this information available. KP is feedback that informs the learner about the movement execution and therefore the characteristics that constitute the movement (e.g., dynamics or relative limb positions). Both have been successful in supporting motor skill acquisition. Research showed that precise KP is generally more successful to support learning of complex movements than KR (Newell, Karl M., 1991; Sharma et al., 2016; Sigrist et al., 2013). KR has been successful in supporting rapid movements such as throwing (Schmidt et al., 2019). Much effort was put into researching how detailed KR and KP should be given and when KP and KR should be given. Findings show that detailed KR and KP lead to higher performance (Schmidt et al., 1989). In addition, infrequent feedback of KR leads to faster skill acquisition and, in contrast, frequent KP leads to faster skill acquisition (Wulf et al., 1998, for details see Schmidt et al., 2019). Movement feedback can be provided at different times. Feedback given coexisting with the movement is called concurrent feedback and feedback given after the movement is called terminal feedback. Inherently concurrent feedback can only be given in the form of KP that is preferred in complex tasks and movements that resemble natural and more ecologically valid situations (Newell, Karl M., 1991; Sigrist et al., 2013). Concurrent feedback can either be provided auditory or visual. In rowing and cycling, auditory and combined (multimodal) auditory/visual feedback improved oar position and sled dynamics, as well as in cycling paddle and crank forces of rider movements (Sigrist et al., 2011, 2013, 2016; Vidal et al., 2020). Notably, which information is fed back depends on the task and varies in terms of effectiveness (Sigrist et al., 2011).

Attributing performance to a permanent change, including determining feedback effectiveness, and not to transient effects, is crucial in analysing motor learning. Observed behaviour may be lost over short rather than long periods of time. Transfer or retention is necessary to distinguish between these factors and observations of control performance over longer time periods. Permanent changes are associated with structural changes either in forming useful schemas and motor programs or reinforcing coordination in self-organization. Transient changes may be regarded to state variables such as fatigue or motivation. Nevertheless, less attention has been paid to skill losses due to transient changes that can occur between training sessions and are associated with the tuning of the motor system to the current task as well as forgetting. Both would lead to performance decrements at the start of each training session and may affect the overall motor skill acquisition. Transient and permanent changes indicate that motor skill learning is not a single process that occurs on one time scale, instead, two or more processes are involved that run in parallel while acquiring a skill.

4.3 Measuring the Acquisition of Motor Skills to Control a Robotic Arm

4.3.1 Skill and Performance Measures

The investigation and measuring of motor skills depend on the motor skill acquired. In sports, this is commonly the type of sport (e.g., Tennis) and the trained movement (e.g., forehand topspin). In machine operation, the acquired skill and thus the measurement depends on the machine (e.g., harvester) and the completed control task (e.g., fell tree). However, there has been a common agreement that skill takes time to develop, and practice is necessary to progress. The evaluation of the acquisition process requires thus the observation of skills in the given task over multiple practice sessions and further the use of retention or transfer tests (see above) to show the actual skill gain (Schmidt et al., 2019).

4.3.1.1 Skill Learning Analysis

The improvement of performance and skill indicators reflects skill development. This development of these indicators can be described with a learning curve. The most prominent learning curve model is the power law of learning/practice, which was widely used to describe cognitive and motor learning (A. Newell & Rosenbloom, P. S., 1980) and "applies to virtually all speed-accuracy trade-offs" (Logan, 1992). Despite the ubiquitous ability of the power law to fit learning data of various types, it has been questioned if the resulting learning curve is an artefact of averaging data over trials and more importantly/worse over participants (Heathcote et al., 2000). Averaging experimental data is a common procedure in factorial designs but reduces the variance and converges to what is known as the learning curve (Brown & Heathcote, 2003). Therefore, the power law is imprecise in describing the actual process of learning and maps only higher-level learning characteristics. For this reason, it is argued that exponential functions, rather than the power law, should be used to fit the data, especially when learning to control robotic arms (Bukchin et al., 2002). Another concern with the use of the power law and the modeling of learning is that learning is not a single process, as the power law of the learning function suggests. Learning is associated with multiple processes due to forgetting and adaptation (K. M. Newell & Vaillancourt, 2001) (see section 4.2). To account for these processes, a function describing motor learning requires learning parameters that reflect these processes, such as the two-timescales power law of learning (K. M. Newell et al., 2009). The two-timescales power law of learning can describe the long-lasting change of performance on a slow time scale, which is commonly known as learning and the more rapid and transient processes such as forgetting between sessions on a fast time scale. The two timescales are seen as major components in the acquisition of motor skills. Therefore, the learning analysis in this thesis was conducted by using the two-timescales power law of learning (cf. Chapter 5). The two-timescale power law of learning is seen as sufficient but not comprehensive to model learning by the author of this thesis.

4.3.1.2 Experimental Paradigm

The task of a harvester operator is outlined in Chapter 3, where the harvester operating task is predominantly defined by using the harvester crane (robotic arm). As described above, the movements of the harvester crane are aiming movements such as grasping a tree or relocating the logs. For this reason, the investigation of motor skill acquisition and operator support systems in this thesis was based on the analysis of aiming movements with a robotic arm within a simulated environment. A common way to research aiming movements in humans is to use the properties of the speed-accuracy trade-off, which refers to the observation that with increasing movement speed, the accuracy of the aiming movement is reduced (MacKenzie, 1992; MacKenzie & Isokoski, 2008; Plamondon & Alimi, 1997). This property of aiming movements can for example be used to determine the strategies used to optimize movement, such as emphasizing speed over accuracy in task completion. In the analysis of aiming movements Fitts' law is often applied to manipulate the movement difficulty and model expected movement times. Fitts' law describes the log linear relationship between movement time and the distance to and the width of a movement target. Fitts (1954) defined the difficulty of a movement by the relation of amplitude (A) and target width (W). Amplitude refers to the distance to the target and width refers to the actual width of the movement target. The combination of amplitude and width indexes the difficulty (ID) of a movement that Fitts derived as logarithmic ratio of two times the amplitude and width (cf. equation below). The manipulation of the amplitude and width of the targets allows realising different movement difficulties.

Index of Difficulty: $$ID = \log_2\left(\frac{2A}{W}\right)$$

Over the years, the use of Fitts' law was extended from human motor information processing to performance research on input devices in human computer action such as the computer mouse or joysticks (Cannon & Leifer, 1990; Cha & Myung, 2013; MacKenzie, 1992) and also robotic arms (Draper et al., 1990). These studies showed the effectiveness of Fitts' law in determining general performance metrics with a given system. All too often, these studies have been criticized for neglecting the context and intent in which Fitts' law was derived, namely to infer the information capacity of the human motor system (Gori et al., 2018). In robotic arm control, it was found that the applicability of Fitts' law to aiming movements did not 1 to 1 transfer to robotic arm control. Assumingly, because Fitts' law was intended to infer human motor capacity and not performance of robotic arm movements (see Dreger et al., 2022). Nonetheless, Fitts' seminal work provided a well-established method for systematically manipulating the difficulty of an aiming movement in the experimental paradigm used in this thesis, and to assess the performance and feedback effectiveness of motor skill acquisition in robotic arm control. To explain the experimental paradigm and the adaptation based on Fitts' task, first, Fitts' task is explained and then the derived adaptation.

The Fitts' task description is drawn from the ISO Standard DIN EN ISO 9241-9 (ISO, 2002) on Fitts' law as well as the guidelines from Soukeroff and MacKenzie (2004). Fitts multidirectional tapping task was designed such that participants make alternating aiming movements between circular targets that are arranged in a circle themselves. Participants are instructed to tap as precise and fast as possible in the centre of the circular targets. The participants begin at a starting position and then follow the targets clockwise. The width of the targets, i.e. the diameter and the distance between the target (amplitude) are manipulated (see Figure 6). To assess the information capacity according to Fitts' law, many different width and amplitudes should be realised (as conditions) and many times presented "perhaps, 15-25" times (Soukoreff & MacKenzie, 2004). The calculation of information capacity uses the average of movement time and accuracy (within the ID) over the number of presentations. Accuracy is measured by constant and variable error (CE, VE). CE refers to the distance of the movement end-point to the circle (target) centre and VE refers to the variability of the movement end-point around the target, which is operationalized as the standard deviation of CE.

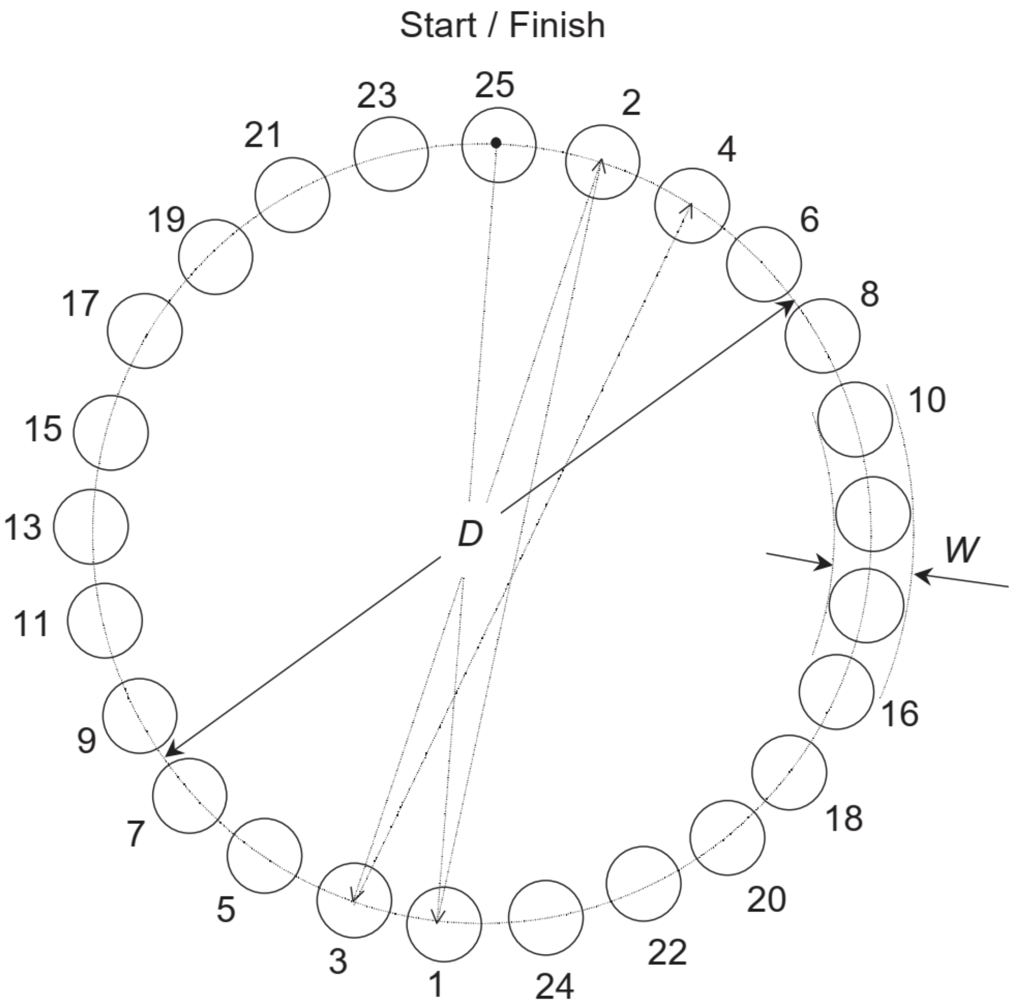

Figure 6. Multidirectional tapping task as described in the ISO standard DIN EN ISO 9241-9 (2002) (figure from Soukeroff and MacKenzie, (2004)). Participants must alternately tap the circular targets in the centre, following the circle clockwise.

In this thesis, the above described Fitts' task was transferred to robotic arm movements that are frequent in the work methods two sided and forward felling of forest harvesters (Ovaskainen et al., 2011). In the application of the work method two-sided felling the tree is felled in front or on the left/right side of the machine and moved across the machine trail to the opposite side where the processing of logs takes place. Forward felling refers to felling the tree in front of the machine and processing the logs close to the machine. Therefore, the number of circle pairs (targets) and presentations was reduced to eight circles and 5-10 presentations (depending on the experiment). In addition, compared to Fitts' task, only the distance and orientation of the circles were varied according to the working methods. The diameter of the circles was kept constant to keep the visual conditions similar across the number of movements, so that difficulty was manipulated solely by the distance between the targets. The start of the movement changed between left and right as the targets were arranged according to the working methods and not in a circle. Participants were instructed to alternately tap the targets with the tip of the robotic arm, also referred to as end-effector, beginning from a starting position. The movement targets are displayed in Figure 7, 24 (Chapters 5, 7).

The performance measures movement time, CE, and VE were adopted from Fitts' task and used to infer motor skill acquisition in terms of performance of the robotic arm movements. Furthermore, skill and performance measures from the controlled joysticks and the robotic arms movement were used. Movement time and accuracy itself provide limited insights to the movement characteristics that are important to provide feedback in terms of KP. Therefore, additional time series measures were recorded to get insides to the bimanual control movements with the joysticks as well as dynamic and spatial information on the trajectory of the end effector in 3D space. Human control input was measured by the joystick deflection of each of the four joystick axes. Position (XYZ) and its time derivatives velocity and acceleration as well as smoothness (in terms of the spectral arc length, SPARC, Balasubramanian et al., 2015, see also Chapter 6) of the end-effector trajectory of the robotic arm were measured to infer the demonstrated control skill.

4.3.2 Simulator Design

Bringing a simulator to life is a tedious development process. Simulators have the purpose of simulating the real world and are especially useful when real world experiments are costly or hazardous. Simulators vary in how good they are in mapping the real world. This is referred to as simulator fidelity (Pool, D.M., 2012). Three main aspects of fidelity are simulated. The physical, the perceptual, and the behavioural fidelity (Feddersen, W. E., 1962; Pool, D.M., 2012; Sinacori, 1978). Physical fidelity refers to how objectively well a simulator maps the real world, for example how well the control joysticks resemble the joysticks in a forestry harvester and how well the robotic arm maps in terms of dimensions and kinematic design the physical properties in the real world. Generally, high physical fidelity is assumed to ensure high behavioural fidelity (Pool, D.M., 2012). Perceptual fidelity refers to the similarity between the perception of the operator with respect to the fidelity of the real harvester. Behavioural fidelity refers to the similarity between the behaviour observed in the simulator and in real-world control. The simulator developed for the research of this thesis was designed for a realistic implementation of the robotic arm and was aimed at ensuring high behavioural validity. Therefore, the dimensions and control of the robotic arm were adapted to a CH9 knuckle boom that is installed on forestry harvesters

(WARATAH Harvester and Forwarder Cranes, 2020). The simulator was a customized low fidelity fixed base simulator that allowed recording of data from robotic arm movements in the virtual environment. The simulation recorded simulation-based parameters of the robotic arm, such as joint and end effector positions and joystick movements, separately for each joystick axis. The virtual environment was adapted to optimally present targets for the Fitts' inspired tapping task. The simulator was continuously developed throughout this thesis to meet the requirements of answering the research questions. Starting from a simulation environment with a robotic arm with joint velocity control (Learning study, Chapter 5) to end-effector control (Comparative study, Chapter 6) to a complex sensory feedback system (Concurrent Feedback study, Chapter 7).

4.3.2.1 Simulator Hardware

Next to a powerful computer, a Chicago truck seat and the Thrustmaster joystick were mounted to a specifically designed frame that was similar across the experimental studies (see Figure 13, Chapter 6). The frame made it possible to adapt the seating position of the participants to their anthropometrics. The Screens of the simulator changed from a Samsung TV Screen with 40" inch in the Learning study to two 45" Xia Mii TV Screens that were used for the Concurrent Feedback study in Chapter 7. In addition, a semi-permeable mirror was used to display visual movement feedback to the participants (see Chapter 7). Sound was provided by two computer speakers in front of the participant.

4.3.2.2 Simulator Software

The initial version of the simulator was designed within a bachelor thesis that was supervised at the Leibniz Research Centre for Working Environment and Human Factors (Kuhlmann, 2020). This initial version served as the basis for continuous simulator development. The simulator was built on a Linux system running ubuntu beaver creek 18.04 in the Learning study and was updated for the following studies (Chapter 6, 7) to ubuntu focal fossa 20.04. As there were varying demands throughout the experiments, the simulator software was developed throughout this thesis. The visualisation of the robotic arm was rendered in GAZEBO and based on the "Open Manipulator Framework" (OMF). The OMF is realizing a virtual robotic arm with 4-degrees-of-freedom as shown in Figure 12,13,22. Sensor data was sent via the Robot Operating System (ROS). The experimental control and the simulator control was implemented in C++. The ROS nodes that allowed joystick control of the system were implemented specifically for the experiments (Kuhlmann, 2020). The functionality to use inverse kinematics was implemented for the Comparative study. The Jacobian inverse technique computed the joint angles of the robotic system as in iterative process based on the goal position in 3D cartesian space. This made it possible to test the effects of inverse kinematics (end-effector control) as operator support system. To generate auditory and visual feedback, the software was extended with python nodes that allow the visualisation of geometric objects in this case the presented spheres in RViz. RViz visualizes current system states and receives data from ROS. Auditory feedback was implemented using PureData, a visual programming environment to process and generate sound. PureData was linked via TCP to a socket realised in a Python node that sends data about the end effector position to the software. PureData can manipulate all sound properties including pitch and volume used for the Concurrent Feedback study in Chapter 7. Both visual and auditory feedback is generated in soft-real time and thus could serve as concurrent feedback.

4.4 Research Objectives and Questions

As already mentioned above, the task of robotic arm control is a motor control task that is assumed to follow human motor skill acquisition. Research on aiming movements and motor control implies that the learner must find a way to control movement by processing information about the body and the environmental conditions in which the movement takes place. The information processing perspective suggests that finding the required parameter values for the executed generalised motor program is to be solved for skilled action. For this, multiple sources of information are used as feedback. Internal and external information help to improve movement and further guide skill acquisition. This thesis aimed to gain knowledge relevant for training design by using state-of-the-art statistical methods and formal modeling to assess skill acquisition and performance limitations of robotic arm operators. The analyses considered multiple time scales and account for involved processes such as skill loss and adaption. Altogether, this served the identification of challenges a learner is facing in the control skill acquisition of robotic arms. To address not only the learning of the robotic arm per se, but also technical support systems to improve the operating skills, the role of motor and sensory support was also investigated. Conclusions drawn from the analysis were fed into the design of sensory support systems that used concurrent feedback to enhance control performance. Therefore, the aim of this thesis was also to provide insight into the usefulness and design of sensory feedback to improve the control performance of the robotic arm.

The more general and specific research questions that were guiding the research and been answered throughout the studies conducted within this thesis were the following:

General Research Questions

Research question 1: How can training methods for robotic arm operators be improved by a systematic analysis of performance limiting factors in the bimanual control of robotic cranes?

Research question 2: How can machine operators be effectively supported with different sensorimotor support systems to ensure high-level performance?

Specific Research Questions

Research question 1.1: What are the limiting joints or dimensions in the acquisition of bimanual robotic arm control?

Research question 1.2: How can the skills of a robotic arm operator be assessed and quantified to evaluate learning in training?

Research question 2.1: How do algorithmic support systems using inverse kinematics affect the acquisition of control skills and what new control challenges arise?

Research question 2.2: How can sensory feedback in terms of auditory and visual support assist operators in real-time to control a robotic arm to enhance performance?

Chapter 5
Analysis of learning the bimanual control of (tele)operating joint space controlled robotic arms with 4 degrees of freedom using the two-timescales power law of learning

Training costs for operators of robotic arms in forestry and construction are high. A systematic analysis of skill development can help to make training more efficient. This research focuses on motor skill development by investigating the bimanual control of a four-DoF robotic arm. The two-time scale power law of learning was used to identify difficulties in control learning. Ten participants acquired the control of the robotic arm in a simulator over ten sessions within seven weeks. Eight movement targets were presented in each of six blocks per session, comprising 432 robotic arm movements. The results suggest that learning varies for each joystick axis, with control of the elbow joint showing the highest learning gain. The base and shoulder joints showed similar learning gains. The wrist joint showed mixed results in terms of use or disuse. Performance increased with retention, suggesting that a longer period of consolidation aided skill acquisition.

A shortage of skilled operators, costly, and extensive training of heavy machine operators in robotic arm control requires to revisit control skill learning. This study showed that focus of training ought to be shifted to specific joints and training requires to emphasize longer resting periods between training sessions.

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5.1 Introduction

Bimanual control of robotic arms requires independent control of multiple degrees of freedom (DoF), regardless of whether the joints are hydraulically or electrically actuated. Robotic arm control is a challenging task (Hartsch et al., 2022) and training human machine operators to perform efficiently and accurately is time consuming and costly (Dunston et al., 2014). In this study, bimanual control refers to the use of two joysticks controlled by the two hands in the (tele)operation of a robotic arm, where the robotic arm is referred to as a single robotic manipulator with four DoF. The control concept, i.e., where joystick movements are mapped to the joint movements of the four-DoF robotic arms, is similar for machines in many industries, such as excavators, forestry machines, and truck cranes (Jin et al., 2021; Westerberg & Shiriaev, 2013). Therefore, faster and more effective learning processes for machine operators to learn input-output transformation and control have far-reaching positive effects on productivity in many industries.

5.1.1 Current Machine Operator Training

Machine operators, for example in forestry, are usually first trained in simulators to improve performance without the risk of damaging expensive machines (Harstela, 2004; So et al., 2014). The control of the robotic arm is taught by experienced instructors (Hartsch et al., 2022). Analogously, experienced instructors in the construction industry also teach apprentices in their training (Bijleveld & Dorée, 2014). The goal of the training is to quickly bring machine operators to a high level of productivity, whereby forest machine operators typically reach the first productivity plateau after nine months (Purfürst, 2007, 2010). After training, productivity continues to increase with work experience, and experienced operators are expected to be at least twice as productive as inexperienced operators (Björheden, 2001; Malinen et al., 2018). Despite training efforts and work experiences, Ovaskainen et al. (2004), however, found productivity to vary by about 40% between forest machine operators on the same machine in similar conditions, thus, there are large gaps in performance that could potentially be reduced through more consistent training, better methods of assessing the learning experience, and digital support during training or on-the-job.

5.1.2 Performance and Learning in Remote and Tele-Operation of Robotic Arms

Approaches to improve performance of robotic arm control with multiple DoFs have been frequently researched in the field of remote and teleoperation of robotic arms across different application domains such as assembly (Henriksen et al., 2016; Jung et al., 2013) and construction (Morosi et al., 2019; Mower et al., 2019; Suzuki & Harashima, 2008). Remotely controlled operations typically pose a challenge for learning to control the robotic arm (Massimino & Sheridan, 1994), and direct visual control in particular supports the learning process (Bukchin et al., 2002).

A particular challenge for learning studies is the variety of control devices (or control regimes). These range from single joysticks (Chintamani et al., 2011), two joysticks (Jung et al., 2013; Morosi et al., 2019), phantoms (Zareinia et al., 2015), joystick and keyboard, to gamepads (Mower et al., 2019). In addition, the control mappings of master and slave e.g., in position vs. rate control (Sorenson & Akin, 1995; Won Kim et al., 1987), or velocity transformations between joystick input and movement output of the robotic arm (Dubey et al., 2001; Everett & Dubey, 1998).

The different controllers and assignments to robot segments are problematic for comparing learning studies and deriving general findings. Nonetheless, almost all studies report performance gains over practice time. This testifies to the ability of human operators to successfully adapt to different control devices and schemes. The fundamental learning effect has been observed in different settings, from simple Fitts' tapping task (Tonet et al., 2007) to complex virtual (Morosi et al., 2019; Sekizuka et al., 2020; So et al., 2014) and real-world (Jung et al., 2013) environments with high ecological validity. Performance measures such as movement speed, time on task, or accuracy, were predominantly used to assess performance improvement in the above studies. Less consideration was given to the effect of exercise on the sensorimotor skill development of operators. For this purpose, mere performance measurements with respect to productivity are generally not sufficient to assess long- and short-term changes in control behaviour. Longer survey periods are required than are usually used in the productivity-oriented studies.

5.1.3 Learning Analysis of Robotic Arm Control

As mentioned above, mastering the control of a robotic arm control, especially in real-world environments, requires long periods of time with many repetitions. However, studies investigating long-term learning over several weeks or months are rare, and when they do exist, these studies focus on productivity improvement (cf. Manner et al., 2020; Purfürst, 2010) rather than operator skill development. For example, studies of surgeon training have been criticized for using short observation periods that conclude before the emergence of learning plateaus (Papachristofi et al., 2016). Observing skill learning over several days could therefore provide detailed information about the permanent changes in performance and the transient adaptation and forgetting processes on short timescales.

Similar to learning studies in the human sensorimotor domain (Joseph et al., 2013; Newell, 1985; Newell et al., 2009) an exponential learning function may also be useful for analysing skill development in learning to operate a robotic arm.

Learning functions jointly model the motor component of learning to control a robotic arm and the mental operations that underlie this process, namely procedural learning of the control mappings for skill-based behaviour (Arzi & Shtub, 1997). The power law of learning (Heathcote et al., 2000; Wallace & Newell, 1983) and exponential decay functions treat learning as a long-lasting behavioural change, which conflates skill acquisition and forgetting into an averaged performance metric. However, in experiments with a single measurement repetition (Bukchin et al., 2002; Goldstain et al., 2007; Joseph et al., 2013) or short intervals between sessions, the cost of forgetting is not considered. To assesses the effects of short-term adaptation processes in human motor learning Newell et al., (2009) introduced a second time scale into the exponential function. This allowed to model changes during the warm-up period at the beginning of an experimental session and to account for learning between and within sessions. Consequently, the added time scale may be useful to illuminate the challenges in short- and long-term motor learning (Newell et al., 2006, 2009), which presumably also occurs when learning bimanual control of a robotic arm.

5.1.4 Specific Difficulties in Robotic Arm Control

Previous research has shown that some robotic arm movements are more challenging to learn than others. For instance, horizontal movements are easier to learn than oblique movements, and vertical movements are more challenging than either (Draper et al., 1990). Therefore, it seems useful to study not only the learning process of the entire robotic arm but also of the individual joints. Moreover, Suzuki and Harashima (2008) used Fitts' law to analyse control input movements of a remote controlled excavator, which was controlled with a single joystick-keyboard, as skill indicators. Here, hand movement complexity correlated with increasing skill, and abrupt changes in movement were negatively associated with task performance. Also Manner (2017) found in a field study that joystick use can serve as skill indicator in log loading with a forestry forwarder. Thus, a detailed analysis of operator joystick control movements across learning could reveal specific challenges in motor development. Therefore, the present study focuses specifically on the analysis of joystick activity. Another advantage of joystick activity analysis is the easy accessibility of the signals within heavy machines for the integration of future operator support systems.

5.1.5 Aim and Hypotheses

The objective of the current study is to identify motor learning patterns that may challenge the learning of robotic arm control and, more generally, explain performance variability in skill development. It is hypothesised that joystick movements of all joints have similar learning curves, but contribute differently to performance enhancement depending on the complexity of the movement. In addition, due to naïve participants and the rather complex operating requirements, a drop in performance in control ability is expected when the robot is not operated for an extended period of time.

5.2 Method

5.2.1 Participants

The study was conducted with ten participants (6f, 4m). The participants were on average M = 28 (SD = 9.29) years old, right-hand dominant, and normal (or corrected-to-normal) vision. The research was approved by the ethics committee of the Leibniz Research Centre for Working Environment and Human Factors under the approval number 200. All participants consented to voluntary participation and had the right to abort participation at any time without negative consequences.

5.2.2 Apparatus

5.2.2.1 Simulator

The simulator consisted of a Chicago truck seat, two Thrustmaster Joysticks and a 40" Samsung TV-Screen. The eye point was kept at 1.25 m, so that the horizontal gaze of the participant intersected the screen at a height of two-thirds from the bottom edge. The distance from the eye point was set to 1.10 m (vis. Angl. V = 43.83°). The simulator was controlled 2 m behind the participants' seat. The joysticks were mounted to an adjustable frame of the seat base and could be adjusted to the participants' anthropometrics.

5.2.2.2 Software and Simulation

The simulator was based on a Linux system (Ubuntu; Beaver Creek). The simulation was created with ROS (Melodic), controlled by a C++ program, and visualized in GAZEBO. The simulated robot arm was the four-joint "Robotis open manipulator" (ROBOTIS Inc., Korea) with a gripper as an end-effector. The manipulator's dimensions were adapted to those of a CH8 knuckle boom, which features in forestry vehicles (i.e., harvesters, forwarders). The simulated environment was a plain white space with a ground plane, shown by a grid with 100 cm line space, which was based on internal dimensions of the simulated model. The robotic arm had a Base joint that allowed for a slewing angle of 342°. The revolute joints (Shoulder, Elbow, Wrist) had a range of 172° degree. Each joint was mapped to one of the joystick axes (Figure 1) aligned with the joystick mapping of forest or construction vehicles (cf., Elton et al., 2009; Westerberg & Shiriaev, 2013). The work range of the robotic arm was 5-100 cm.

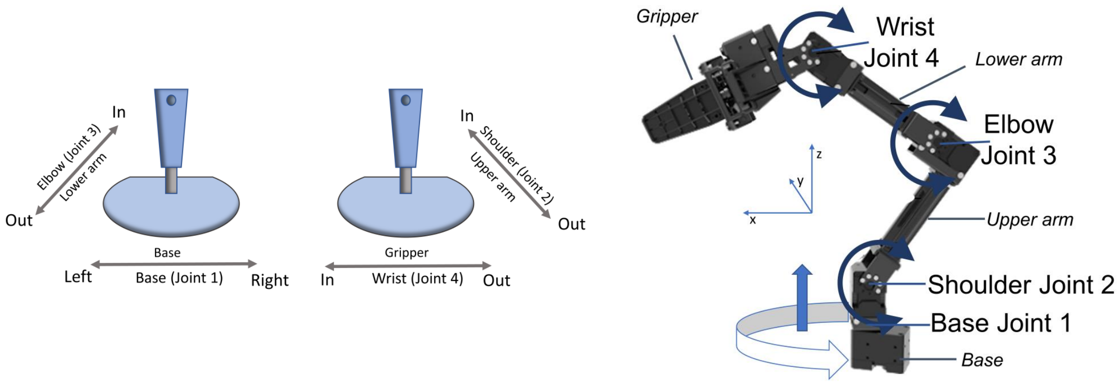


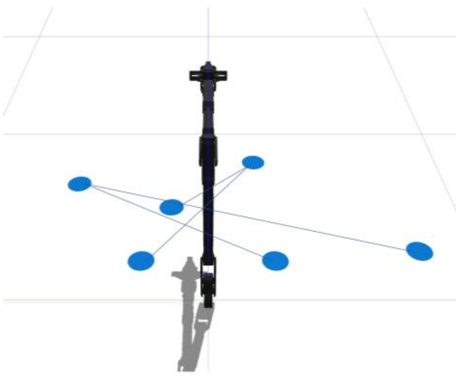
Figure 7. Joysticks with control mapping (left). The arrows indicate the joystick movement direction and the effect on the controlled joint. Robotic arm with movement directions and labels (right).

The precision movements for lifting and lowering the robotic arm as well as the gripper control was mapped to the right joystick. The rotating and reaching was mapped to the left joystick. The simulator recorded at a sampling rate of 40 Hz.

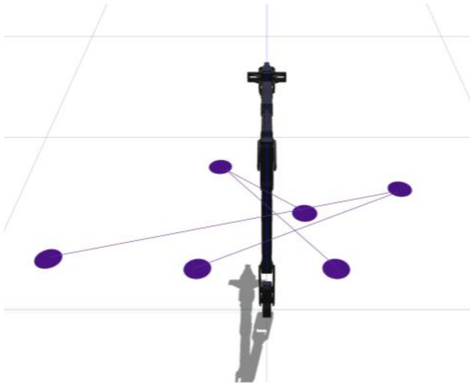
5.2.2.3 Visualisation of Fitts Inspired Task

Within GAZEBO, circles were rendered that served as targets of the robotic arm reaching movement. All targets had the same size. The radius was 5 cm and the circles were coloured in purple or blue. The reaching movement was varied by the position of the circles on the ground, inspired by Fitts' Index of Difficulty. Two circles were present at any given time for the participant. The first circle was on the left side (of an imagery straight line separating the front view of the operator in left and right) the second circle was placed on the right side. Four different spacings of target circles were used. The circles were placed diagonal to each other so that the participants had to manipulate all degrees of freedom of the robotic arm to complete the task successfully. The colours blue and purple indicated the start of the tap series of aiming movements. Blue circles indicated to start on the left side whereas purple indicated to start at the right side with the movement.

The location of the targets was adapted to correspond to common robotic arm path in various application domains i.e., forestry or loading lorries (cf., Ovaskainen et al., 2011). For instance, gripping a tree in front of the machine and felling it to the side where the logs are piled. These movements were abstracted to the placement of the circular targets (see Figure 2), of which the difficulty was systematically manipulated by the distance between the two targets using Fitts Index of Difficulty (for details Soukoreff & MacKenzie, 2004). The resulting four difficulties of the movements were Index of Difficulty = 2.5, 3.0, 3.3 3.9. The target coordinates are shown in Table 7. All targets were positioned inside the workspace of the robotic arm.



(a) Start left



(b) Start right

Figure 8. Shown are four target pairs that indicated the movement start left (a, blue) and indicating the movement start on the right (b, purple).

Table 7. Coordinates (in cm) of blue movement target pairs. Purple targets are mirrored.

x_1	y_1	x_2	y_2
65	55	25	-80
20	25	80	-20
65	55	20	-25
50	15	80	-20

*Note X = depth and Y = lateral.

5.2.1 Procedure and Design

The experiment was conducted in a dimly lit laboratory room. After the participants were informed about the study details and provided signed consent, they received instructions on how the two joysticks controlled robotic arm movements. First, they performed a brief training session of four reaching movements with two oversized (diam. 15 cm) target pairs to familiarize themselves with the joystick and testing procedure. After this training, the actual task was initiated. The task consisted of six blocks of trials, comprising 72 aiming movements (10 taps i.e., nine movements, with eight target pairs). Once the task was completed, participants filled a demographic survey that included questions of prior experience. Overall, the experiment lasted 3.5 h to 4 h depending on the learning performance. Each participant exercised an average of every 2.1 days over nine sessions. A tenth session was a conducted as a retention session, which took place exactly 14 days after the ninth session.

The experiment followed a 2 (Start) × 4 (Movement Target) × 6 (Block) × 10 (Session) repeated measures design. The presentation of targets was randomized. The tapping start was alternated for each block between left and right so that a single block had eight targets starting either on the left and then on the right side or vice versa. Between each target pair, nine movements with 10 taps resulted in a total of 80 taps and 72 paths per Block. Within one session, participants had to complete 480 taps and 432 movements. Overall, the data comprised 4800 taps and 4320 movements per participant.

5.3 Results

The statistical analysis was performed in MATLAB version 2021a and R version 4.1.1. All statistical analyses were performed with an alpha level of .05.

5.3.1 Performance and Skill Indicators and Data Pre-Processing

The performance and skill indicators were chosen based on those used in Fitts' task and in teleoperation research on robotic arms, both of which analyse aiming movements (cf., Bukchin et al., 2002; Mower et al., 2019; Soukoreff & MacKenzie, 2004). For each movement, the XY-position of the gripper was determined by the contact of the gripper with the ground plane at zero vertical height. The time (in seconds) between the release of the gripper (from the ground) and tap (on the ground/target) was treated as movement time (in seconds) and submitted as a dependent variable for subsequent analyses. Within each session, the movement time, and the distance (in cm) of the tap at ground contact to the target centre (constant error, CE) was calculated. Additionally, the variability of CE measured as standard deviation of CE (variable error, VE) was used. Movements longer than 2 SD of the mean average movement time of the target within the same block were excluded from further analyses. This reduced the total number of movements from 43200 to 40797. Excluded movements included trials where the gripper was stuck in the ground plane due to a lack of control skills, which created anomalies in the physics simulation.

Control skill was analysed based on the joystick control and the joystick deflection velocity signal used to derive the input acceleration. Before this, the velocity data was filtered with a second order Butterworth-low-pass-zero-phase filter with a cut of frequency of Fc = 6 Hz (fs = 40 Hz, fn = 20 Hz) that is recommend for use in the biomechanical analysis of human movement (Crenna et al., 2021;

Winter, 2009). The first zero-crossing before and after acceleration peaks was determined for the movements of the different joystick axes. The period from the zero-crossing before and to the zero-crossing after the acceleration peak was defined as control segment in each case.

5.3.2 Control Performance Analysis

Movement time, CE and VE were assessed as indicators of progress in bimanual learning. A repeated measures ANOVA with Sessions as univariate factor was conducted. Movement time was significantly reduced across sessions ($F(1.73, 15.59) = 79.71$, $p < .001$, $\omega^2_p = 0.83$; see Figure 9), with the longest movement times in session one ($M = 16.06$, $SD = 5.83$) and the shortest movement times in session eight ($M = 7.18$, $SD = 1.44$). The linear model with Session as a predictor was significantly different from the null model ($F(8,81) = 54.02$, $p < .001$), showing substantial learning effects.

Movement accuracy was assessed via CE and VE. Separate repeated measures ANOVA were conducted with CE and VE across the nine Sessions that unveiled a significant effect of CE ($F(1.56, 14.02) = 8.70$, $p = .005$, $\omega^2_p = 0.13$) and VE ($F(1.73, 15.60) = 8.09$, $p = .005$, $\omega^2_p = 0.23$). These analyses support a significant decline for VE ($F(8, 81) = 3.91$, $p < .001$) but not for CE ($F(8, 81) = 9.25$, $p = .068$). Thus, the accuracy in terms of CE shows a tendency to significantly improve, and the accuracy in terms of VE significantly improves from session one to session nine as displayed in Figure 9.

5.3.3 Retention (Performance)

To assess retention, performance was reassessed 14 days after the last session. Repeated measures ANOVA revealed that, contrary to our expectations, movement time significantly improved in the retention session ten ($F(1, 9) = 6.79$, $p = .028$, $\eta^2_p = 0.43$). In addition, movement time was reduced in all experimental blocks of session ten ($F(2.83, 25.44) = 10.11$, $p < .001$, $\eta^2_p = 0.53$). However, CE and VE did not reveal any differences in retention compared to session nine ($p > .05$), although significant CE reduction ($F(3.18, 28.59) = 2.91$, $p < .049$, $\eta^2_p = 0.24$) and a tendency towards less VE ($F(2.46, 22.15) = 2.71$, $p < .079$, $\eta^2_p = 0.23$) was observed within session ten.

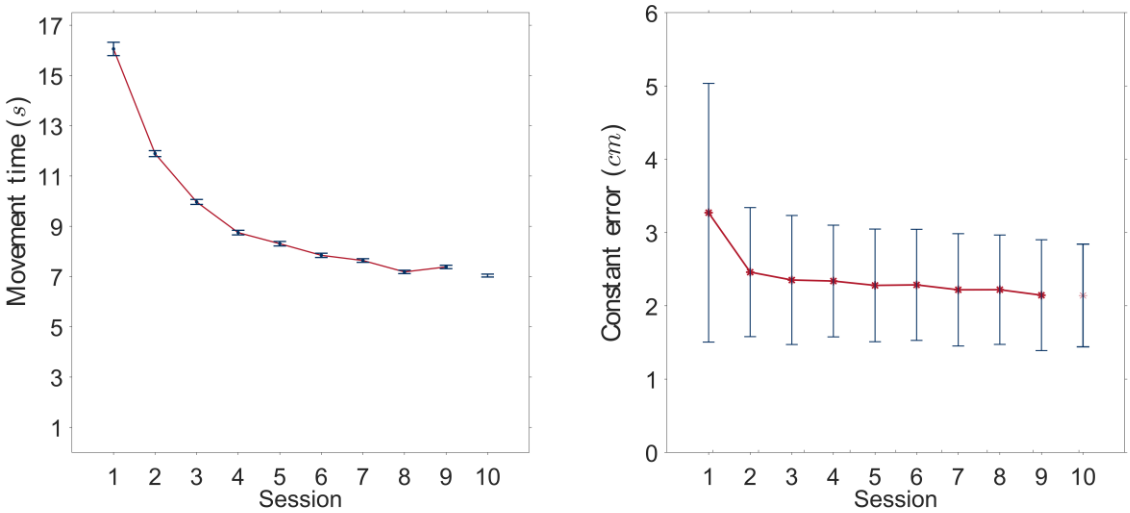


Figure 9. Left: average movement time in seconds (s) per experimental session. Error bars show the standard error of the mean. Right: average constant error (CE) in cm of movements per experimental session. The error bars show the variable error (VE) which is the standard deviation of the constant error.

5.3.4 Control Skill Analysis

5.3.4.1 Joystick Input Analysis (Segments)

The number of joystick acceleration segments was treated as an indicator for control skill. Lower segment count is suggestive of more targeted movements and higher control skill. Segment counts were accounted for each of the four robotic arm joints (see Figure 7, Base, Shoulder, Elbow, Wrist). Segment counts of each joint were submitted to separate one-way repeated measures analyses of variance (ANOVAs) for the factor Session; corrected alpha level of .0125. The factor Session was significant for Base ($F(1.88,16.88) = 16.88$, $p < .001$, $\omega^2_p = 0.42$), Elbow ($F(1.52, 13.65) = 24.13$, $p < .001$, $\omega^2_p = 0.52$), and Shoulder ($F(1.34, 12.09) = 21.36$, $p < .001$, $\omega^2_p = 0.53$), but not for the Wrist ($F(2.03, 18.30) = 2.57$, $p = .116$, $\omega^2_p = 0.07$) joint. In other words, control performance was more fluid with completed sessions and participants demonstrated motor learning and furthermore acquired increasing control skill for three out of four joints.

5.3.4.2 Skill Learning (In-Depth Analysis)

The learning curves of segment count were analysed to determine the exerted control skill of the joints separately (and in detail). Here, a two-time scale power law of learning function was fitted to the data of each participant (cf., Newell et al., 2009) to derive fitted estimates for five parameters. The formula considers slow (across sessions) and fast (within session) learning: The slow-learning parameter indicates general learning, while the fast-learning parameter denotes the decrement at the start of each session, which acknowledges the role of forgetting and adaptation. Forgetting can be regarded as a loss of control skill between training sessions, apparent in the re-uptake (warm-up decrement) of a task after the previous session; adaptation reflects the tuning of the motor system to the controls.

Fast + Slow Time Scale: $V_j\ (n) = V_{inf} + a_s e^{-\gamma sn} + a_j\ e^{-\gamma j\ (n-nj-1)}$

The model denotes V_{inf} as asymptote performance and the initial start of slow learning a_s and the learning rate $-\gamma_s$. The fast time scale is described by the initial start a_j and the respective learning rate (warm-up decrement), $-\gamma_j$. n_j is the last trial on day j. With n-n_{j-1} resetting the trial number to 1 at the start of each session to account for the warm-up decrement. The fast time scale with five constant parameters was implemented as described in Newell (2009). The model was fitted with a Levenberg-Marquardt algorithm to the averaged control segment counts on block level across sessions for each participant and joint separately, using least squares to reduce error in estimation between predicted and the observed data. The parameters were bound during the fitting to have the appropriate sign and range (cf., Joseph et al., 2013). Next, estimates that did not show a positive r^2 fit (see Table 7) were excluded. This is congruent with the plots of learning curves where it is visually evident the *Wrist* joint data do not vary significantly across sessions (see Figure 10c and Figure 12). Notably, all excluded fits involved the *Wrist* joint data. This means that the learning model could not account for the *Wrist* joint data. Thus, all analyses from henceforth exclude *Wrist* joint data. This reduced the number of learning curves for further consideration from N = 40 to n = 30. The resulting data set comprised estimates for all five parameters (V_{inf}, a_s, γ_s, a_j, γ_j) and fits for the subsequent analyses of learning. The averaged joint model parameters are shown in Table 8.

Table 8. Mean model parameters and standard deviation listed for each joint.

Joints	Parameters					
	r^2	V_{inf}	a_s	γ_s	a_j	γ_j
Base	0.69(0.28)	1.91 (0.56)	3.37(2.21)	0.13(0.07)	1.12(0.21)	0.22(0.41)
Elbow	0.83(0.16)	1.72(0.69)	4.98(3.05)	0.16(0.08)	1.24(0.37)	0.51(0.52)
Wrist*	-0.53(1.25)	0.26(0.51)	2.51(3.05)	0.22(0.33)	1.01(0.02)	0.40(0.51)
Shoulder	0.79(0.12)	1.82(0.85)	3.71(2.12)	0.12(0.08)	1.47(0.58)	0.23(0.38)

*Note: Wrist joint data was excluded from analysis due to low overall fits

5.3.4.3 Slow, Fast Learning and Skill Gain

The average slow learning rate $-\gamma_s$ indicated overall skill development i.e., how fast the control of a joint is improved by the participants across all experimental sessions. Low slow learning rates were found for the control of Shoulder and Base joint, which showed that participants learned slower than the Elbow joint. With respect to fast within session learning, the Shoulder joint revealed the highest warm-up decrement (a_j) compared to the other joints. In contrast, the Base joint showed the lowest warm-up decrement (a_j). Both Elbow and Shoulder joints showed high within session learning rates (γ_j). The learning curves of the participants are illustrated for each joint separately in Figure 10.

5.3.4.4 Parameter Analysis

In addition, the joints were compared by all (V_{inf}, a_s, γ_s, a_j, γ_j) model parameters separately with five repeated measures ANOVAs. The start parameter αj of fast learning, the asymptote performance V_{inf} as well as the slow and the fast-learning rate γ_s and γ_j did not show significant effects ($p > .05$). However, a significant effect for the start of the slow learning αs ($F(1.16, 10.43) = 8.42$, $p = .013$, $\omega^2_p = 0.48$) was found and thus overall learning. The estimated marginal means were calculated to make pairwise contrasts with Tukey adjusted p-values of the initial start performance (a_s). It was found that the Elbow joint ($M = 4.98$, $SD = 3.05$) was significantly higher than the Base joint ($M = 3.37$, $SD = 2.21$, $p = .003$). Thus, the Elbow joint requires more control inputs at the start of the learning compared to the Base joint.

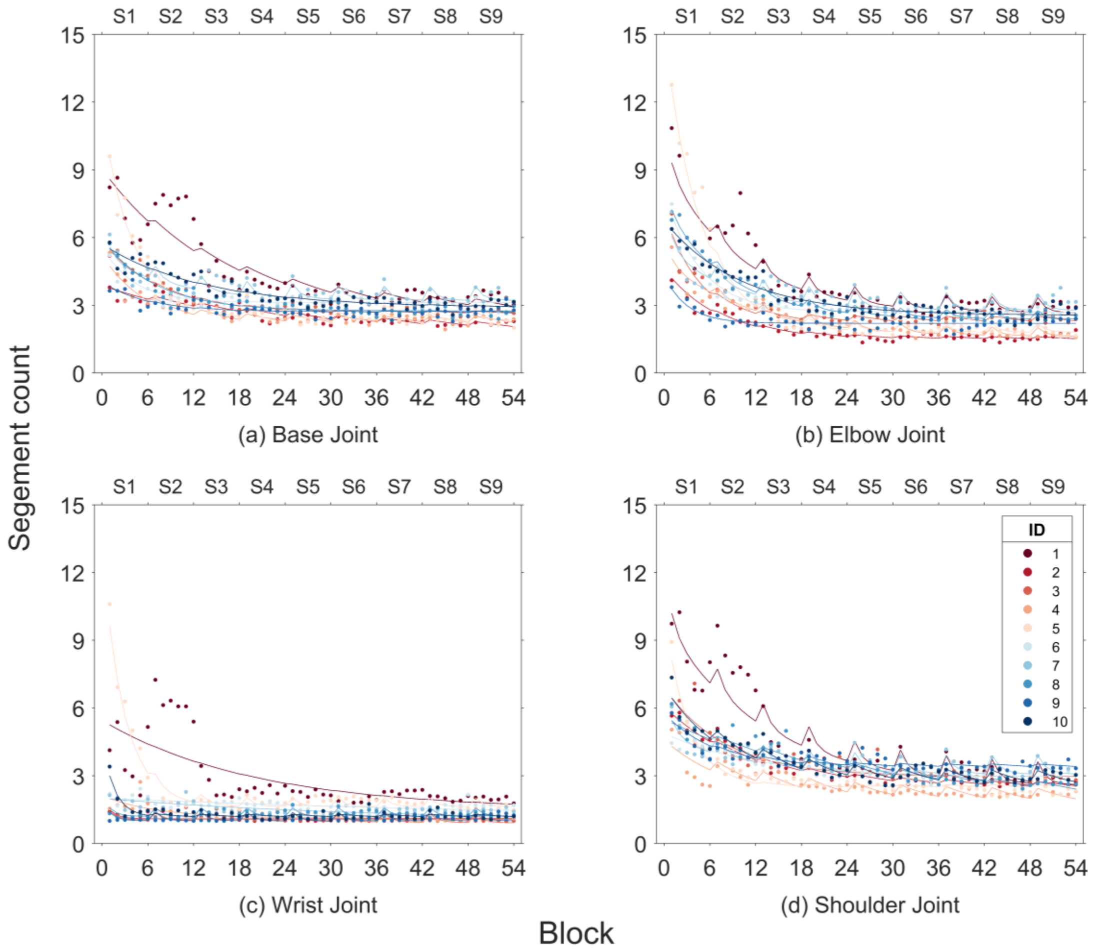


Figure 10. Mean segment count of each participant (ID) for each block displayed for the Base (a), the Elbow (b), the Wrist (c), and the Shoulder (d) joint. Fitted are the learning curves of the two-time scale model (straight lines) to the empirical data (dots). Six blocks equal one session (S). Displayed are nine Sessions (S1-S9) comprising 54 experimental blocks.

Furthermore, the actual gain of learned control (a_s/V_{inf}) was calculated by determining the ratio of the initial skill as and the trained (asymptote) skill level V_{inf}. This ratio indicates the relative amount of learning and, hence, indexes control difficulty. Figure 11 shows that the mean skill gain is greatest for the Elbow ($M_{as/Vinf}$ = 3.14) compared to the Base ($M_{as/Vinf}$ = 1.78). and Shoulder joint ($M_{as/Vinf}$ = 1.80) (F(1.54, 13.88) = 10.27, p = .003, ω^2_p = 0.53).

The loss of control skill at session start was determined by the ratio of the skill at session start and the trained (asymptote) skill level (a_j/V_{inf}) (see Figure 5). Here, the Elbow joint ($M_{aj/Vinf}$ = 0.81) showed on average the greatest loss of the control skill but not significantly different from Base ($M_{aj/Vinf}$ = 0.61) and Shoulder ($M_{aj/Vinf}$ = 0.64) joint (p > .05).

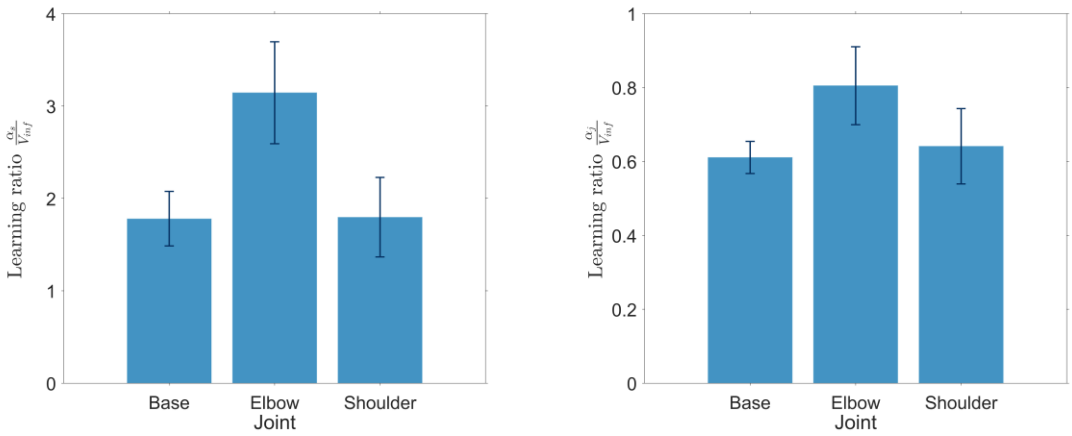


Figure 11. Averaged slow learning ratio (a_s/V_{inf}) for each joint (left). Averaged fast learning (a_f/V_{inf}) ratio for each joint (right). Arrows denote the standard error of the mean. *Note that the Wrist joint data is based on low number of learning curves

5.3.4.5 Retention (Skill)

Retention session ten compared to session nine showed a significant reduction in control segments for all joints equally ($F(1, 9) = 11.24$, $p = .008$, $\eta^2_p = 0.55$). Furthermore the joints showed a significant difference in control segments (($F(3, 27) = 75.66$, $p < .001$, $\eta^2_p = 0.89$), cf. Table 8 V_{inf}). Improvements over blocks were not observed and thus no change of control segments within a session occurred ($p > .05$).

To compare learning rates within session nine and the retention session ten the slow time-scale power law of learning function was fitted. The model did not fit the data and was thus discarded ($r^2 < 0$). The data suggested a linear relationship. Therefore, a linear model based on ordinary least squares was fitted, that described the data ($r^2 > 0$) and the slopes were compared as learning rates. The learning rates showed no differences between learning session nine and retention session ten ($p > .05$).

5.3.4.6 Individual Skill Learning

In addition to the parameter evaluation and skill gain analyses, the slow (γ_s) and fast (γ_f) learning parameters for each participant were ranked in descending order based on their magnitude and the frequency of a joint within each rank was assessed. This analysis aimed to get a clearer picture of the demand that learning the joint control imposes on the learner and to account for individual learning characteristics (slopes) of the joints. The frequencies are shown for the slow learning rate in Table 9 and for the fast-learning rate in Table 10.

All joints (Wrist excluded) were represented within all ranks of slow learning. The Shoulder joint was most frequent in rank three. The Elbow joint was predominantly found in the first and second rank, showing most learning parameters in rank one. The Base joint was evenly distributed over ranks having the modal value in rank two. As example, the individual learning curves for each joint of participant four are illustrated in Figure 12.

Table 9. Ranked frequencies of the joints based on the individual ranking of the slow learning rate (γ_s).

Rank	Joint		
	Base	Elbow	Shoulder
1	3	5	2
2	4	4	2
3	3	1	6

Table 10. Ranked frequencies of the joints based on the individual ranking of the fast learning rate (γ_j).

Rank	Joint		
	Base	Elbow	Shoulder
1	4	4	2
2	3	2	5
3	3	4	3

The fast-learning parameters showed a similar pattern to the slow learning parameters for the Base joint. The learning parameter of the Elbow joints were most frequent in Rank one and three, whereas the Shoulder joint was most present in rank two.

In conclusion, the Elbow joint showed high learning rates for slow and either high or low fast learning rates. The Base joint showed evenly distributed learning rates for both slow and fast learning rates. The Shoulder joint showed low slow and intermediate to low fast learning rates.

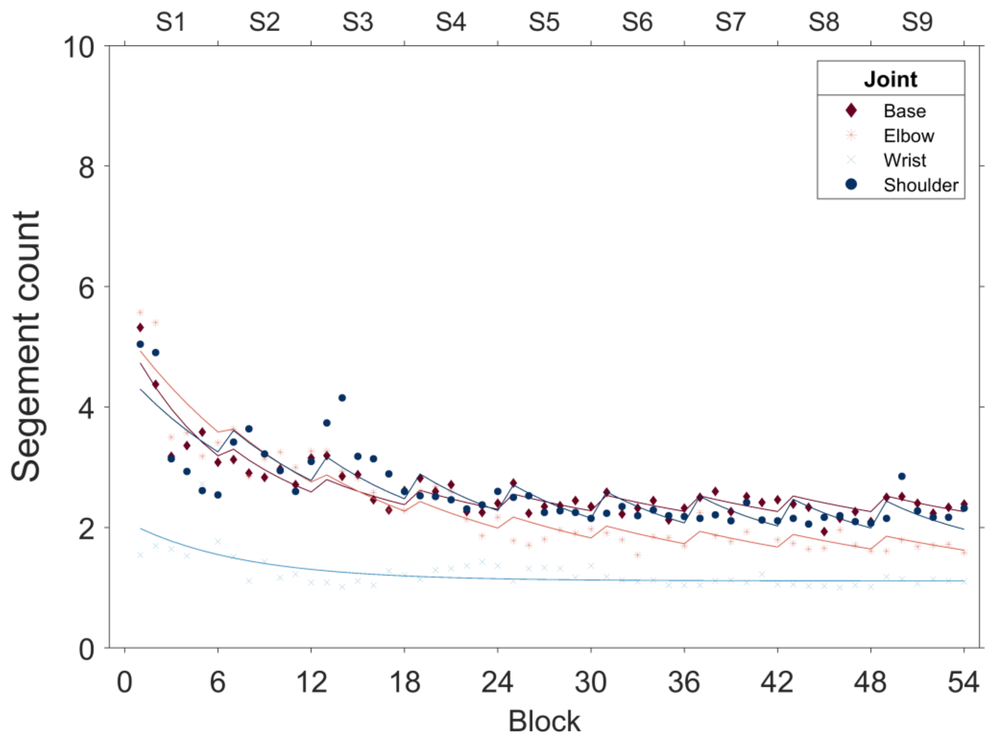


Figure 12. Illustration of segment count of sessions for each Joint of participant 4.

In addition to the ranking of joint parameters, the learning rates were compared within a two-way repeated measures ANOVA to investigate if fast and slow learning rates interact with the controlled joint. No significant interaction of slow, fast learning rate, and joint was found. Nonetheless, a significant main effect was found for the controlled joints ($F(2,17.97) = 3.58$, $p = .049$, $\omega^2_p = 0.28$). Specifically, the Elbow joint ($M = 0.33$, $SD = 0.4$) showed higher learning rates than the Base ($M = 0.18$, $SD = 0.29$) and Shoulder joint ($M = 0.17$, $SD = 0.27$).

5.3.4.7 Control Skill and Performance Prediction

To make use of the segment analyses in performance assessment, it was analysed which joint relates the most to movement time, constant error, and variable error. Therefore, a linear regression was fitted where each performance variable was predicted, given the number of control inputs measured in segment count. The Base joint was removed from the analysis due to a high variance inflation factor VIF > 10. Movement time was found to be significantly predicted by all remaining joints. Notably, an increase in control segments of Elbow and Shoulder joint increased movement time whereas an increase in control segments to the Wrist joint reduced movement time. The constant error and variable error were significantly predicted by the Wrist joint inputs. Here, an increase of control segments of the Wrist joint raised accuracy (see Table 11).

Table 11. Regression model parameters predicting movement time from joystick input segments.

MT			
Predictor	*Beta*	*t*	*p*
Elbow	1.56	7.09	<.001***
Wrist	-1.67	-6.82	<.001***
Shoulder	1.68	7.40	<.001***
r^2 = 0.82			
CE			
	Beta	*t*	*p*
Elbow	0.12	1.29	.202
Wrist	0.73	7.13	<.001***
Shoulder	-0.17	-1.80	.076
r^2 = 0.57			
VE			
	Beta	*t*	*p*
Elbow	0.06	2.00	.049
Wrist	0.18	5.38	<.001***
Shoulder	0.01	0.39	.696
r^2 = 0.61			

*** significant <.001

5.4 Discussion

The aim of this study was to analyse learning progress in the operation of a robotic arm to derive recommendations for improving the training of machine operators. To this end, novices were trained over nine days, and a tenth retention session, controlling a four-DoF robotic arm and analysed both short term adaptations and longer-term learning gains. Skill development and performance of the robotic arm movement was investigated both under the assumption that participants would continuously improve their skill and that the joints would contribute differently to performance.

5.4.1 Control Performance

In line with Bukchin et al., (2002; 2007; 1994), a significant learning progression (across and within sessions) for all measures of control skill and performance was found. Participants were able to control the robotic arm from the beginning of the experiment with high accuracy and stabilised performance across sessions. However, they did not show improvements in constant error. In contrast, movement time and variable error decreased continuously across sessions with the largest decrease within the first session. Performance further improved in retention in terms of movement time and in contrast to our expectations no performance loss was observed. Accuracy was similar during learning and retention. Overall, the participants' learning strategy emphasized speed over accuracy.

5.4.2 Control Skill Development

Control skill is reflected in the deliberate bimanual inputs to the joysticks. Therefore, this study focused on the control movement reflected by the deflection of each joystick axis that mapped to the corresponding joint of the robot arm. The fitted learning curves unveiled different learning rates for each controlled joint. More specifically, the Base joint control appears easy to learn as the required skill gain was lower compared to the Elbow joint. At the same time the Base joint showed a small warm-up decrement. The control of the lower robotic arm via the Elbow joint showed the highest skill gain. For this joint learning is taking place at high rates, allowing the highest warm-up decrement between joints to be rapidly decreased. The control of the upper robotic arm via the Shoulder joint revealed intermediate learning gains and rates that were lower than the Elbow joint and comparable to the Base joint on slow and fast time scales. Learning to control the Wrist joint showed mixed findings. The Wrist joint data could only be fitted to few participants by the two time scale model. This suggests that learning to control the Wrist joint did not take place for most of the participants. Notably, the retention session showed that the required control input to the joysticks was reduced after 14 days. Thus, control skill further increased without active training which could be regarded to further consolidation of motor movement (Krakauer, 2009). Differences in terms of learning rates in retention compared to acquisition did not occur.

The prediction of movement time by the control segments showed that all joints but the Base joint explain movement time variance. Movement time increased with more input actions of the lower and upper robotic arm. This suggests explorative or uncoordinated use of these joints, which could be improved by partial task training in which individual joints are first trained separately.

The result of low skill gain of the Base joint is consistent with the findings of Draper et al., (1990), who found horizontal movements to be easier than diagonal or vertical movements. However, as the slewing motion is concentric and not strictly linear, it was additionally assumed that the concentricity of the movement is responsible for the strong facilitation of control as found in Dreger et al., (2022). It appears that the upper robotic arm element controlled by the Shoulder joint is easier to resume in repeated sessions than the lower element (Elbow). The Shoulder joint is, to a large extent, controlling both a single (vertical) dimension and is used to bridge longer distances. This may have eased the learning process. The high plateau of the learning function and the high number of control inputs within the entire movement may come from the involvement of the Shoulder joint in the gross movements of robotic arm motions. In contrast, the second arm element and the gripper are responsible for fine control. This is relevant for in-depth motion and movement accuracy that is visually demanding and largely carried out by extending the second element to enable full arm reach and using the gripper. A different mapping of the joystick axis such as mapping elbow and shoulder joint to the same joystick could thus be a remedy to overcome control challenges for in-depth motion. Moreover, these movements are off the concentric orbit and time-consuming due to challenging motions (cf., Dreger et al., 2022). This suggests that learning to control the Wrist joint did not take place for most of the participants, or if so, was following one or more time scales. The low control segment count and fitting problem of the Wrist joint may come from two different control strategies. A first strategy would be to neglect or minimize the use of the Wrist joint as much as possible, due to the required learning effort to skilfully manoeuvre the gripper to the target. This would explain the low number of control inputs to the Wrist joint in skilled performance as well as the low fit of the learning function compared to the other joints. Further this would also explain the lack of improved accuracy across sessions. The second strategy would be to integrate the Wrist control in the movement, which would lead to a higher number of control inputs compared to ignoring the joint. According to the learning curves, it was assumed that both occurred within the data, although with a strong emphasis towards neglecting the Wrist joint. To determine if the disuse of the Wrist joint is a well-developed strategy or simply reflects a freezing of DoFs in the initial phase of learning as proposed by (Bernstein, Nikolai A., 1967; Newell & Vaillancourt, 2001) further analyses need to be conducted.

5.4.3 Implications for Training and Work Design

The results suggest that training of the rotational (Base joint) and vertical movement (Shoulder joint) is only indicative for performance measured in terms of time. In contrast, the learner is challenged most by controlling both Elbow and Wrist joint that contribute to both accuracy and movement time. Therefore, we recommend focusing training on guiding the development of the forward model (cf., Wolpert et al., 2011) of the use of Elbow and Wrist joint. To effectively built the forward model the properties of control in terms of the required kinematic transformation from hand to Elbow joint and Wrist joint movement as well as the dynamics need to be trained. This can be achieved by exposing the trainee to isolated movements of the respective joint and further combine the joints. Movements must target a wide range of joint angles to induce variability. The Base and Shoulder joint could be fixed for this purpose. The dynamics can be trained by using different extents of deflection to control the joysticks, which means that participants need to apply different movement speeds. One way to achieve complex kinematics is by deviating from the concentric nature by avoiding rotation in the movement of joint velocity controlled robotic arms (see Dreger et al., 2022). In repetition training, this could be realised with allocating time on movements that require to reach ahead or to the base of the robotic arm. For example, in forestry, these movements would be gripping movements ahead and felling motions close to the base. In construction, the digging location could be located either close or directly in front of the machine.

5.4.4 Limitations

The aim of this study was to assess skill development via control inputs, as manual input determines the movement of the robotic crane. Nevertheless, the authors are aware that the general analyses of joystick-inputs have limitations in explaining motor behaviour that is synthesised from numerous basic actions. Therefore, the analysis of individual styles may be necessary to make training more effective. In addition, the limited visual fidelity of the virtual experimental setup used could be responsible for the continuous high constant error.

5.4.5 Conclusion

Learning the control of a four-DoF robotic arm with forward kinematics shows continuous improvements for all joints across the experimental session, although different learning curves were observed. To conclude, curvilinear (rotating) motions are easily learned while rectilinear precision movements challenge the operator. Regarding fine control, it was assumed that strategies such as deliberately reducing of DoFs were applied to reduce the control effort as much as possible. That is in line with theories that propose a reduction of active degrees of freedom in motor learning (Mitra et al., 1998; Newell & Vaillancourt, 2001). Future digital learning aids and conventional training ought to focus on supporting aiming in the depth of the 3D space with the robotic arm and facilitating the precision of the gripping.

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Chapter 6
Comparing Operator learning, Performance, Cognitive Load, and Trajectories of End-Effector and Joint-Controlled Robotic Arms for Support System Design

Advances in inverse kinematics algorithms allow human operators to easily control the end-effector of robotic arms with multiple joints. This is simpler than simultaneously controlling multiple independent rate-controlled joints that interact with each other to move the end-effector. This paper extends the findings of applied studies by adding in-depth analyses and new indicators for assessing learning, which are relevant for the design of training and support systems. Two independent groups of novices were trained in a simulator, either on end-effector or joint-control within four consecutive sessions. The development of motor control and the impact on robotic arm movement is described in terms of differences in forgetting, adaptation, cognitive machine operator workload, accuracy, and robotic arm trajectories. End-effector control through inverse kinematics results in faster movement times for lower accuracy levels to joint-based control. Movement times of both control modes are similar after training. Adaptation and forgetting are insignificant to the learning of end-effector control. End-effector control reduced cognitive effort and workload, enabling participants to significantly reduce trajectory length. Finally, end-effector control ameliorated entry level learning difficulties in motor control training. Trajectory quality and characteristics are recommended for evaluating end-effector control performance. Furthermore, risks of cognitive underload during control tasks need to be considered.

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6.1 Introduction

Large machines such as excavators and forest harvesters often require human operators to manually control robotic arms with multiple individually controlled joints. Conventionally, robotic arm control schemes that map multiple joints to joysticks are difficult to learn and tend to result in poor performance, from simple tracking tasks [1] to laparoscopic surgery [2]. Substantial training time is often necessary to achieve skilled performance (cf., [3]). Thus, improving operating skill through better training [3] and assistive technology [4] can have a significant impact on productivity as well as mitigate safety risks posed by low-skilled operators. Acquired motor control skills determine the efficiency of the robotic arm movements trained [5] and therefore task-relevant performance, e.g. productivity in m3/h of forestry harvesters [6]. Motor learning reduces movement variability and increases accuracy [8]–[10]. Operating skill can be defined as learned motor behavior acquired by training that results in a persistent change of behavior [7].

Recent advances in control automation allow the end-effector instead of each joint of the robot arm to be controlled separately, which reduces the number of controlled arm elements and therefore facilitates motor control learning [11].

6.1.1 Comparing End-Effector and Joint-Control

In the construction domain, two studies [12], [13] have consistently demonstrated that an end-effector controller developed for an excavator and backhoe resulted in lower task completion times, higher fuel efficiency and productivity across basic tasks (i.e., digging, soil flattening, line tracking). In the forestry domain, two studies [14], [11] have shown that end-effector control for log loading with forwarders leads to faster task completion, higher productivity, lower total path distance, and lower joystick activation frequency. Although these studies were centred on end-effector controllers that were specifically designed for their use cases, their results were fairly consistent. Novices tend to benefit from end-effector control. Nonetheless, these studies suffered from several limitations.

First of all, these studies do not allow us to readily determine if the reported advantages of end-effector control depend on the pre-existing expertise of the human operators. Most of the above studies used novice operators wherever possible. However, this was not consistent, due to ongoing vocational training during the test periods or the inclusion of few participants with previous experience e.g., [12], [11]. In addition, two of these studies were conducted on a single day, therefore it was unclear whether the benefits observed had a long-term impact on handling skills. A notable exception was Manner [11] as well as Wallersteiner and colleagues [14] who performed testing across four practice days. However, both control schemes were tested in [14] at each practice day, although the objective was not to investigate learning and re-learning effects within the group of novices. Instead, the objective was to counterbalance the presentation of the different control schemes within the same pool of participants, assuming that there was no general learning effect between the different test conditions. Arguably, this was an improvement over the other studies [12], [13] who counterbalanced their test conditions within a single day, which potentially confused the general effects of learning and fatigue across test conditions.

All previous studies consistently found that end-effector controllers support better learning of operator skill. Typically, task completion times or domain-specific measures of productivity were assessed, which could have been achieved at the cost of other aspects, for example, faster task completion times can be achieved at lower levels of accuracy (speed-accuracy tradeoff). Thus, previous studies might be difficult to compare with one another, given that their application domains are likely to have varying levels of expected performance. Results collected in the field [14], [11] can be highly specific and not easily generalizable. In addition, previous studies have not measured non-performative aspects that are critical for assessing ease of learning, such as subjective mental load, which is also important for assessing undesirable cognitive states with higher levels of automation. Overall, learning of control skill is best understood by models that can describe how aspects of motor control changes over time [15]. Learning analysis models can help provide insight into the development of expert performance, which is necessary to reduce the significant productivity variation between operators [16], using specific performance quality measures. These insights can then be profitably applied to the design of training and support systems that can train machine operators onboard machines.

The current study was designed to address these limitations of previous studies by inviting näive participants, which were randomly assigned to the different control schemes and to learn the control of a robotic arm across multiple sessions.

6.1.2 Modelling Learning and Skill Indicators

What are the controlled dimensions that limit overall performance and could require special training or technical support? To answer this question, it is necessary to go beyond discrete performance metrics from single sessions and use learning functions whose parameters can be fitted to motor learning data. This allows us to track skill progression throughout learning and determine when learning (or any benefit rendered by technology) plateaus. In addition, this can reveal processes that determine the progress of learning, such as forgetting, and motor adaptation [17],[18]. Learning can be different for the control of different joints or control dimensions. To date, no studies have reported the rates of control improvement estimated by a model that tracks changes of control parameters across time and control dimensions.

Control skill can be derived from how human operators manipulate and move the control sticks. Here, kinematic landmarks identify comparable movement characteristics in both end-effector and joint-control schemes. To elaborate, kinematic landmarks are characteristic temporal events in human movements, expressed by minima, maxima, and zero crossings of the time derivatives of positions [19]. These landmarks emerge during the learning process and can, thus, serve as useful indicators of skill level and operating demands (see [5]). Such landmarks could be rapid directional changes in joystick movements that indicate that, for a given movement, a change in movement direction distinguishes completed sub-movements and, furthermore, phases of aiming movements that are driven by feed forward or feedback control [19]. Together, these landmarks determine the trajectories of end-effectors. Therefore, the end-effector trajectories can serve as an index of the operators' control skill. Movement trajectories and the quality of these trajectories will be used to better assess control performance. A presumption is that the direct control of the end effector will lead to more target-focused trajectories. Thus, the shape of the trajectories could be relevant for work design and for the design of robotic arms of heavy machinery. In addition, trajectory smoothness can also indicate how well the machine operator is operating the machine. In human aiming movements, smoothness generally means fewer corrective movements and thus jerky movements [20]. Similar to how smoothness can be considered a quality measure for the efficiency and precision of human movements [21], the authors assume that this measure can also be applied to the movement trajectories of robot arms controlled by humans.

Skill development with joint-control systems will continue to be relevant, despite the growing implementation of end-effector control. Large machines continue to be widely deployed, still observe a rate-controlled joint-control scheme and will not be rendered obsolete overnight. Furthermore, skilled performance is a major productivity constraint for experienced machine and robotic arm operators, and research into skill development is needed [16], [22], [23]. Thus, the current work also reports how naïve users learn such systems at the same level of detail as end-effector control systems.

Finally, learning involves cognitive effort and workload of the robotic arm operator, and end-effector control systems could serve to reduce this effort. Cognitive resources are limited, and cognitive overload impairs learning [20], [24], [25]. Therefore, training methods must be adapted to the characteristics of human information processing, especially with regard to increasingly demanding operating environments [26], e.g. the information presented for teleoperation.

In summary, the current work builds on previous studies that have shown that end-effector control is superior to joint-control for learning to operate robotic arms. The current work contributes to the previous literature by directly measuring the learning process and introducing a comprehensive quality assessment of the control movements, in terms of accuracy, smoothness, and trajectory analysis. This is achieved by fitting learning functions to joystick control movements, as opposed to the predominately selective reporting of discrete performance measures. In addition, this work includes a subjective assessment of mental load within and across training sessions to infer the impact of learning the two control schemes on cognition. Furthermore, the experimental design of the current study improves on previous study designs by systematically manipulating movement difficulty.

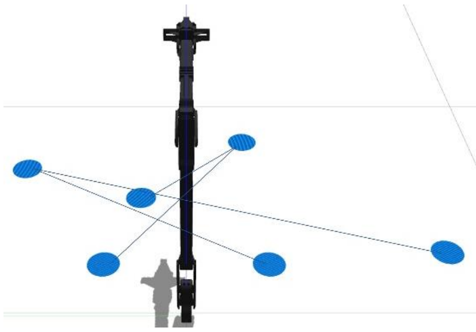
6.2 Methods

6.2.1 Participants and Apparatus

A total of N = 32 (F = 22, M = 10) participants with a mean age of M = 25.37 (SD = 6.64) were invited to participate in a simulator experiment. They were randomly assigned to learn either an end-effector control system or a joint-control system, but not both. All participants consented to the instructions, were novice to the task of robotic arm control and had according to self-reports a dominant right hand. Due to technical problems with the end-effector control n = 5 participants were excluded so that the end-effector control group consisted of n = 17 (F = 13) and the joint-control group consisted of n = 10 (F = 6) participants.

The simulator (Fig. 13a) comprised a grammar seat (Chicago 1040673-C), two joysticks (Thrustmaster T.16000M FCS) and a Samsung tv screen 55" (Samsung LE40C750R2Z). The simulation software was written in C++, ROS, and visualized by GAZEBO. Participants were located at 1.1 m distance to the screen resulting in a visual angle of V = 43.83°. The control mapping for end-effector and joint-control is outlined in Fig. 14. The end-effector controls the tip of the robotic arm by manipulating the X, Y, and Z direction (Fig. 14b). The joint-control controls each joint separately in the directions shown in Fig. 14a.

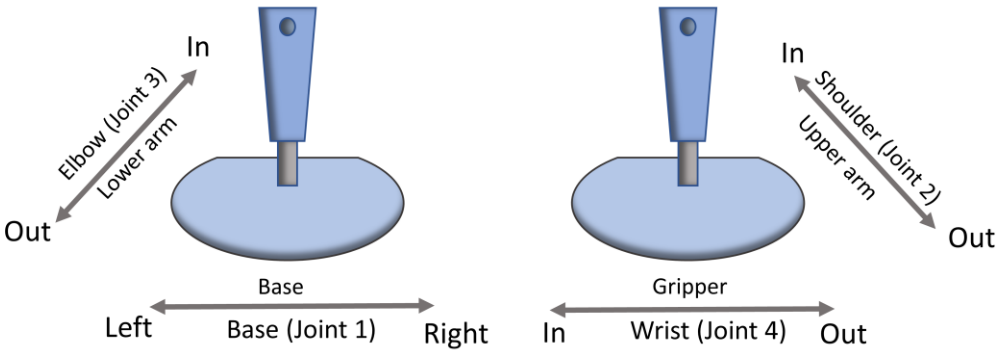
(b) Blue and purple targets



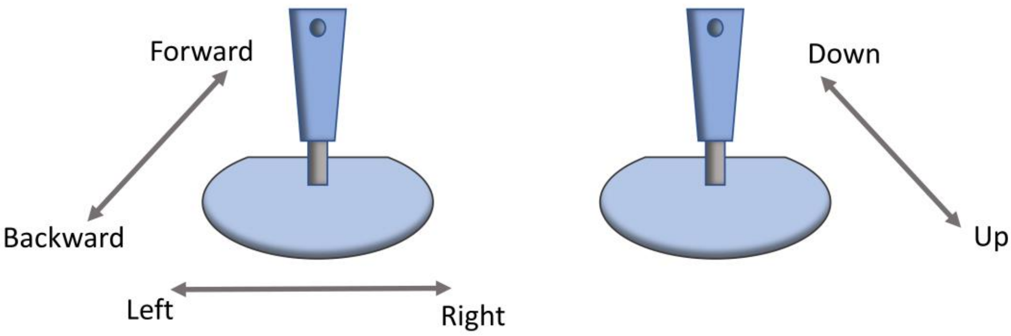
(a) Robotic arm simulator

(c) Blue targets and movements

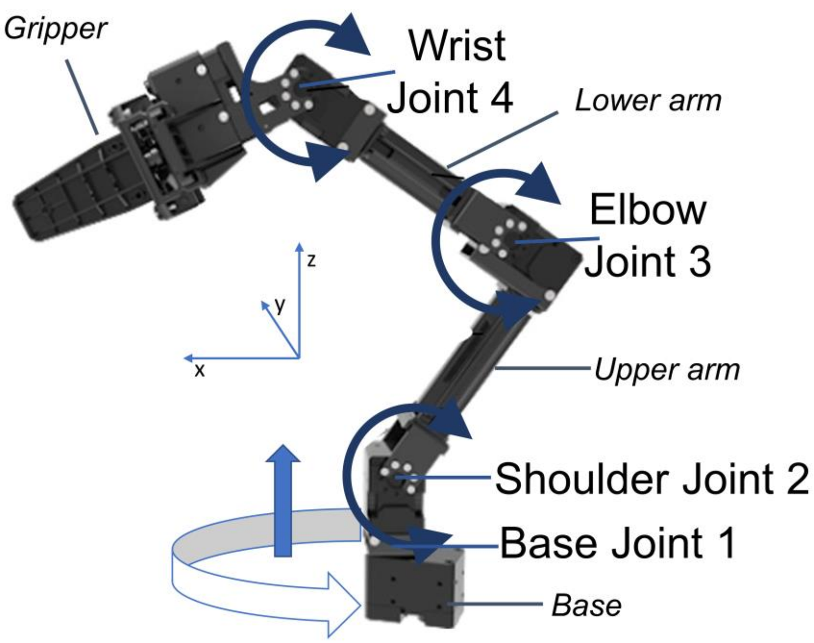
Figure 13. Shown is the simulator set up (a) and the simulation environment including the robotic arm and all target circles (b). In (c), the blue target pairs and movement paths are outlined.



(a) Joint-control



(b) End-effector control



(c) Robotic arm control mapping and joint labels

Figure 14. Displayed is the control mapping of the joysticks with the robotic arm for (a) joint- and (b) end-effector control. The labelled robotic arm is displayed on the right (c), with arrows indicating the joints movement's direction.

6.2.2 Stimuli and Task Description

The visualized robotic arm was built on the open manipulator framework (ROBOTIS Inc., Korea) and adapted to the dimensions of a CH8 knuckle boom. The simulation showed the robotic arm, that was situated on a white, grided floor, in a tilted bird's eye-view (Fig. 13b,c). Movement targets were displayed as two circles in blue or purple. Two circles were shown at a time and defined the movement, that started either left or right. The two target circles had the same diameter (10 cm). Four different movement distances and thus circle combination of two circles were presented. The distance and location were chosen according to harvester work methods and represented frequent crane movements [17].

6.2.3 Procedure and Design

The sessions took place within two consecutive weeks. Two sessions were held with a one-day interval within one week (e.g., Tuesday and Thursday). The days were the same in week one and week two. The experimental sessions started with a short training (~4 min.) comprising two targets (diam. 30 cm) and four movements to familiarize with the joystick mapping. Subsequently, the task of interest was started by the examiner. The task was executed in six consecutive blocks. Within each Block eight targets were sequentially presented.

The presentation sequence was randomized. The movement start was either on the right (purple) or on the left side (blue) (see Fig. 13b). Four presented targets started left and four right. Nine movements between the two presented target circles were executed and thus the targets were tapped ten times. An experiment block started alternately with left or right movements. The movement start was balanced across participants, so that one participant started first on the left (blue targets) and the following participant on the right (purple targets). Within block three and block six the RSME rating was performed. After 432 movements were executed within one session, the NASA TLX and demographic questions were administered. Overall, the participants executed 1728 movements across all four sessions. The statistical design of the experiment was a 2(start: left-right) × 4(Target distance) × 6(Block) × 4(Session) × 2(Control Scheme) factorial design with Control Scheme as a between-subjects factor and Start, Block, Target, and Session as within-subjects factors.

6.2.4 Subjective Measures

The perceived workload and the cognitive effort were assessed with the widely used NASA Task Load Index (TLX) in the raw version [27] and the Rating Scale Cognitive Effort respectively (RSME; [28]). The NASA TLX consists of six scales: Cognitive Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration and was used to assess perceived workload after the task was completed. The workload evaluation was surveyed on a 21-gradient scale. The scale represents evaluation scores from 0 ('no workload') to 100 ('high workload') with five percent increments. The RSME requires a single paper and pencil rating on a scale from 0 ('absolutely not effortful') to 150 ('extremely effortful'). The RSME was used to survey cognitive effort during the experiment.

6.2.5 Objective Measures and Data Pre-Processing

Performance and skill were measured by different objective measures. Performance was assessed by movement time in seconds and tapping accuracy in cm. The distance measures refer to internal distance measures of the simulation. Movement time was defined as the time from lift of to tap down and thus the time the end-effector took from one target circle to the other (cf. Fig. 13c). Accuracy was measured by the distance of the end effecter at tap down i.e., at a height of 0.03 cm, to the target circle (constant error) and variable error that was the standard deviation of the constant error.

Skill was assessed by the count of kinematic joystick acceleration events and trajectory smoothness. Kinematic joystick acceleration events were defined as acceleration segments in the joystick deflection and determined as period from the first zero crossing before and after an acceleration peak. The segment count was used to assess the control skill learning within a single session and between sessions. Here the two time scale power law of learning [18] was used.

Fast + Slow Time Scale:

$$V_j\,(n) = V_{inf} + a_s e^{-\gamma sn} + a_j\, e^{-\gamma j\,(n - nj\text{-}1)} \quad (1)$$

The model describes the persistent change that occurs across the experimental sessions on a slow time scale and adaptation and forgetting in motor learning that occur within a single session on a fast time scale. The model allows to delineate maximum (asymptote) performance V_{inf}, the slow $-\gamma_s$. and the fast $-\gamma j$ learning rate. The former rate describes control improvement across all and the latter within each session. Further the initial level at the beginning of the learning series αs and each session αj are determined. For details see [17] and [5].

The movement smoothness was analysed with the spectral arc-length (SPARC). The SPARC allows to calculate movement smoothness independent of confounds of duration and amplitude and is a more robust measure than log dimensionless jerk (LDIJ). The SPARC was calculated in accordance with [29] and the procedure was carried out as follows:

1: Determine the movement segments based on the tap down in the targets.
2: Compute the Fourier magnitude spectrum of the velocity of the movement.
3: Normalize the Fourier magnitude spectrum by the DC component ($V(0)$).
4: Compute the spectral arc length (SPARC) as smoothness measure based on the discrete-time Fourier transform for each movement.
5: Compute the average SPARC for each Target.

$$SPARC \triangleq -\int_0^{\omega c} \left[\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{V}(\omega)}{d\omega}\right)^2\right]^{\frac{1}{2}} d\omega;\ \hat{V}(\omega) = \frac{V(\omega)}{V(0)} \quad (2)$$

$$\omega_c \triangleq min\left\{\omega_c^{max}, min\{\omega, \hat{V}(r) < \bar{V}\,\forall\, r > \omega\}\right\}$$

SPARC flexibly adapt the cut of frequency $\boldsymbol{\omega_c}$ based on the amplitude threshold $\bar{V}$ of the Fourier magnitude spectrum. In accordance with movement filtering recommendations from [32] ω_c^{max} = 12π was chosen, which equals 6Hz. As amplitude threshold $\bar{V}$ = 0.03 was chosen to balance noise with the sensitivity of the SPARC computation. In the above formula $\hat{V}$ denotes the normalized spectrum with respect to the DC component $V(0)$.

The data processing was carried out with MATLAB version 2021a and the statistical analyses with R version 4.1.1. All data was sampled at a rate of fs = 74Hz. Velocity data was filtered with a second order Butterworth-low-pass-zero-phase filter with a cut of frequency of fc = 6Hz (fn = 37Hz). The statistical analysis was carried out with mixed factors analysis of variances (ANOVA) and student t-tests. Sphericity was adapted by Greenhouse-Geisser correction if necessary. All tests were performed with the confidence level alpha of a = 0.05 to reject the null hypothesis.

6.3 Results

6.3.1 Performance Analysis

General performance was assessed by movement time and accuracy. For each performance metric, a 4 (Session) x 2 (Control scheme) ANOVA was performed. Movement time was significantly higher of joint (M = 11.66 s, SD = 4.47 s) compared to end-effector control (*M* = 9.65 s, *SD* = 3.30 s) ($F(1, 24) = 29.50$, $p < .001$, $\omega^2_p = 0.52$). Further movement time reduced significantly with passed sessions ($F(1.68, 40.40) = 118.92$, $p < .001$, $\omega^2_p = 0.71$). The interaction of sessions and control scheme showed that that movement time of joint and end-effector control evolves significantly different across learning sessions ($F(1.68, 40.40) = 14.76$, $p < .001$, $\omega^2_p = 0.22$). Fig. 15 displays the development of the movement time. Due to the convergence of movement times of the control schemes, an exploratory planned pairwise contrast of the control scheme in session 4 was conducted. In the planned contrast, no significant difference was found between the control schemes ($p = .47$).

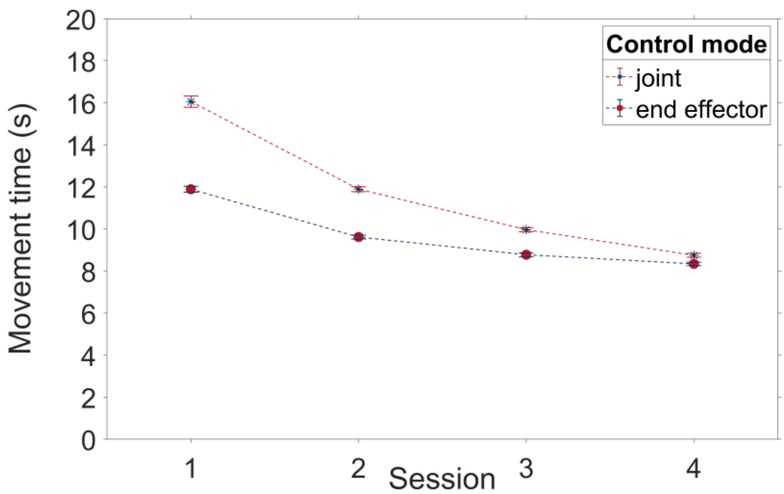


Figure 15. Movement time in seconds (s) shown for joint (red) and end-effector (blue) control across the four experimental sessions.

In the analysis of the accuracy, the constant error was significantly higher for end-effector (*M* = 3.21 cm, *SD* = 1.91 cm) compared to joint (*M* = 2.60 cm, *SD* = 1.21 cm) control ($F(1, 24) = 5.39$, p = .029, $\omega^2_p = 0.14$). Moreover, the constant error reduced similarly for both control schemes across sessions ($F(1.82,43.74) = 10.38$, $p < .001$, $\omega^2_p = 0.10$). Both joint (*M* = 1.12 cm, *SD* = 0.9 cm) and end-effector (*M* = 1.48 cm, *SD* = 0.74 cm) control did not differ significantly with regards to the variable error (p = .010). However, errors due to variability significantly reduced across sessions ($F(1.49, 35.73) = 13.65$, $p < .001$, $\omega^2_p = 0.16$). The gain in accuracy and the stability of the movements are illustrated in Fig. 16.

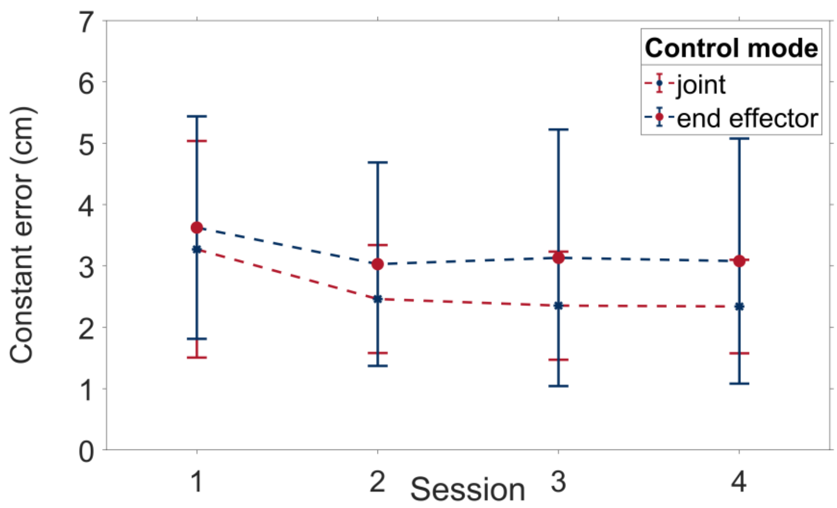


Figure 16. The accuracy of the movement displayed as constant (dots) and variable error (Error bars (SD)) in cm of joint (red) and effector (blue) Control.

6.3.2 Control Skill Analysis

To infer motor learning of control skill, the control inputs to the joysticks and the resulting robotic arm trajectories were assessed. The control inputs, operationalized as count of joystick acceleration segments within a movement, were compared for the control schemes by a 4 (Session) x 2 (Control scheme) ANOVA. Three ANOVAs compared the three joystick axes that are controlled within both control schemes against each other separately (Joint-control: Base Joint, Elbow Joint, Shoulder Joint vs. End-effector control: horizontal depth, vertical). Control inputs were found to decrease across sessions for each joystick axis (BasHorSession: ($F(2.19, 54.79) = 39.68$, $p < .001$, $\omega^2_p = 0.34$); ElbDepSession: ($F(1.60, 40.03) = 33.97$, $p < .001$, $\omega^2_p = 0.37$); ShoVertSession: ($F(1.82, 53.90) = 45.38$, $p < .001$, ω^2_p = 0.23). A difference with respect to control inputs was solely found for the front-back deflection of the left joystick that controls the Elbow joint and depth, respectively. Here, the end-effector control (*M* =

4.29 segments, *SD* = 0.74 segments) showed more inputs than the joint-control (*M* = 3.62 segments, *SD* = 1.54 segments).

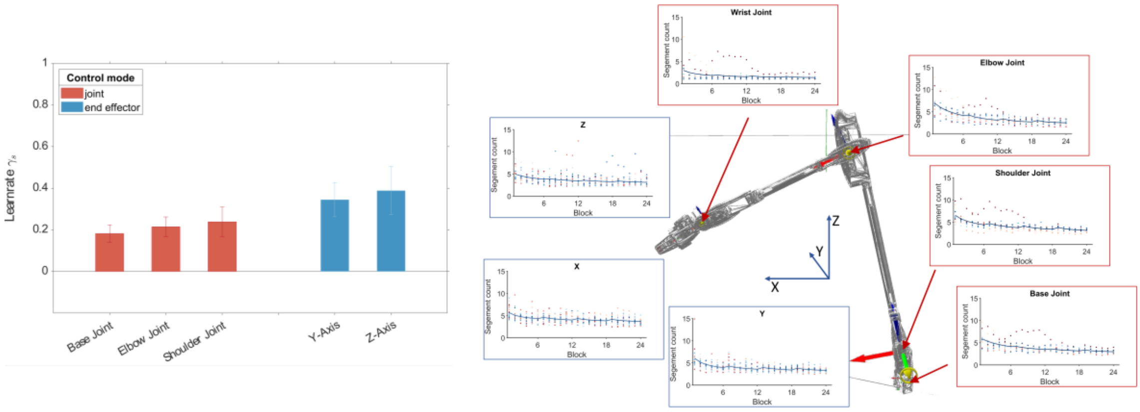
6.3.2.1 Learning Evaluation

To further quantify motor learning, the participants' individual learning progress was assessed by the learning rate via fitting the two time scales power law of learning [18] to the control inputs. (see Section II.E and Fig. 17).

Only parameters of models with a positive r^2 fit were included. The Wrist joint data from the joint-control and the X-direction data from end-effector control were therefore excluded from the analysis. Apparently, learning of these joints/movement directions do not follow the two time scales power law of learning. For the remaining joints (Base, Elbow, Shoulder) and controlled dimensions (Y, Z), the learning rate was assessed. The learning rate $-\gamma_s$ for the axes controlling the lateral movement (Base) with joint-control was lower than the horizontal movement with end-effector control (End-effector $M_{\gamma s}$ = 0.35; Joint $M_{\gamma s}$ = 0.18). A substantial difference was also found for the right joystick axes controlling the upper arm (Shoulder) with joint ($M_{\gamma s}$ = 0.24) and the vertical movement with end-effector ($M_{\gamma s}$ = 0.39) control. Thus, the learning is faster for all included controlled joystick axes with end-effector than with joint-control. In Fig. 17 the average slow learning rates and learning curves are shown.

Furthermore, short-lived effects on skill learning showed that the uptake of the lateral/slewing (Y, Base) showed lower learning rates for end-effector control compared to joint-control (End-effector: $M_{\gamma j}$ = 0.24, Joint: $M_{\gamma i}$ = 0. 29). The raising and lowering (Z, Shoulder) of the robotic arm showed a lower learning rate for end-effector control compared to joint control (End-effector $M_{\gamma s}$ = 0.18; Joint $M_{\gamma s}$ = 0.44). The plateau of the learning function is conceived as required input for trained movements. The inputs were found to plateau at *M* = 1.77, for lateral movements with end-effector control whereas at *M* = 1.45 for slewing movements with joint-control. The vertical and lifting movement (Z, Shoulder) shows for end-effector control a plateau at *M* = 0.95 and *M* = 1.71 for joint-control, respectively.

To summarize, the slow learning rates are higher for end-effector control compared to joint-control for included joystick axes. The fast-learning rates are lower for end-effector than for joint-control and learning curves had low fits for the Wrist Joint in joint- and the X-direction (depth) with end-effector-control.



(a) Learning rates (b) Fitted learning curves

Figure 17. Skill learning rates displayed for the different joints in joint-control (red) and for the different 3D directions of end-effector control blue (a). In (b) the averaged fitted learning curve is shown in blue. Dots represent average segment counts per block coloured for each participant. *Note that the Wrist joint and the X direction showed low model fits and were not included in the analysis.

6.3.2.2 Trajectory Analysis

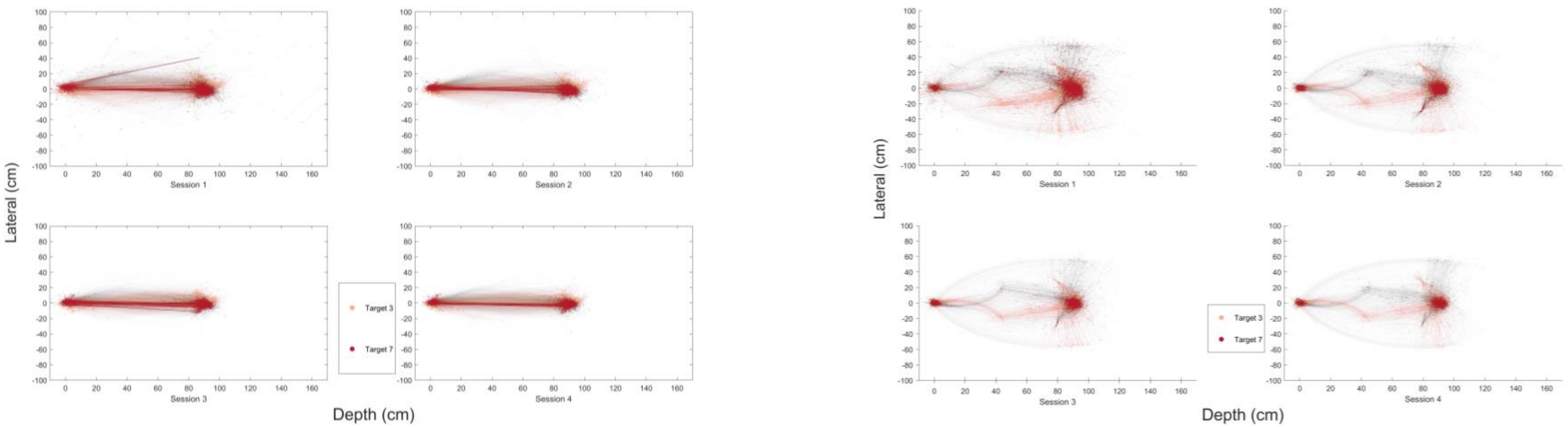
Control skill is reflected in the resulting trajectory of the robotic arm. To evaluate the trajectories, the trajectory length, the lateral and vertical expanse, and smoothness were compared. The analyses showed substantially shorter trajectories with end-effector control (M = 137.16 cm, SD = 52.73 cm) than with joint-control (M = 217.81 cm, SD = 94.03 cm) ($F(1, 25) = 76.34$, $p < .001$, $\omega^2_p = 0.74$). This manifest difference reduces with completed sessions but remains considerably large ($F(1.25, 31.21) = 15.09$, $p = .009$, $\omega^2_p = 0.06$).

6.3.2.3 Lateral and Vertical Displacement

The lateral and vertical components of the control trajectory were analyzed separately to detail how different control schemes influenced control quality. For this, the trajectories were rotated within cartesian space for each target pair, so that the target centres were located on the X-axis (depth) and the movement start on the origin of the coordinate system. The rotation made it possible to compare the lateral displacement as well as the vertical displacement of the trajectories.

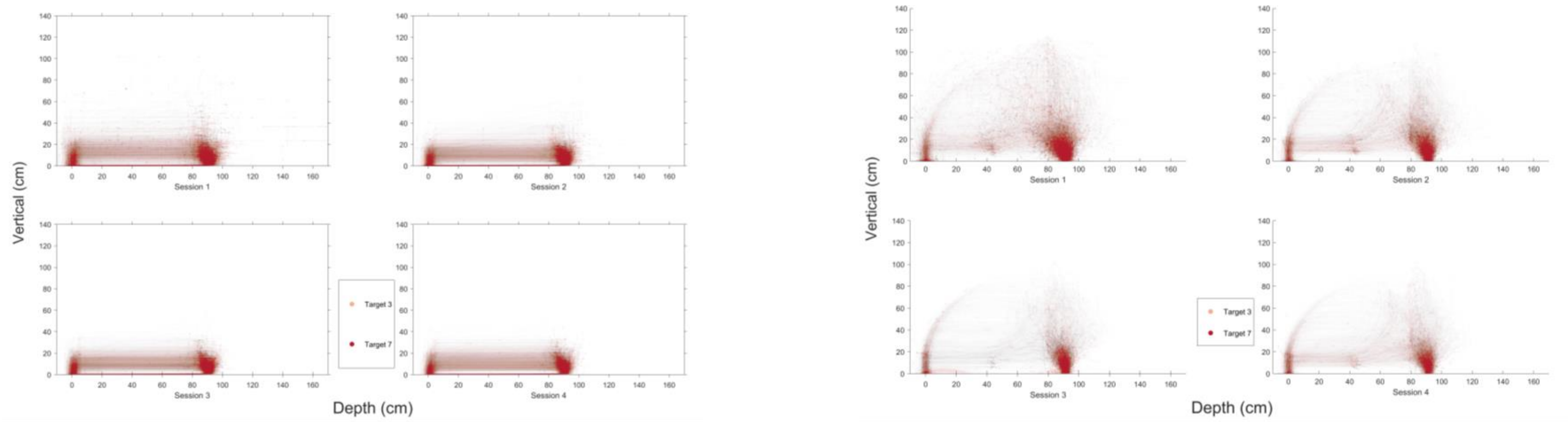
The lateral displacement was assessed by the root mean square deviation (RMSE) from the X-axis. The movements are visualized in Fig. 18 for each session separately. Each line represents a single movement. From session one to four, the movement ellipse grew narrower for both end-effector and joint-control (cf. Fig. 18b). Additionally, random movements that scattered around the trajectories were significantly reduced across sessions ($F(1.96, 48.92) = 27.52$, $p < .001$, $\omega^2_p = 0.17$). However, the end-effector control's lateral displacement was significantly lower than lateral displacement with joint-control ($F(1, 25) = 198.17$, $p < .001$, $\omega^2_p = 0.88$). This relation appeared stable across sessions ($F(1.96, 48.92) = 0.4$, $p = .665$, $\omega^2_p = 0$).

The vertical displacement of the end-effectors' trajectory was constant across the four training sessions for end-effector and joint-control ($F(1.78, 44.51) = 4.92$, $p = .014$, $\omega^2_p = 0.02$). The trajectory height with joint-control was significantly higher than with end-effector control ($F(1, 25) = 35.40$, $p < .001$, $\omega^2_p = 0.56$). Trends of vertical displacement did not significantly differ between both control schemes (interaction effect $p > .05$). Fig. 18 and Fig. 19 show that the trajectories of the two control schemes are fundamentally different. Movement trajectories with joint-control resembled roughly a semicircle while, in contrast, the end-effector control movement observed an inverted U-shape.



(a) End-effector control (b) Joint-control

Figure 18. Displayed are the accumulated trajectories, rotated in the X-plane. Shown is the lateral displacement of each trajectory for the mirrored targets 3 and 7. Target 7 is shaded red and target 3 light orange. More intense colours represent more movement trajectories.



(a) End-effector control (b) Joint-control

Figure 19. Displayed are the accumulated trajectories, rotated in the X-plane. Shown is the vertical height of each trajectory of the mirrored targets 3 and 7. Target 7 is shaded red and target 3 is shaded light orange. More intense colours represent more movement trajectories.

6.3.2.3.1 *Movement Smoothness*

Smoothness serves as an indicator for skill development and can reveal movement characteristics induced by learning patterns of the two control schemes. Smoothness was calculated as SPARC for the robotic arm trajectories. The averaged SPARC data was submitted to a 4 (Session) x 2 (Control scheme) ANOVA. The analysis revealed that the SPARC significantly increased from session one to session four ($F(1, 25) = 71.75$, $p < .001$, $\omega^2_p = 0.26$; cf. Fig. 20). Thus, smoothness improvement is greater for joint-control than for end-effector control $F(1.93, 48.23) = 15.20$, $p < .001$, $\omega^2_p = 0.07$. However, the trajectories are significantly smoother from session one onwards with end-effector compared to joint-control ($F(1.96, 49.02) = 7.30$, $p = .012$, $\omega^2_p = 0.19$; see Fig. 20).

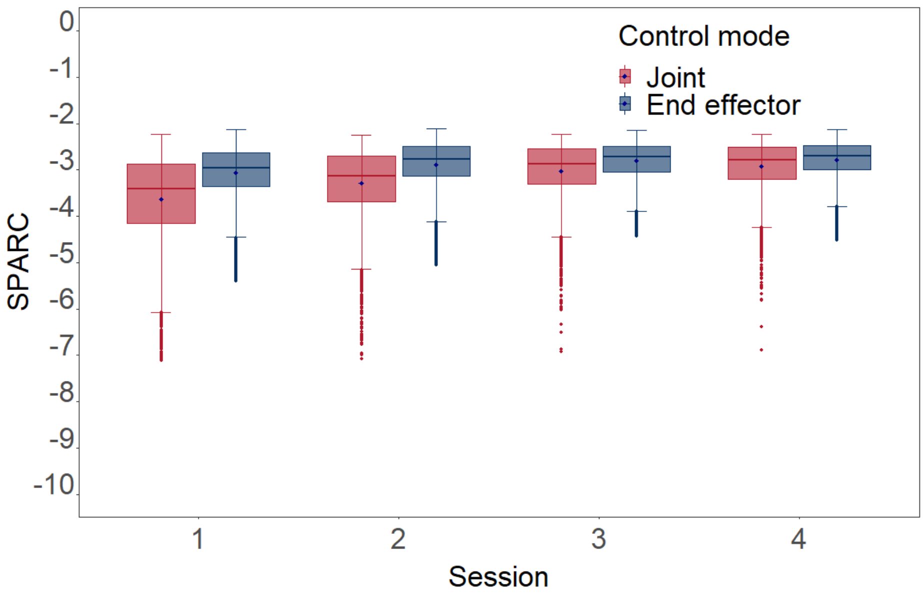


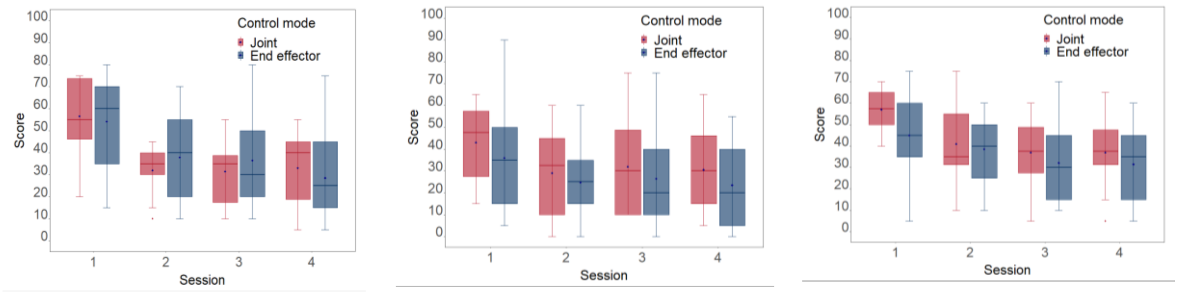
Figure 20. Trajectory smoothness assessed by SPARC of the robotic arm with end-effector (blue) and joint-control (red).

6.3.3 Subjective Measures

The perceived cognitive demand and effort of the participants while learning was assessed by two subjective measures. The NASA TLX that served as overall assessment of the perceived workload and the Rating Scale Mental Effort (RSME) to monitor the development of the perceived mental effort throughout the sessions.

6.3.3.1 NASA TLX

Each scale of the NASA TLX was compared with a 4 (Session) x 2 (Control scheme) ANOVA. The subjective Mental Demand ($F(2.18, 54.59) = 13.53$, $p < .001$, $\omega^2_p = 0.19$), Effort ($F(2.32, 58.01) = 8.96$, p <.001, $\omega^2_p = 0.12$), and Frustration ($F(2.32, 58.01) = 5.78$, $p = .005$, $\omega^2_p = 0.05$) declined significantly with completed experimental sessions for both control schemes. Fig. 21a shows the decline of Mental Demand and Fig. 21b of Frustration that is pronounced from session one to session two. In contrast, perceived Effort declines more gradually (see Fig. 21c). Comparing the control schemes did not reveal any significant differences of all NASA TLX scales (p > .05). In general, the means ranged between 30 (TD, PD) and 50 (PF, MD, ER, FR).



(a) Mental Demand *(b) Frustration* *(c) Effort*

Figure 21. NASA TLX Mental Demand (a), Frustration (b), Effort (c), rating for joint- (red) and end-effector (blue) control scheme of session one to four.

6.3.3.2 RSME

The RSME ratings within block three (1) and six (2) were submitted to a 2(Measurement time) x 2(Control scheme) x 4(Session) ANOVA and found that the ratings change significantly from session one to four (F(1.55, 38.80) = 23.65, p < .001, ω^2_p = 0.09). The ANOVA further revealed an interaction of the measurement time with the control scheme (F(1, 25) = 4.85, p = .037, ω^2_p = 0.04). Mental effort increased for the joint- and declined for the end-effector control throughout a session (cf. Fig. 22). Overall, the mental effort required is low. To examine changes in mental effort from session one to four, these sessions were compared using a post-hoc t-test. Both groups were novices in the first session and were treated as trained operators in the fourth session. The analysis showed that the invested mental effort is similar between control schemes within the first session (t(26.4) = 1.18, p = . 0.248). In contrast, the cognitive effort declined more with end-effector control compared to joint-control within the fourth session (t(33) = 2.18, p =.039).

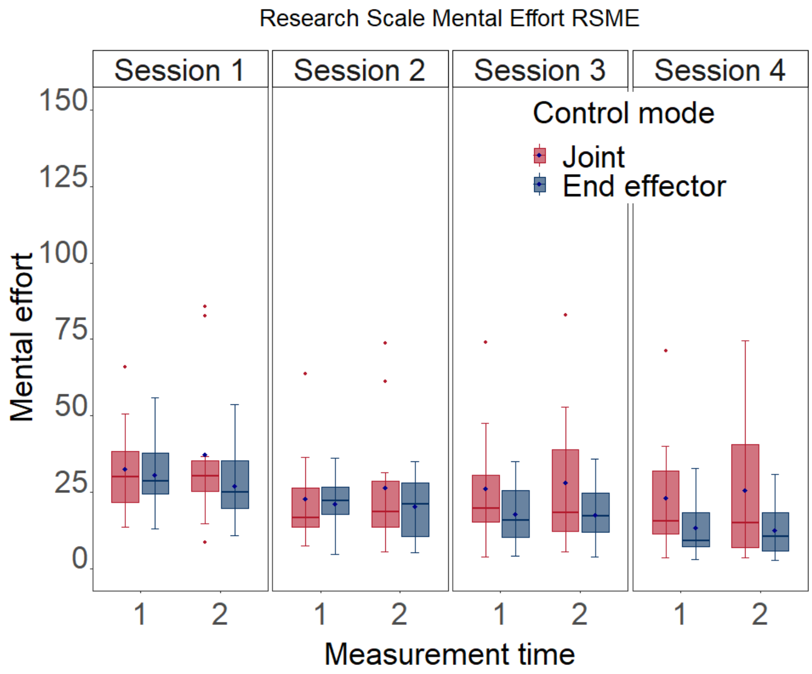


Figure 22. Mental effort rating of joint- (red) and end-effector control scheme (blue) at Measurement time 1 (half the session) and two (at the end of the session) for each of the four sessions.

6.4 Discussion

This study compared learning bimanual rate-based control of a robot arm with either a joint- or end-effector control scheme. Given [13], [14], [30], we expected the end-effector control to result in better control performance. However, of particular interest was the quality assessment of the robotic arm movements assessing accuracy, smoothness, movement trajectories and the control skill development. Furthermore, the subjective cognitive load across and within training sessions was analyzed.

Consistent with previous studies, this study also shows better performance (i.e., faster movement) with end-effector control (cf. [13], [14], [30]). Interestingly, the movement times for both control schemes converged in the last session. This means that previously reported advantages of end-effector control for faster movement times are likely to have reflected the earlier stages of learning. In the current study, these movement time advantages of end-effector control are no longer apparent after three training sessions. This result corresponds with a similar non-significant trend found in [11]. Like [11], end-effector control resulted in more efficient trajectories that were significantly shorter in the current study. In addition, the findings provide details to show that these short trajectories were achieved by following a more direct line from one target circle to the other. The reduced lateral and, especially, the vertical displacement of the trajectory led to the observed gain in efficiency (see Fig. 6

and 7); the vertical displacement was a straight uniform movement. This movement can be implemented with end-effector control through a single joystick input. Smooth uniform movement also implies fewer control errors during learning, which is associated with better motor performance [31]. Furthermore, the analysis of the movement smoothness showed that end-effector trajectories are smooth from the beginning, whereas joint-control learning is characterized by jerky movements in the early sessions.

The short movement times in sessions one and two with end-effector control are reflected in their higher skill learning rates, when compared to joint-control learning. Participants quickly learnt the control mapping, as shown by the movement times in these early sessions, which corroborate the findings on movement times and productivity in [14] and on control inputs in [11]. This study extends previous findings by using joystick inputs to model non-linear learning curves of skill development. Based on the learning curves, the current study was able to show that forgetting and motor adaptation are significantly reduced with end-effector compared to joint-control within, and between, training sessions. These can be important drivers of the efficiency gains noted in this and previous studies.

The analysis of control inputs led to an unexpected result as for both control schemes, namely a similar count of control inputs between them. This contrasts with [16] that reported fewer control inputs with end-effector control but did not differentiate between joystick axes. In particular, the analysis showed that there was an increase of dedicated inputs of the joystick axis, which controls the forward-backward movement of the end-effector, compared to joint-control. This suggests that end-effector control requires a qualitatively different control strategy. The back-and-forth movements of the robotic arm are generated by a single axis control in end-effector control. Conversely, at least one, but in most cases two, involved joints are required with joint-control, so control inputs may have been divided across axes.

In accordance with [8]–[10], movement variability decreased and stabilised with learning. However, end-effector control movements were less accurate than joint-control from the start. This suggests that end-effector control favour a control strategy that emphasizes speed over accuracy. This possibility has not been reported, given the previous emphasis on productivity measures such as moved soil or logs of the applied studies of [11]–[14]. This could not be explained in the detailed trajectory analyses. Follow-up studies are necessary to clarify this contradiction. Overall, this finding serves as a caution against using single metrics to compare the performance for tasks that involve aiming movements that are subject to speed-accuracy trade-offs.

Learning the control schemes affected the involvement of cognitive resources. In accordance with studies on human movement [7], [20], this study found that Frustration, Mental Demand, and Effort assessed with the NASA-TLX as well as Mental Effort assessed with the RSME, decreased over time with both control schemes. As expected, performance and skill gains were associated with reduced cognitive demand and effort. Mental relief was greatest from session one to session two. Strikingly, the perceived mental effort increased towards the end of the sessions for joint-control, whereas it remained stable for end-effector control. This may be an effect of cognitive depletion or fatigue [32]. Thus, achieving and maintaining comparable performance requires more cognitive investment with joint-control than with end-effector control. The above discussed lack of accuracy with end-effector control may also be explained by the results of the cognitive workload analysis. Similar effects on levels of automation can be explained by the malleable resources theory [32]. Here, the reduction in mental workload reduces the overall attentional capacity to focus on task performance.

Finally, a simulated environment provides constant reproducible conditions for all participants, which cannot be achieved in field testing. Nonetheless, it cannot provide all task-relevant information, e.g., binocular depth cues or work task requirements. Careful testing is required to ensure that end-effector control will deliver similar results in the real world. Generally, our results suggest that accuracy could be improved via support system design or specific training. Here, the focus should also be on managing the cognitive load of operators that learn joint-control. In contrast, operators using end-effector control may have to cope with underload conditions at work and can be provided with additional work task information in early phases of training.

6.5 Conclusion

End-effector control of robotic arms eases operator learning and provides significant benefits to control performance, by enabling operators to achieve efficient trajectories. Accurate control remains a challenge with both control schemes for newly trained operators. Future work should focus on aiding precision further to increase skilled performance. A major challenge will be to achieve high performance with reduced operator load. New ways of training top-level performance will be required to leverage the cognitive resources, which are newly available given novel control schemes, to mitigate potential disadvantages of cognitive underload.

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Chapter 7
Evaluation of different feedback designs for target guidance in human controlled robotic cranes: a comparison between high and low performance groups

Labour shortages and costly operator training are driving the need for digital on-board robotic crane operator support in forestry and construction. This simulator study aimed to investigate the effects of concurrent auditory (pitch/loudness) and visual (brightness/size) feedback to support aiming movements with a robotic crane. The feedback was designed non-linear and linear. Thirty-six participants completed ten blocks of 32 movements of the robotic crane, bimanually controlled by joysticks, including a block for initial performance assessment. Movement time, accuracy, trajectory, and smoothness were measured as indicators of performance and skill as well as acceptance in terms of usefulness and satisfaction. After training, auditory compared to visual feedback resulted for low performers in higher movement accuracy. Especially non-linear pitch feedback showed accuracy benefits for this group. No significant performance improvement was found for high performers movement time, accuracy, and smoothness. There was no effect of linear or non-linear mapping of the feedback. Perceived satisfaction was generally higher with auditory feedback than with visual feedback, and satisfaction was rated higher by low performers than perceived usefulness. The results suggest that real-time support by auditory feedback can increase operator accuracy. Adequately designed auditory feedback generally outperforms visual feedback and seems to have high potential for skilled and unskilled operators.

This chapter is an edited version of the following paper:

Dreger, F.A., & Rinkenauer, G. (Under Review). Evaluation of different feedback designs for target guidance in human controlled robotic cranes: a comparison between high and low performance groups. *Applied Ergonomics,* 2023.

7.1 Introduction

Costly machine operator training and labour shortages are driving the forestry and construction industries to improve machine operator performance through digital operator support. The goal to raise productivity requires the development of effective support systems that can be used on-board of machines during operation. Crucial to operator performance is the ability to bimanually control a robotic crane, which determines the productivity and safety of operations in the forestry and construction industries (Purfürst, 2010). Even experienced operators show large productivity differences (Ovaskainen et al., 2004, 2011), much of which can be attributed to poor robotic crane control (Hartsch et al., 2022). Reduced training needs could already be achieved by introducing technical support via direct crane tip control (also referred to as end-effector control) (Manner et al., 2017). End-effector control allows the operator to directly control the movement of the tip of the robotic crane, rather than controlling each joint separately. However, joint-based control systems are still on the market and will continue to be for some time to come. Regardless of the type of control system, studies show that the achievable movement accuracy is a challenge for all systems (Dreger, Rinkenauer, et al., 2023). Therefore, the aim of this study is to investigate the extent to which the accuracy of robotic crane control can be improved through enhanced sensory operator feedback.

7.1.1 Forms of Feedback

Since bimanual robotic crane control is largely a motor control task, feedback must be suitable for improving human movement capabilities. There are two types of information that humans use as feedback to refine motor movement. First, information from inherent feedback that is accessible to the performer by perceiving the environment and proprioception. Second, information from augmented feedback that is not generally available to the performer or is difficult to access (Schmidt et al., 2019). The augmented feedback can be in the form of knowledge of results (KR), which is the information about the movement outcome after the movement, or in the form of knowledge of performance (KP), which is information about the movement characteristics. Both types of information can be of help to the performer to improve motor movement (Keogh & Hume, 2012; Magill & Anderson, 2017; Oppici et al., 2021; Schmidt et al., 2019; Sharma et al., 2016; Zhu et al., 2020).

7.1.1.1 Concurrent Movement Feedback

Concurrent feedback combines KP and KR and is provided continuously throughout the supported movement. Feedback can be given by experienced operators and trainers or via digital support. Concurrent feedback can be provided as information on the whole movement or a specific part of the movement to be improved. Concurrent movement feedback was found to be especially helpful, to support learning of complex movements (Wulf et al., 1999). Particularly, in early learning stages, movement execution with concurrent feedback was improved (Wulf et al., 1998). Even in virtual environments, concurrent feedback could outperform real-task training and coaching for example in table tennis (Todorov et al., 1997). The feedback of KP and KR is more effective when it leads to an external rather than an internal focus of attention (Shea & Wulf, 1999). In robotic crane control, the position of the end-effector attracts the external focus of the operator's attention in movement control (Häggström et al., 2015), therefore, providing information on the end-effector appears useful. In addition, the usefulness of concurrent feedback is closely related to the complexity of the task and the skill level. Complex tasks and low skill levels can benefit more from concurrent feedback than vice versa (Wulf et al., 1998). Auditory feedback has been shown to be particularly suitable for complex 3D movements such as rowing (see Effenberg et al., 2011) and was effective in early stages of skill acquisition. Conversely, proficient performers can be distracted from concurrent feedback (Wulf et al., 1998). Robotic crane control requires learning complex bimanual hand movements, especially the transformation from joystick input to robotic crane movement needs to be mastered. Therefore, concurrent feedback may be of help to improve the performance of robotic crane control.

7.1.1.2 Visual Movement Feedback

Concurrent feedback was often provided visually via displays and improved rowing movements using symbolic oar and blade representations (Sigrist et al., 2011, 2013). In robotic crane control, visual concurrent feedback has yet not been investigated. It is worth noting that in robotic crane control, visual feedback must be carefully designed. This is because the control task is already predominantly visual. Providing feedback through the same modality can therefore overload the visual system since the same cognitive resources are claimed (Wickens, 2002). One way to reduce the visual load of presentation is to use augmented reality (AR) displays, which overlay the real world and thus allow feedback to be presented in the visual field in such a way that it is only slightly distracting. This is also referred to as contact analogue presentation, which showed benefits over conventional information presentation in, e.g., controlling robotic cranes or driving cars (Ding et al., 2022; Eriksson et al., 2019).

7.1.1.3 Auditory Movement Feedback

Typically, auditory feedback for motor behaviour was used in the form of alarms that alerted to indicate deviations from the correct movements such as in dance and gymnastics (Baudry et al., 2006; Clarkson et al., 1986). Auditory feedback on the hand position in swimming has been shown to improve crawling technique (Chollet et al., 1988). More complex concurrent auditory feedback effectively improved dancing, rowing, and cycling performance (Effenberg et al., 2016; O'Brien et al., 2020; Sigrist et al., 2016; Sigrist, Roland et al., 2011). The feedback was used to provide information on a single movement element but also on the whole movement (Effenberg et al., 2016). A special type of concurrent auditory feedback is sonification. Sonification as concurrent feedback sets sound for movement variables such as spatial position or dynamics of certain limbs during movement, e.g. paddle forces in cycling, or of variables external to the human body such as oar position in rowing (Effenberg, 2005; Vidal et al., 2020). To use the information provided by sonification, a certain amount of movement representation/training must already be present (Sigrist et al., 2013). Sonification uses sound properties such as timbre, stereo balance, volume, and pitch to provide concurrent feedback. These auditory properties can be mapped to different movement variables at a time to create a combined sound pattern. In particular, stereo balance and pitch feedback were useful to support optimal rowing performance (Sigrist et al., 2011).

In conclusion concurrent auditory and visual feedback can benefit the execution and learning of motor tasks (Sigrist et al., 2013). Both visual and auditory feedback are helpful, specifically for low performers and when more complex skills are required, which according to Wulf & Shea, (2002) involve the control of multiple degrees of freedom and have an ecological application. As bimanual control of robotic cranes is considered complex, concurrent feedback is assumed to be useful to support operators. Nonetheless, studies on sonification as accompanying feedback for dynamics or task errors are rare in sports science and even rarer in human factors.

7.1.2 Feedback in Robotic Crane Control

Auditory feedback has already been applied in robotic crane control. A study with sounds of different discretised frequencies showed shorter movement times in the feedback condition (Mavridis et al., 2015). The movements were conducted with a 2D stick figure manipulator visualised on a notebook controlled with two joysticks.

Visual concurrent feedback in augmented reality (AR) was used to improve the performance of a hydraulic robotic crane. AR aided the operator in overcoming control shortcomings introduced by the asymmetric workspace mapping of master (joystick deflection) and slave (crane movement) of a hydraulic manipulator (Ding et al., 2022). Improvements were found in terms of task completion time, where kettle bells placed on barrels were lifted and moved from one barrel to another.

To make use of auditory and visual feedback in training and support systems, the design of feedback during the movement, the timing of feedback, and auditory and visual properties such as pitch and shape of feedback remain to be investigated. Both auditory feedback and visual AR feedback appear suitable to support robotic crane operators. Therefore, it seems worthwhile further investigating the effectiveness of designing different auditory and visual feedback when operating robotic cranes.

7.1.3 Aim of the Study

The aim of this study was to analyse the effectiveness of concurrent auditory and visual feedback to enhance robotic crane movement precision and to evaluate the cognitive load, acceptance, and usefulness of the feedback. Additionally, the effects of feedback on movement time and skill of robotic crane movements should be assessed. Feedback for both modalities was designed to follow a non-linear or linear dependence on target distance. The non-linear feedback amplified movement changes the closer the robotic crane tip got to the target. Previous research suggests that auditory feedback is superior to visual feedback (Mavridis et al., 2015; Wickens, 2002), and non-linear feedback is superior to linear feedback. Both are hypothesised to be more effective for low than for high performers in robotic crane control (Wulf et al., 1998).

7.2 Method

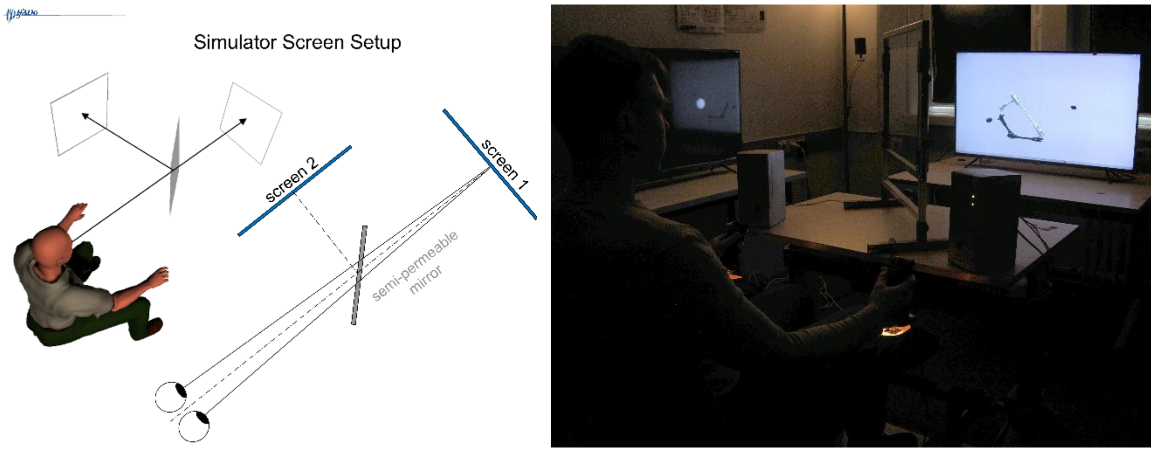
7.2.1 Participants

Thirty-six participants (male = 20, female = 16) novice to the task of controlling a robotic arm, right-handed (self-reported), with normal or corrected to normal vision (stereoscopic vision test, Walraven, 1972) and self-reported normal hearing ability consented to participate in the study. Participants were recruited students and employees from the Technical University Dortmund and were between 18 and 35 years old (M = 24.19 years; SD = 4.31 years).

7.2.2 Simulator

The simulator was a fixed-base robotic crane simulator consisting of a Chicago truck seat and two joysticks. Two Xiao Mii 55-inch TV screens combined with a semi-permeable mirror and two speakers provided the visual and auditory environment. The simulator setup is shown in Figure 23. The screens were placed at 90° angle to each other, with one screen in front of the participant and the other on the left side. In between the front screen and the participant was the semi-permeable mirror placed at 45° to the line of sight of the participant. The participant could see information on the front screen and information from the left screen mirrored in the semi-permeable mirror (see Figure 23a). The robotic crane had 4 degrees of freedom (DoF) and was velocity controlled via the joints that mapped to the joysticks. The exact mapping is shown in Figure 24. The simulator was running on Ubuntu version

20.04. The visualisation of the robotic crane ("Robotis Open Manipulator"; ROBOTIS Inc., Korea) was rendered using GAZEBO. The experimental control was implemented in C++ and Python 3. The visual feedback was rendered using RViz and concurrent auditory feedback was created with PureData. All software communicated via ROS noetic.



(a) (b)

Figure 23. Schematic drawing (a) of the simulator setup with screen 2 displaying the feedback and the semi permeable mirror bringing the feedback in the field of view of the participants directed to the main front screen 1. The used simulator setup (b).

The simulation showed the robotic crane from a bird's-eye view on a gridded floor and a white background (cf. Figure 25). Movement targets were pairs of flat circles laid out on the ground with a diameter of d = 0.1 m. The circles determined movement start and end. Four targets indicated the start of movement on the left side by blue colour. The same targets, mirrored, indicated the start of movement on the right side in purple colour (cf. Dreger et al., 2023). Eight different pairs of circles were presented and thus eight different movements were performed using the robotic crane.

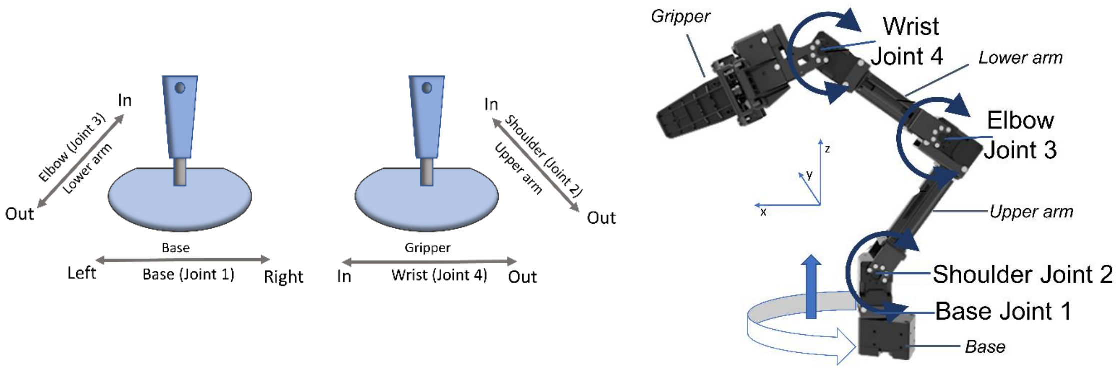


Figure 24. Joysticks with control mapping (left). The arrows indicate the joystick movement direction and the effect on the controlled joint. Robotic crane with movement directions and labels (right) (Figure from Dreger et al., 2023).

Figure 25. Shown are four target pairs that indicated the movement start left (a, blue) and indicating the movement start on the right (b, purple).

7.2.3 Concurrent Movement Feedback Design

Concurrent visual or auditive feedback on the distance to the target was given for the last 66% of the total distance between the two target circles. This part of an aiming movement is deemed the landing or homing in phase after the peak velocity of the movement (Meyer et al., 1988). All resulting mappings of visual and auditory feedback are shown in Figure 26. The starting point of all mappings was a non-linear function to which the corresponding linear mapping was derived.

7.2.3.1 Auditory Feedback

Auditory feedback was provided by either modulating the loudness or the pitch. For this, loudness and pitch were mapped onto the distance of 66% of the total distance between each target pair.

Pitch was modulated by frequency. The predominant frequency was chosen such that the sound was comfortable for the participants by using three overtones and at the same time had a mostly flat isophone loudness contour for the given frequency range. The frequency range was 180 Hz to 246.67 Hz, which was mapped onto the distance to the target. Loudness was manipulated by sound pressure level expressed in dB. For this, the range from 46.67 to 60 dB was mapped on the distance to the target. The pitch of loudness increased with closing in the target centre. Both loudness and pitch were mapped linearly and non-linearly. The non-linearity was aimed to be in line with human perception (cf. sound intensity).

7.2.3.1.1 *Loudness*

For the loudness feedback, the distance information of the end-effector to the target was simulated as the approach to a spherical sound source. The sound intensity was set to be 60 dB at the cranes end-effector distance to the target *r* = 0. The change in sound intensity as a function of distance was simulated according to the inverse square law $I(r) \propto \frac{1}{r^2}$. The sound pressure level was calculated as the logarithmized ratio of the sound intensity with a reference sound source I_0. The reference sound intensity is usually assumed to be $I_0 = 10^{-12}\ W/m^2$ (*W* = Watt) (Weinzierl, 2008). This results in the sound intensity level as a function of distance (see also Weinzierl, 2008) with:

Sound Intensity Level: $$L_I(r) = 10\log_{10}\frac{I(r)}{I_0} \quad (1)$$

The design of the feedback mapping was then implemented in the experiment in such a way that the loudness within the feedback range decreased from 60 dB to 46.7 dB as the distance to the target *r* increases. The nonlinear behaviour was determined by equation (2) and the linear behaviour by equation (3). Both functions are shown comparatively in Figure 26.

Non-linear mapping: $$Sound\ Intensity\ Level(r) = 40 + (20 \cdot \frac{L_I(r)}{60}) \quad (2)$$

Linear mapping: $$Sound\ pressure\ Level\ (r) = 60 - \mathrm{r} \cdot 13.33 \quad (3)$$

7.2.3.1.2 *Pitch*

For pitch feedback, an analogous scenario to loudness was used for distance information. Therefore, the same nonlinear function (see Eq. 1) was used to map frequency (in Hz) to distance (*F*(*r*)) in the range from 246.7 Hz to 180 Hz. That is, the pitch decreases as the distance r increases. The mapping is determined by equations (4) for the non-linear and equation (5) for the linear behaviour of the pitch feedback (see also Figure 26)

Non-linear mapping: $$Frequency(r) = 146.67 + (100 \cdot \frac{F(r)}{60}) \quad (4)$$

Linear mapping: $$Frequency(r) = 180 + (1 - r) * 66.67 \quad (5)$$

7.2.3.2 Visual Feedback

Visual feedback was provided in the visually attended region, which means that the visual feedback was always close to the end-effector of the robotic crane and followed the movement. Either the brightness of one grey circle or the size of two grey circles was mapped. Both brightness and size were mapped to 66% of the total distance for each target. Examples of the visual feedback are shown in Figure 27.

7.2.3.2.1 *Size*

Size refers to an expansion of a grey circle that was nested within another circle of fixed size (*d* = *π*). With approaching the target, the inner grey circle increased in size until both circles matched. A complete match occurred when the end effector was in the target centre. The expansion of the inner circle was mapped either non-linearly (eq. 6) or linearly (eq. 7). The non-linear mapping was modelled on the change in visual angle (in rad), analogous to the change in retinal size as a person approaches an object.

Non-Linear mapping:
$$Size_{Visual\ Angle}(r) \ = 2 * \text{atan}\left(\frac{0.1}{2 * \text{r}}\right) \tag{6}$$

Linear mapping:
$$Size(r) \ = 0.09 + (\pi - 0.09) * (1 - r) \tag{7}$$

7.2.3.2.2 *Brightness*

To manipulate brightness with the RViz software, the alpha value (range 0-1) of the grey circle was scaled. Humans are more sensitive to decreases in brightness than increases, therefore, the brightness was mapped to decrease as the target was approached until it disappeared when the end-effector was in the centre of the target. Stevens' power law (Marks & Stevens, 1966) was used to map brightness non-linearly to reflect human perception of brightness (eq. 8, see Figure 26).

Non-linear mapping:
$$Brightness(r) = (r * 0.1)^{0.33} \tag{8}$$

The linear mapping of brightness used a threshold constant to ensure that the circle disappeared when the end-effector was at the centre of the target, not earlier. This threshold is simulator dependent and was 0.37 in the current study. The linear mapping was implemented as described in equation nine.

Linear mapping:
$$Brightness(r) = \ \text{Threshold} * (1 - r) \tag{9}$$

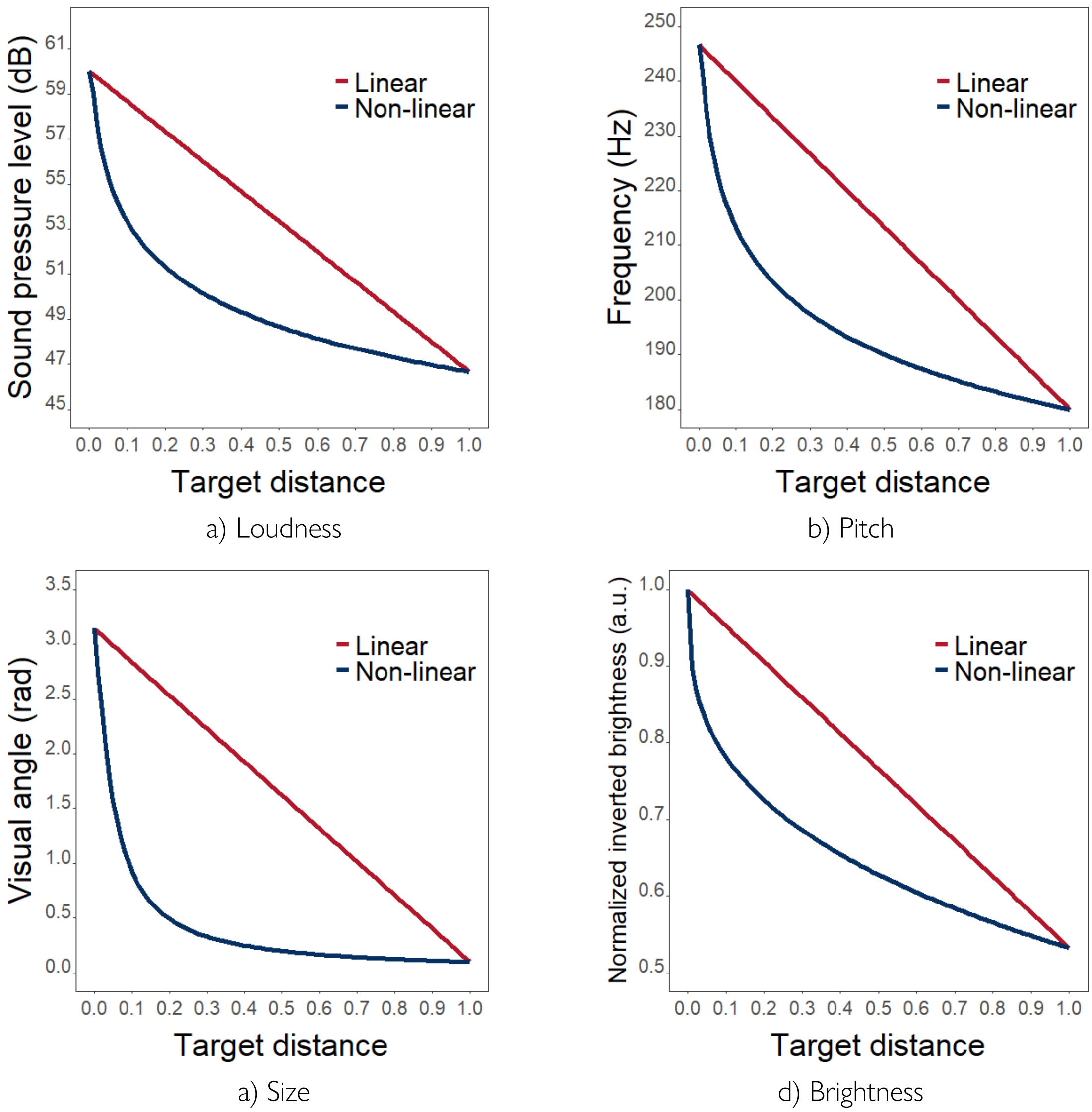
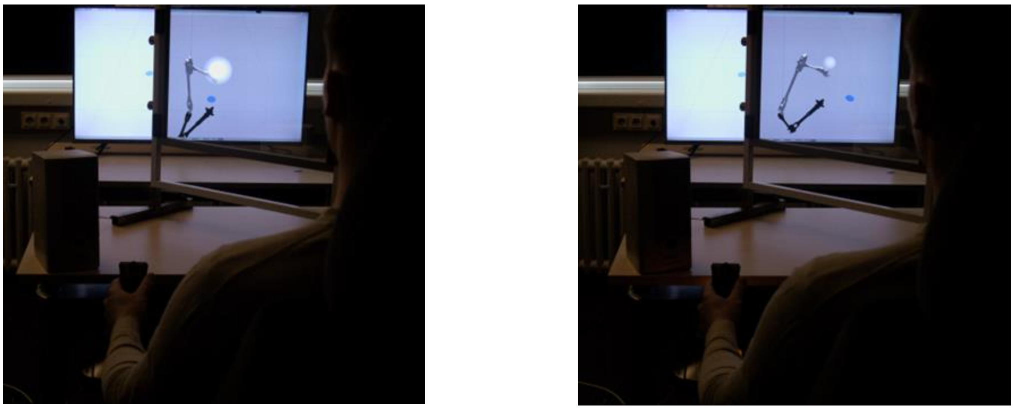


Figure 26. Auditory and visual linear and non-linear feedback design of a) loudness, b) pitch, c) size, and d) brightness. The target distance is the distance at which feedback is present, which is 66% of the total distance between the targets. The curves show the change of feedback while approaching the target centre. *Note. Brightness is inverted for better comparability.



(a) Size (b) Brightness

Figure 27. Example of the visual feedback designs as implemented in the robotic arm simulator showing a) size and b) brightness feedback.

7.2.4 Procedure and Instructional Design

All participants were informed of the purpose of the study, the current corona regulations during the experiment and were given written instructions afterwards. Then, participants went to the simulator where the seat and joystick positions were adapted to their preferences. The experiment started with a short demonstration of two movements with two oversized targets to help memorise the mapping of the joysticks. Then, the actual robotic crane control task started. The first block was always a block without movement feedback for performer group assessment. This was followed by eight feedback and one no feedback block. The sequence of the nine blocks was pre-determined by a Latin square design and thus balanced across all participants to avoid learning effects. Each block consisted of eight targets with four movements each. Thus, each feedback category had 32 movements per participant (320 in total). A short survey was administered after each feedback block. This survey assessed acceptance with the Van der Laan scale and the mental load using the NASA TLX-R. The robotic crane control task was followed by a short demographic survey, after which the laboratory session ended. Overall, the experiment took 3.5 h to complete. The experiment was conducted as a within-subjects design, so that every participant was exposed to each feedback condition.

7.2.4.1 Dependant Variables

7.2.4.1.1 *Objective Measures*

Performance: Control performance was based on objective measures of the robotic crane movement. Movement time, accuracy in terms of constant error (distance to target centre at movement end) and variable error (standard deviation of constant error) were calculated to infer overall performance.

Skill: Skilled movements are characterised by a reduction in variability that should be reflected in the movement smoothness of the robotic crane. As with human movements, smoothness is a general criterion of movement skill. Smoothness was assessed by the spectral arc length of the robotic crane movement (for details see Balasubramanian et al., 2012, 2015). As additional indicator the lateral and vertical deviation of the executed trajectory from a straight line was evaluated using the root mean squared error (RMSE), (cf. Dreger, Rinkenauer, et al., 2023).

7.2.4.1.2 *Self-Report Measures*

Self-report measures were used to evaluate the acceptance, usability, and mental load of the feedback. Acceptance was surveyed using a semantic-differential scale (Van Der Laan et al., 1997) on nine bipolar one-dimensional (e.g., useful-useless) ratings from -2 to 2 with five steps. Mean responses on the usefulness and satisfaction scales were calculated considering reverse phrasing of respective items. The NASA TLX-R was used to infer subjective cognitive load on six dimensions: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration. The NASA TLX was used in the 21-item version, providing task load measures based on 5% increments for each dimension (Hart & Staveland, 1988).

7.2.5 Statistical Analysis

The data pre-processing was carried out with MATLAB 2021a and R version 4.1.1. Performance and skill measures were compared using repeated measures and mixed-effects ANOVA. All statistical tests were conducted using an alpha level of .05.

7.3 Results

Data recording problems of two participants in which not all feedback could be provided required to recruit two additional participants.

The initial training block without feedback was used to classify low and high performers using a median split based on movement time, as low performers and early learning stages benefit from concurrent feedback (Wulf et al., 1998). Movement time in learning robotic crane control has been shown to be emphasised over accuracy and is more relevant for discriminating performance of robotic crane movements (Dreger, Chuang, et al., 2023). The no-feedback condition was excluded due to the training effects of performing the condition twice compared to other feedbacks. To rule out the possibility that the median split affected the balancing of learning effects, chi-squared tests for each feedback were conducted to compare the feedback distribution across the experimental session for low and high performance (see Table 1). All feedbacks were unaffected by learning ($p > .265$).

Table 12. Results of comparing the distribution of low and high performers across the experimental session for each feedback.

N = 36 Low vs. high performer	χ^2	*df*	*p*
Pitch-L	2	8	*.981*
Loud-L	8	8	.434
Pitch-NL	4	8	.434
Loud-NL	6	8	.647
Scale-L	6	8	.647
Scale-NL	8	8	.434
Bright-NL	4	8	.857
Bright-L	10	8	.265

7.3.1 Effects of High and Low Performer Group on Performance

A mixed-effects ANOVA was performed to compare the effect of Performer Group and Feedback on movement time. High performers showed significantly shorter movement times than low performers ($F(1, 32) = 18.98$, $p < .001$, $\eta^2_p = 0.37$). The different types of feedback showed a tendency to be significantly different in terms of movement time ($F(3.65, 116.86) = 2.18$, $p = .081$, $\eta^2_p = 0.04$). No significant interaction effect of Feedback and Performer Group on movement time was found ($p > 0.5$). A further mixed-effects ANOVA was performed to analyse the effect of Performer Group and Feedback on the constant error (accuracy). No main effects of either Performer Group or Feedback were found ($p > .05$). However, the analysis revealed a significant interaction between Performer Group and Feedback on accuracy, which was examined further below ($F(6.01, 192.35) = 2.15$, $p = .05$, $\eta^2_p = 0.06$).

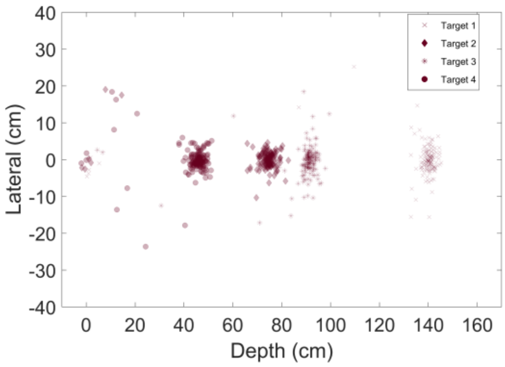
In addition, a mixed-effects ANOVA showed that trajectory smoothness was higher for high ($M = -3.23$, $SD = 0.94$) compared to low ($M = -3.65$, $SD = 1.15$) performers ($F(1, 32) = 8.40$, $p = .007$, $\eta^2_p = 0.21$). Feedback Modality and Linearity did not show significant effects on trajectory smoothness.

7.3.2 Analysis of Performer Group Feedback Interaction

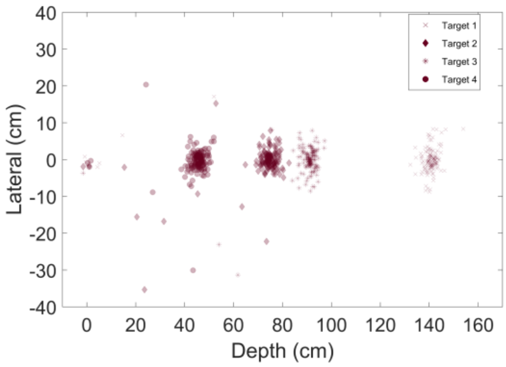
A repeated measures ANOVA revealed no effect of feedback on constant error for high performers ($p > .05$). In contrast, this analysis revealed a significant difference in constant error between the feedback conditions for low performers ($F(4.37, 69.90) = 2.65$, $p = .036$, $\eta^2_p= 0.23$, descriptive statistics in Table 2). Therefore, the following performance and skill analyses will focus on low performers. Tukey adjusted post-hoc pairwise comparisons showed that nonlinear pitch feedback outperformed visual linear size feedback ($p = .022$) (see Figure 5). Furthermore, a tendency was found that non-linear pitch feedback outperformed non-linear size feedback ($p = .056$) and non-linear loudness feedback showed a tendency to outperform visual linear size (p = .095) feedback. Variable error had no effect and therefore performance was constant across all feedbacks. (p > .05).

Table 13. Mean constant error with standard deviations in paratheses (N = 18).

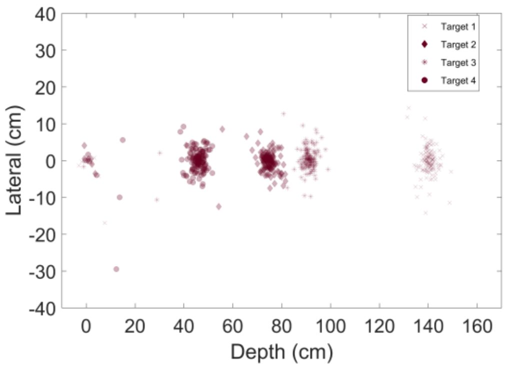
Feedback		Pitch L	Loud L	Pitch NL	Loud NL	Scale L	Scale NL	Bright NL	Bright L
Constant Error	*M* *(SD)*	3.75 (1.46)	3.58 (1.46)	3.34 (1.38)	3.45 (1.38)	4.21 (1.89)	4.09 (1.60)	3.59 (1.53)	3.60 (1.53)



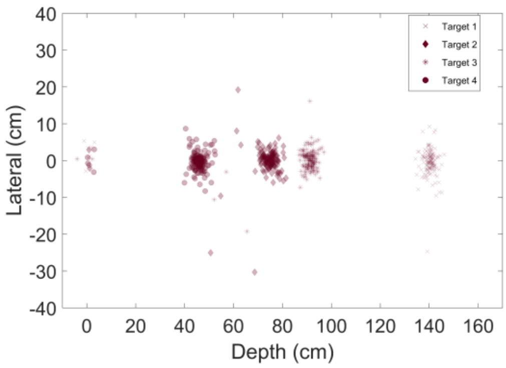
Pitch-L



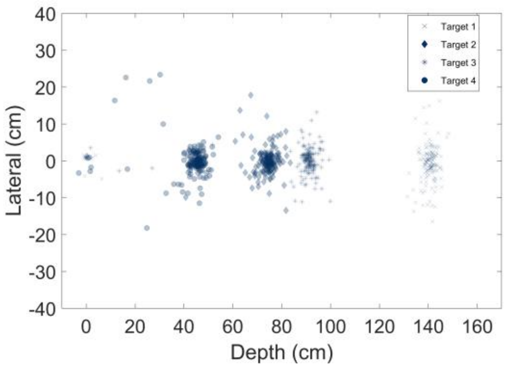
Loud-L



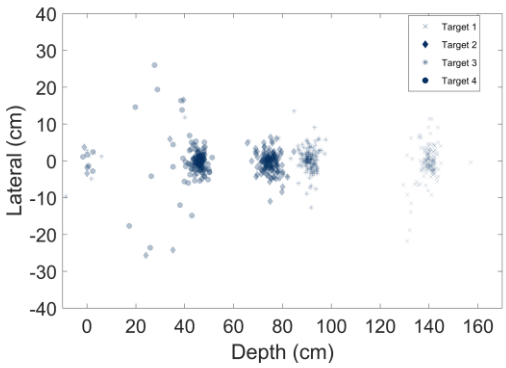
Loud-NL



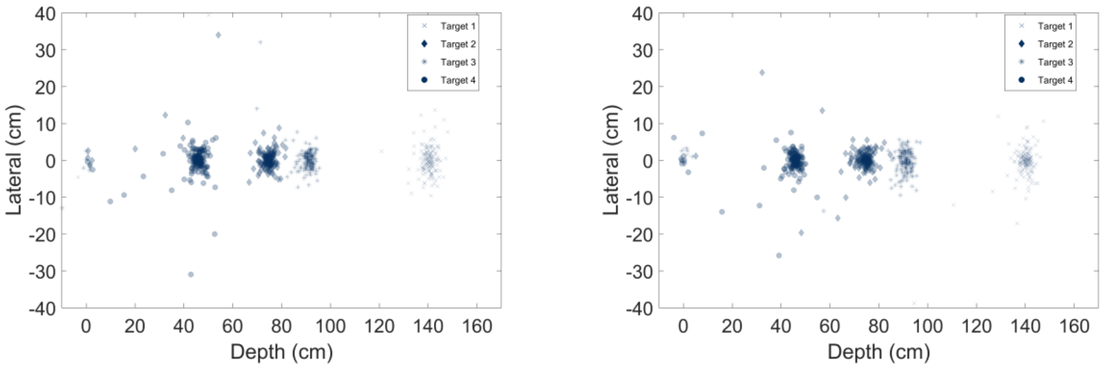
Pitch-NL



Size-NL



Size-L



Bright-NL Bright-L

Figure 28. The constant error of each target is displayed for each feedback condition. The colours indicate the modality, with dark red for auditory, blue for visual feedback. The target location is rotated on the depth axis and thus represents movement length. The distribution of target endpoints is shown for four different movement difficulties that are averaged at block level in the analysis. Data points around zero represent start errors.

7.3.3 Modality and Linear/Non-Linear Feedback

A two-factor repeated measures ANOVA testing the effects of Modality and Linearity on constant error showed that accuracy was higher with auditory compared to visual feedback ($F(1, 17) = 6.02$, $p = .027$, $\eta^2_p = 0.26$). Thus, low performers could make use of the auditory information to improve their movement accuracy (cf. Figure 6). Linearity was not found to have a significant effect on constant error or to interact with Modality. There was no difference between loudness and pitch feedback within the auditory conditions. ($p > .05$). Descriptively non-linear pitch feedback showed the lowest constant error (cf. Table 2). Despite the effect on constant error, neither auditory nor visual feedback reduced movement time. ($p > .05$). Variable error, i.e. the movement stability and smoothness, was similar for auditory and visual feedback ($p > .05$).

Furthermore, no significant effect of Modality was found on the lateral and vertical expansion of the trajectory measured by the root mean square error of the distance (in cm) of the trajectory from a straight line between the start and end of the movement.

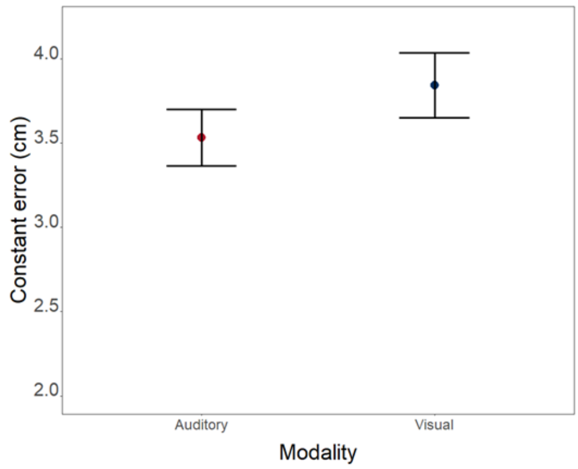


Figure 29. Distance to the target centre for the aiming movement measured as mean constant error for the auditory and visual modality and without feedback. Error bars represent standard errors.

7.3.4 Self-Report Measures

Two two-factor repeated measures ANOVAs comparing the scores of the NASA TLX Scales and Modality or Linearity revealed no significant differences between the different modalities and the linear and non-linear mapping of the feedback (p > .05). There were also no significant differences between low and high performers observed (p >.05). However, the main effect of Scale showed significant differences between the six NASA TLX scales ($F(2.59, 90.74) = 9.79$, $p < .001$, $\eta^2_p = 0.22$). Post-hoc analysis showed that effort was perceived higher than temporal demand, frustration, and physical demand (p < .05). Mental demand was perceived higher than physical demand and temporal demand (p < .05). In addition, performance was perceived lower than physical and temporal demand (p < .05, see Figure 30).

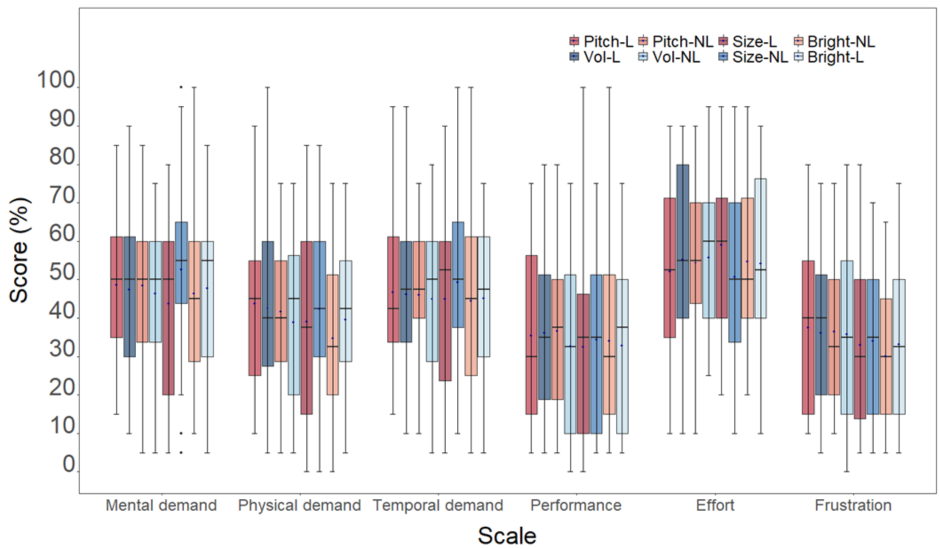


Figure 30. NASA TLX scores in percent (%) for the feedback conditions shown for all NASA TLX scales. The blue diamond indicates the mean score.

Figure 31 shows the usefulness and satisfaction with the feedback. Nine (out of 324) missing data points from the usefulness scale were replaced by the mean of the respective feedback rating to ensure that all data could be used in the following analysis. Two mixed-effects ANOVAs were performed with Scale and either Modality or Linearity as the within factor and Performer Group as the between factor. Significant main effects were found for Performer Group ($F(1, 34) = 4.29$, $p = .046$, $\eta^2_p = 0.11$) and (usefulness and satisfaction) Scale ($F(1, 34) = 53.22$, $p < .001$, $\eta^2_p = 0.61$). Additionally, a tendency to significance was found for Modality ($F(1, 34) = 3.98$, $p = .054$, $\eta^2_p = 0.10$). A significant interaction effect was found between Performer Group and Scale ($F(1, 34) = 7.52$, $p = .010$, $\eta^2_p = 0.18$) as well as Scale and Modality ($F(1, 34) = 29.65$, $p < .001$, $\eta^2_p = 0.47$). The post-hoc analyses showed that high performers rated usefulness and acceptance higher than low performers, and that the general perceived usefulness of feedback was higher than perceived satisfaction with feedback. Furthermore, visual feedback was rated higher overall than auditory feedback. The Tukey-adjusted post-hoc pairwise comparison of the interactions showed that auditory feedback had low satisfaction, but high usefulness scores ($p < .05$) and that auditory feedback was less satisfying than visual feedback ($p < .05$). In contrast, satisfaction and usefulness were rated similarly for visual feedback. Low performers showed lower satisfaction than usefulness scores ($p < .05$) and lower satisfaction than high performers ($p < .05$).

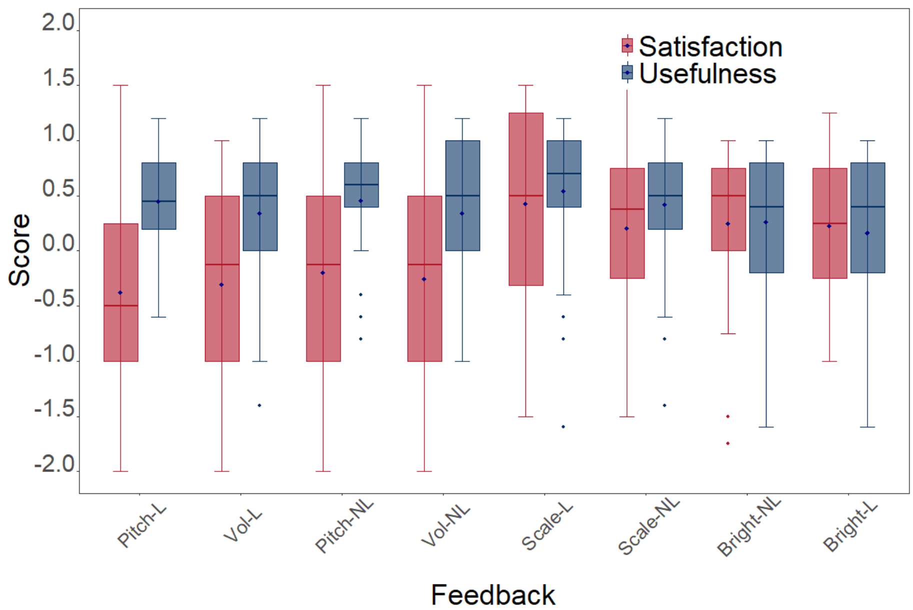


Figure 31. Usefulness and satisfaction score assessed with the Van der acceptance scale on a range from -2 (negative) to 2 (positive) for each movement feedback. The whiskers show the interquartile range, the lines in the boxes show the median and the diamonds show the mean.

7.4 Discussion

This study aimed to investigate the performance, skill, and self-reported task load, usefulness, and satisfaction of visual or auditory concurrent feedback to improve movement accuracy in manual robotic crane control. The effect of the mapping function (non-linear or linear) of the feedback was also investigated.

The results show that the effectiveness of the feedback given depended on the participants' level of performance after the training. Feedback benefited low performers but not high performers. This is in line with (Wulf et al., 1998, 1999) who found concurrent feedback more effective in the early stages of learning a complex skill. High performers may deem feedback as irrelevant or even distracting information, or conversely, accuracy feedback was more useful for low performers. It could also be a deliberate choice to use or ignore feedback.

In spite of efforts to present visual feedback close to the end-effector and without visual interference, neither performance nor skill could be improved on the basis of concurrent visual movement information. This finding is consistent with the claims of multiple resource theory that would expect lower performance if two information draw on the same cognitive resource (Wickens, 2002). However, these findings are in contrast to Sigrist et al., (2011), who found that visual feedback was helpful to improve oar position and blade orientation in rowing. This may lie in the nature of the rowing task, where each hand of the rower is separately handling the oar and blade. In addition, the focus in rowing is on speed and course of the boat, where information from the blades is not as much interfering as visual feedback on end-effector position in robotic crane control. Furthermore, feedback characteristics such as a simple visual representation of the paddle by a curved line may help visual appeal. Consistent with the predictions of Wickens, (2002) and the findings of Chen et al., (2016); Effenberg et al., (2016); Sigrist et al., (2013); and Vidal et al., (2020), auditory feedback was useful in improving the accuracy of low performers. Within auditory feedback, no difference in accuracy was found between pitch and loudness feedback. However, non-linear pitch feedback was descriptively superior to linear pitch and loudness feedback. The usefulness of pitch feedback in robotic crane control was also demonstrated by Mavridis et al. (2015) in reducing movement times, although accuracy was not assessed in this study. In contrast, the movement time was not affected by the different types of feedback, which can be because accuracy was targeted in the feedback design of the current study.

The non-linear or linear feedback mapping showed no significant effects. About the absence of the effect can only be speculated. Either because the effects of linear and non-linear conditions compensated for one another across different feedback designs, or because feedback design needs to be further tuned to the respective feedback concept and human perception.

The accuracy measures were found to be supported by the self-report measures. No differences were found between the feedback types in terms of task load. The ratings indicate a low cognitive task load despite perceived mental effort. The effort may represent the mental load of the participants associated with controlling the robotic crane and learning the motor transformations, which may be conflated with the effects of the designed feedback in the evaluation.

Acceptance in terms of usefulness and satisfaction showed that there is a difference between perceived usefulness of feedback and satisfaction with feedback. Notably, auditory feedback is perceived as more satisfying than visual feedback. Satisfaction is associated with attributes such as pleasant, nice, and desirable. This is in contrast to other experiments with sonification, where auditory feedback is perceived as annoying (Bazilinskyy et al., 2019), especially when sinusoidal tones are used instead of sounds (e.g., chords) (Effenberg et al., 2005). This may be explained by the moderating effect of perceived usefulness on satisfaction (Venkatesh & Davis, 1996). In contrast, the usefulness of the feedback was rated lower than satisfaction, where all feedbacks were rated negatively. This may be partially due to the increased visual load of visual feedback and the non-linear mapping, which failed to improve performance in terms of movement times (especially in the visual modality).

7.5 Limitations

When interpreting the results, several limitations need to be considered. Bimanual robotic crane movements are highly complex, and motor control can change significantly with different movement targets. This means that aiming for real objects in 3D space may require additional feedback information to maintain high accuracy. Furthermore, results are only applicable to low performers in the early stages of building experience in robotic crane control. Nonetheless the authors believe, that with an improved feedback design, more experienced operators can also benefit from auditory feedback. In addition, the simulator used served to provide excellent controllability of the experiment but remains a simplification in terms of fidelity and ecological validity of the task. Although transfer to real-world application can be successful (Ovaskainen, 2005; Ranta, 2009), the feedback must be tested in real-world operations. The experiment was designed such that learning across participants was reduced to avoid corresponding confounds. This means that concurrent feedback, when present, improves performance, but the effect must still show improved long-term performance. Finally, the tested sample comprised students and staff from an academic background that may limit the generalisability of the results, however, this ensured the complete novelty of the task and the same training level while using the feedback.

To conclude, this study was the first attempt to systematically provide feedback based on human perceptual characteristics to enhance the accuracy of bimanually controlled robotic crane movements. Auditory feedback yielded higher accuracy and was perceived as more satisfying than visual feedback for low performers. Further auditory mappings and characteristics need to be explored to extend use to more experienced operators and to improve the usefulness of the feedback regarding the improvement of movement time.

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Chapter 8
Discussion and Conclusion

The aim of this dissertation was: (1) to gain insight into the challenges that forest machine operation poses to the operator, (2) to gain knowledge on machine operator work practices in logging operations by the systematic, human-centred modeling of the work process, (3) to contribute to the refinement of the training of machine operator control skills, i.e. the analysis of operating skills of the machine operators, and (4) to derive implications for the use of motor support and real-time sensory feedback. To this end, five scientific studies have been conducted. In the applied, qualitative and conceptual part of this thesis, a literature review with interviews (Chapter 2, Work Practice study) and a hierarchical task analysis (Chapter 3, HTA study) were conducted, from which the final theoretical and experimental questions were derived. The theoretical framework of this thesis (Chapter 4) served as the basis for the empirical investigations. The empirical part comprised investigations on the learnability of robotic arm control without motor support (Chapter 5, Learning study), with motor support (Chapter 6, Comparative study) and on the effectiveness of visual and auditory feedback (Chapter 7, Concurrent Feedback study). The three experimental studies on the acquisition of control skills and the potential use of motor support and sensory feedback to improve operator performance are therefore at the heart of this thesis.

In the following, the main findings will be summarized and discussed in the light of measures useful to determine skill acquisition in training and the use of motor control support and sensory feedback to ease learning as well as enhance performance. The structure will follow the structure of the research questions described in Section 4.4. First the performance limiting factors and learning regarding training will be discussed in Sections 8.1 and 8.2 and, second, the effects of sensorimotor support will be reviewed. Furthermore, the theoretical implications for the study of the operation of articulated robotic arms are discussed. Section 8.3 elaborates the application relevance and relates the findings from the empirical studies to the starting point of this thesis, the analysis of work practices, and the design of the operator work task. Finally, the scope and limitations of the contribution will be outlined and recommendations for future research will be provided.

8.1 Discussion of Empirical Results on Skill Acquisition of Robotic Arm Control

In this thesis, knowledge gaps on the acquisition of the control skill of a robotic arm were addressed, with the particular aim of shedding light on the challenges and factors that can limit performance and skill acquisition. Limiting factors can be the motor control of a certain joint or dimension of the robotic arm that is learned slower than other joints, therefore delaying learning. The theoretical framework of this work was Schmidt's schema theory (Schmidt, 1975), which was complemented by concepts from dynamic systems theory. Speaking in terms of schema theory, a special interest was on how the operator control inputs to the system with the joysticks are changing through practice and therefore the motor control parameters of the GMPs emerge. The process of learning was assumed to occur differently for joints, so do the parameters of the GMPs emerge at a different rate. In addition, the parameters and schema formation are affected by the decay of control ability between sessions, which may be regarded as forgetting, or by the adaptation and tuning of the motor system (dynamic systems theory), which is evident in a warm-up decrement. In layman's terms, to get used to the controls.

Below, the results of the three empirical studies are discussed. Section 8.1.1 and Section 8.1.2 summarise the results of the Learning study (Chapter 5) and the Comparative study (Chapter 6). Herein also the contribution to the methodological advancements in operator training and the implications based on motor control theories are outlined. Section 8.1.3 describes the results of the Concurrent Feedback study (Chapter 7) and the implications from the Comparative study (Chapter 6), therefore outlining the general effectiveness of the different sensory and motor operator support systems.

8.1.1 Performance Limiting Factors

The Learning study and the Comparative study (Chapters 5 and 6) addressed the knowledge gaps on the limiting factors that affect performance improvements in the learning process and thus contributed to answering the research questions on how to advance training of machine operators (Research question 1). For that, kinematic joystick events as skill indicators and performance measures such as movement times and accuracy were analysed. In the Learning study, the participants controlled each joint of the robotic crane separately, which is currently the foremost control type in heavy machinery, whereas in the Comparative study (Chapter 6), participants controlled solely the crane tip. To analyse operator skill as prerequisite for performance, the first time a learning curve model was fitted to joystick input data. The results of the Learning study showed that the Wrist joint and the use of the Elbow joint of the robotic arm required most gain in control skill compared to the use of the

Base and Shoulder joint (cf. Figure 6, Chapter 5), which were easier to learn. Therefore, especially the Elbow joint is suspected to delay or limit the overall performance improvement of the aiming movement. The Wrist joint at the end of the articulated chain of joints responsible for gripper movement showed mixed results in terms of difficulty and usage. The joint appeared to be unused in a large percentage of movements, where it remains to be analysed whether the joint is not used as a strategy to improve efficiency and performance or inability to control the joint. The latter could refer to the problem of degrees of freedom and the proposed phenomenon of stepwise freezing and releasing degrees of freedom in acquisition, as described in dynamics system theory (Bernstein, Nikolai A., 1967). Nonetheless, the Wrist joint input to the joystick was distinctive in predicting the accuracy of the movement and may be used as an indicator for predicting performance improvements in training. So far, no research has analysed control difficulty of each joint separately in skill acquisition of joint controlled robotic arms; research on the control of excavators has shown that abrupt control movements are negatively associated with performance and further specific movement directions (e.g., lateral movements are easier compared to other directions) impose different difficulties on the operator. This is in line with the initially observed jerky movements of joint control in the Comparative study. The Learning study in Chapter 5 could help to understand the challenges of joystick control in the widespread, conventional control mapping, where the joints are controlled individually. The findings suggest that it might make sense to train difficult joints separately before learning to handle the complete chain of robotic arm joints and to reduce the negative impact of these joints on learning and performance.

Current developments no longer rely on the control of separate joints but offer support in the form that only the end-effector needs to be operated and the required joint positions are computed in real-time. Recent studies have investigated the performance of end-effector controls in applied settings (e.g., Manner et al., 2017). In line with the Comparative study in Chapter 6, these studies find reduced training needs inferred from shorter movement times, movement distance, or productivity and report on the ease of use for novice operators. The three controlled dimensions of the end effector movement make the learning and mental representation of the inverse model for successful joint control obsolete. Therefore, the evaluation of performance and skill indicators must be different for end-effector compared to joint-control systems. The analysis of end-effector control showed unexpected results regarding the accuracy of the movement and the learning curve of movement time. The findings revealed that with increased practice, the joint control group exerts similar, or higher performance in terms of movement time than the end effector control group. This convergence was only reported as non-significant trend in an applied setting (Manner et al., 2017), whereas the accuracy has not been addressed much in the literature, as field specific productivity metrics were predominantly used for performance assessment. The explanation for the unexpected findings could lie in the speed-accuracy trade-off of the movements. That is, the end-effector control group tends to emphasise speed over accuracy similar to human aiming movements (Meyer et al., 1988; Schmidt et al., 1979). Another explanation could lie in the malleable (flexible) attentional resources theory (Young & Stanton, 2002) in the field of automation research on support systems that take over (parts) of the control task. The theory states that humans adapt their invested cognitive resources to current task demand, i.e., workload. End effector control in the Comparative study of Chapter 6 showed that the workload associated with end-effector control was lower than that associated with joint control and may therefore require fewer cognitive resources, resulting in lower accuracy and limit performance.

8.1.2 Time Scales and Skill Development

Skill acquisition refers to an increase in performance (skill) that can be acquired through practice over a period of time (A. Newell & Rosenbloom, P. S., 1980; Schmidt, 1975). Changes in robotic arm control skills (persistent and transient) emerge over different periods of time and can do so to varying degrees for the controlled joints (as shown in the Learning study and the Comparative study). Both studies assessed improvement in terms of deliberate inputs to the joysticks to quantify skill acquisition and describe progress across and within sessions. In the Learning study, robotic arm control skill acquisition was shown to be exponential for joint controlled Base, Shoulder, and Elbow joints, like virtually all learning. Although learning curves provide obvious means to determine learning outcome of skill and performance, they are rarely used in analysing robotic arm control literature, and if so, movements are modelled on performance level (cf. movement time; Bukchin et al., 2002). Moreover, in fields of human-robot and heavy machine control, movement time is generally measured in cross-sectional designs or single repeated measures session focusing on performance increase with e.g., different input devices or inspect time delays in teleoperation (Tonet et al., 2007; Zareinia et al., 2015). In single repeated measurements, the analysis of learning development is impossible, however, research efforts on input devices show the awareness of the existing operating problems of robotic manipulators. For example Mower et al., (2019) showed that constraining degrees of freedom of the robot and thus reducing the number of controlled joints of robotic arms eases the control task with a gamepad. Both the Learning and the Comparative study therefore contributed to the literature by using a psychological approach to analyse control skill learning across extended periods of time, based on the parameters of a proven learning model. Joystick inputs as a direct behavioural output of the (machine) operator were used to describe long-term control skill development (cross-sessions). As described in section 8.1.1 the modeling over multiple sessions could reveal performance limiting factors and can help tailor training according to individual progress. For example, it was shown that three out of four joints improve across sessions and a first plateau is achieved after the fourth session (see also Dreger et al., 2022). The learning and Comparative study conducted in this thesis further contribute to the understanding of control skill learning by examining learning on two different time scales. This has shown that skill improves not only as an average movement time across sessions but also within sessions. In addition the two timescales made it possible to assess the acquisition process and infer skill decays occurring between training sessions. So far, this has only been reported for trail-making tasks of actual human movements (Joseph et al., 2013). The Learning and the Comparative study demonstrated that skill decrements on short timescales correlate with skill gain across sessions. For instance, the Elbow joint required to gain most skill but also showed greatest losses between sessions. Learning end effector control did not suffer under skill/warm-up decrements. Surprisingly, retention tests in the Learning study showed that skill further increased within a fourteen-day interval. Retention sessions are used to determine how much skill is retained, and thus, conversely some sort of loss is often observed. The finding of the Learning study suggests further processing of the learned skill in the rest period. Similar effects were found only in part task training of trenching and loading trucks with excavators (So et al., 2013). In terms of the general performance metrics, it was shown that skill and performance increased with completed sessions, however, the improvement in terms of accuracy plateaued earlier than movement time (after two sessions). Whether this relates to the emphasis of the learner on movement time or simply a lack of relevant context information such as occlusion or relative size about the movement target needs to be addressed in further research.

In conclusion, the challenges of joint control with the Elbow and Wrist joint suggest that precision control is specifically difficult (see Chapter 5). In line with this notion and despite improved movement times, accuracy with end effector control remained difficult (see Chapter 6) and poses an overarching operating challenge.

8.1.3 Training Design

One of the aims of this thesis was to inform the training of heavy machine operators for operating robotic arms and the development of onboard feedback systems. Evidence from the learning and Comparative study suggests that training, independent of machine control type, should emphasise accuracy in movement execution. This can be achieved by enhanced variability of movements in training sessions as proposed by schema theory (Schmidt, 2003; Wulf & Schmidt, 1997) as well as part task training as proposed by Wickens et al., (2013), which focuses on gripping and precision movements. The results from the Learning study show that the training design should also consider the warm-up decrement of the control task. For example, by reserving training time for joints where the skill-loss between sessions is greatest, to quickly bring up skills to the post-loss levels. In addition, training sessions that specifically focus on the control task may regard a larger intersession interval to allow for the improvement gain observed between the last skill acquisition session and retention in the Learning study. Another note may be on the metrics used to evaluate the control task, where the control skill could be reflected in joystick input behaviour. As the end-effector of large machines is more difficult to detect with sensing, the joystick signals bear valuable data that can be used to determine skill levels and predict performance in training. In this regard, the two time scales power law of learning also serves the analysis of motor control data in operating a multi-joint crane and can be used to predict the performance of operators at the end of the training as well as to analyse the specific control challenges the individual operator is facing throughout operation. Thus, the training could be adapted to the specific weaknesses and needs of the robotic arm operator. The technological advances of end-effector control cannot disguise the remaining difficulty of accuracy in robotic arm control that is not resolved with the facilitated joystick-robotic arm mapping. Moreover, the trajectories taken by the participants change with the control scheme, and thus new performance markers must be used. For example, often the utilized parallel joints are used as an indicator for the operator's handling performance in joint-controlled operation, that is obsolete with end-effector control as the joints are not controlled individually. Furthermore, the facilitation of complex movements of such a robotic arm with end-effector control may inspire new work methods that can positively affect the productivity of the work system. Ultimately, the new movement possibilities and potential changes in work method application may also affect the overall machine design.

8.2 Effects of Motor and Sensory Support on Skill Acquisition and Performance Enhancement

The Comparative study (Chapter 6) and the Concurrent Feedback study (Chapter 7) served to answer the research question of how to effectively aid operators via motor support systems and sensory feedback in real-time. The Comparative study presented in Chapter 6 confirmed the benefits of motor support in terms of end-effector control in a laboratory task where the difficulty was systematically manipulated, unwanted learning effects between control schemes per design excluded, and new skill and performance measures implemented. End-effector control eases the internal representation of the operators' forward model of the transformation between joysticks and robotic arm joints as the system computes the inverse kinematics of the movement and therefore facilitates skill acquisition. Results of the Comparative study showed significantly reduced movement times and higher learning rates for novice operators with end-effector control. This finding is in line with previous research that found shorter movement times with end effector control and fast performance gains in terms of productivity of novices in construction and forestry (Elton & Book, 2011; Manner et al., 2017; Wallersteiner et al., 1993). However, the Comparative study found that precision movements still need to be supported with end-effector control. Generally, learning end-effector control was rapid and the need for extensive training was low for lateral and vertical movements according to the learning curve modelling. The results from the Comparative study made it possible to draw conclusions on how performance improvements and short movement paths with end effector control are achieved. The movement trajectories showed reduced lateral and vertical spread, allowing a more direct way to the target compared with joint control. In line, Manner et al. (2017) showed in a field study that vertical clearance was reduced with end effector control while loading logs on a forwarder. Moreover, another performance indicator could be the smoothness of the movement, where positive effects of end effector control were observed. Such new trajectory-based performance measures (like smoothness and path deviation) were introduced to obtain a more comprehensive performance assessment that can be applied in future training and onboard systems. The analysis of cognitive workload with end-effector control showed a largely reduced cognitive workload when using end-effector control. Likewise, perceived mental effort was reduced with end effector control compared with joint control, that can lead to increasing subjective well-being of the operators. Nonetheless, end-effector control can also potentially make the control task boring and monotonous and by this create performance decrements associated with perceived underload. Notably, the workload for joint control was still increasing within the practice sessions compared with end-effector control, while the performance of the two control types converged. This observation reduced the performance benefits of end-effector control for trained operators and left the workload reduction to be the major long-term gain of end-effector control. However, the reduction of workload is only a benefit in overload situations and needs to be viewed with caution, low workload may become underload in automation use accompanied with negative effects such as fatigue and engaging in secondary tasks. The general aim should be to calibrate workload in such a way that neither over- nor underload prevails during the entire duration of the work task.

Also, the Comparative study (adding to the results of the Learning study) suggests that the operation of robotic arms with both joint and end-effector control could benefit from additional support to help the operator improve the accuracy of the target movements. For this reason, concurrent sensory feedback was developed in the Feedback study (Chapter 7) to support the landing phase (also called homing in phase) of the movement. The landing phase starts after peak velocity of the movement and finishes when the movement stops in the target area. Auditory or visual concurrent feedback on target distance (of the end effector) was given linear or nonlinear. The nonlinear feedback led to a higher resolution of the movement in the target area aimed at making movement changes more noticeable. The results of Chapter 7 showed that low performer benefited from target distance feedback, whereas high performers did not. This was in line with findings on concurrent feedback of motor control experiments of (Wulf et al., 1998) that found frequency of concurrent feedback to be useful for early learning stages and low performance in human movements. Consistent with multiple resource theory (Wickens, 2002) the data showed that accuracy was supported best by auditory compared to visual feedback in low performers. Even though visual information was designed such that visual behaviour could focus on the end effector, the interference with the primary task evidently impaired the use of visual information on performance. The designed auditory feedback did not affect movement times, conversely, visual feedback slowed the movement. The highest accuracy was achieved with non-linear pitch feedback. Similarly, concurrent auditory feedback on the blade orientation and sled velocity was useful in rowing training (Effenberg, 2005; Sigrist et al., 2011). However, in Sigrist (2013) also abstracted icons in terms of visual feedback yielded better performance in rowing, and multimodal approaches were promoted.

In robotic arm control, two studies reported the benefits of auditory feedback for hydraulic robotic arm control. Ding et al. (2022) used position error feedback based on pitch and loudness that was triggered when the view on the target was occluded by the robotic arm, and auditory feedback was also useful to control a stick figure crane (Mavridis et al., 2015). This bolsters the notion that auditory feedback is useful in crane control, however, the success appears to depend on the design aspects of when and how the feedback is provided. In contrast to the motor support in the Comparative study (Chapter 6), which showed a general marked reduction in control effort and movement times due to computing inverse kinematics, only very selective sensory feedback designs in the Feedback study (Chapter 7) increased accuracy. Concurrent auditory feedback in the form of pitch modulation showed the potential to increase the accuracy of the movement with the robotic arm and possibly onboard machines. However, visual and loudness feedback was not useful in either linear or nonlinear mapping. These findings of the Feedback study implicate that the operators' initial performance level needs to be assessed before Feedback is given, and only auditory feedback may be used in future support systems.

The auditory feedback within the Feedback study in Chapter 7 showed higher acceptance compared to visual feedback, which contradicts findings from driver assistance systems where continuous sounds are rated annoying (Bazilinskyy et al., 2019). However, the moderating effect of the perceived usefulness of the system may explain the different results (Venkatesh & Davis, 1996). In addition, the working environment of robotic arm operators is very noisy, and the usefulness of auditory feedback must be evaluated in this context. The challenge in advancing auditory feedback will be to find the optimal frequency range or sound characteristic to effectively support the operator. Balancing comfort and audibility will be one of the challenges of implementation, as lower frequencies are more acceptable but more difficult to be perceived, while noise of the engine, chainsaws, and vibrations from the machine exacerbate hearing nuanced sound changes.

8.3 Relevance for Application

The basis of the empirical studies was the applied context of forest machine operation. Here, the results of the empirical studies (Chapters 5-7) and especially the conceptual studies (Chapters 2 and 3) can be used to derive further implications for the work and training design of forestry machines.

The Work Practice study and the HTA showed that the complexity of the control task of human operators in forestry vehicles is determined by the control of the harvester crane in the context of the demanding operating environment, the forest. Machine instructors identified the training of crane movements as the key role in promoting productivity and mitigate cognitive overload of the operator. A prerequisite for efficient movements is the correct setting of the crane speed. Here, the learning analysis and specifically the smoothness assessment can be used to systematically match the crane speed setting with the operator skill. Nonetheless, the findings also show that the skilful coordination of the entire work process (with crane control as the prerequisite at the heart of all operations) including the secondary task of driving in rocky, steep, and rugged conditions with poor visibility requires extensive learning and is part of the skilful machine handling. As a result, the position of the machine on the machine trail significantly affects crane movements, thus, both crane control and machine positioning need to be taught together for efficient felling operations. The positioning of the machine highlights the problem of finding the appropriate distance and trajectory leading to an acceptable accuracy for efficient gripping of the target (the trees) as well as the correct log pile location. Furthermore, the choice of the right distance indicates the need for precise control to be able to cope with movements within the entire work range of the crane. The literature analysis on positive and negative work practices also revealed that using the crane close to the machine or at large distances negatively affects productivity. Similarly in log loading, large angles of the crane with respect to the forward directions of the machines reduce efficiency, here, the results of the Comparative study can connect to the assessment of loading efficiency as additionally performance and learning criterion of the trajectory evaluation, and thus contribute to the design of favourable work practices in felling operation.

Generally, there is a general lack of scientific knowledge on the efficiency of work practices that was unveiled in the Work Practice study. The investigation of work practices in the scientific literature rarely focuses on crane use, but rather on the design of the work task itself, such as work shifts, the effects of steep terrain or log pile size on productivity. The HTA in Chapter 3 extends common work task analyses in forestry, that assess the productivity of the operators and not the operators' task goals that drive actual behaviour. By focussing on operator task goals, the HTA provides a systematic basis for the design of training concepts and the analysis of work practices in future research. For example, the HTA can be used to plan (part task) training, where the hierarchical levels and branches provide the possibility of scaling training complexity.

The analysis and feedback design in the studies presented in the Chapters 5-7, have shown that learning analysis can be used to uncover trainee challenges and to target training more specifically to operators' weaknesses in fine control of harvester cranes. In addition, prediction of skill development based on learning curves can help to evaluate the effectiveness of parts of the training programme and estimate the required individual training duration. For the operation can be recommended to design working practices in a way that intense use of the more difficult joints can be reduced as much as possible, and short distances are realised during tree handling, e.g., by positioning of the machine appropriately. Nevertheless, training may focus by special sessions on the joints that are difficult to learn and control. A key role in the application will be the end-effector control, which is increasingly implemented in new forest harvester machines. However, this raises the need to shift the emphasis of training from transformation learning to more specific training of the accuracy and quality of the aiming movement in a given work method. A major benefit is that the low workload associated with end effector control potentially allows to increase the task load in training to learn other tasks outside robotic crane operation. For instance, pursuing to focus on work practices early on to reduce overall training time. Current performance indicators such as parallel joint use can be complemented or even replaced by trajectory analyses and movement smoothness, in addition to the commonly used productivity analyses. To innovate training and specifically decentralise training from training centres to onboard systems, the changes found in trajectories and smoothness can be applied in onboard skill assessment. Furthermore, the auditory real-time feedback could be used to enhance the position of the aggregate at the stem and guide it towards a desired log pile location.

8.4 Limitations and Scope of the Contribution

The contribution of this thesis is made to the control skill acquisition, training, and performance feedback of robotic arms in a controlled setting. The studies were performed in a low fidelity simulated environment with a simple visualisation and an abstraction of the real-world control task that come with disadvantages and benefits for assessment. However, the simulator set-up was designed for the analysis of the robotic arm movements and control input of the operator, which is not easily possible in field studies. Here, the simulator provided excellent experimental control, high data quality, and the reproducibility of behaviour. Nonetheless, participants were not experiencing the constraints like safety hazards associated with soil and tree handling and the productivity requirements a professional machine operator faces. This may have increased the variability in movement exploration and execution across participants compared with real world operation. Thus, the actual learning is expected to be slower and the motivation to use feedback to be higher in real world settings. The task within the environment was tapping circular targets on the floor to standardize the movement series with regard to difficulty, nevertheless the high number of repetitions and the 2D target layout may cause underload conditions in the experimental series (Chapter 3), increasing the likelihood of fatigue, boredom or demotivation and thus, lower overall performance compared to the real world. In addition, the movements under investigation were conducted with 4-degrees-of-freedom robotic arms, therefore, the application to 6 or 7 degrees-of-freedom cranes needs evidence. The same holds for different input devices such as keyboard and touch combinations. Furthermore, this thesis can only infer skill acquisition from behavioural observations, so structural changes in cognition in terms of psychophysiological processes are outside the scope of this thesis.

Lastly, learning is an individual development. The learning curves used, and the analysis is useful to determine control-related challenges across participants and provide the opportunity to analyse individual skill levels. However, to ensure that the methods used, and conclusions drawn on skill development are effective in training, bifurcations in training design need to be implemented to cater for individual skill levels, which was beyond the scope of this thesis.

8.5 Recommendations for Future Research and Outlook

There are several directions that future research can and should take to continue to provide meaningful insights into the training of robotic arm operating skills and performance feedback, including the design of sensory feedback, the effects of motor support in terms of automation on operator behaviour, and the structure of training.

In terms of sensory feedback design, the effectiveness will be primarily determined by the resolution of the mapped movement change on the feedback properties. For that, the exact mappings of the concurrent feedback on the respective auditory and visual property need to derive new mapping functions with varying resolutions to advance the tuning of the support system in accordance with human information processing. It may well be that these refinements will increase the usefulness of given feedback for currently less successful feedback such as loudness distance feedback. In addition, approaches that use multiple modalities at a time may be researched in terms of the beneficence for control skill acquisition. Sigrist et al. (2013) recommend the use of multimodal feedback for complex motor tasks, however, the usefulness and composition need to be researched for bimanual control tasks. The core challenge is to provide the best feedback, the optimal amount of feedback, at the optimal point in time. This is where another line of research can connect, to make feedback as usable and efficient as possible and to raise skills to the highest possible level. In this regard the concurrent feedback must be compared to terminal feedback that is provided after movement completion. This should also clarify the amount of feedback given, for example, if a simple advice is enough or if guidance is more useful to achieve high performance. This is even more relevant if support is aimed at eliminating differences between experienced operators as control differences in control skill may be more subtle. Another major step is the transfer to actual work and training environments. The skill assessment methods used need to be tested in real training of machine operators using higher fidelity simulators in training centres and on real machines. Especially with the focus on on-board systems, the acceptance and usefulness of concurrent feedback in forestry and construction need to be evaluated.

As the forestry industry, like any other industry, is striving towards the increased use of automation such as motor support via end-effector control, the level of automation of the robotic arms will play a fundamental role in future operator behaviour feedback research. Feedback must adapt to the qualitative new role and the associated behaviour of the operator, thus mitigating the negative effects of the introduction of automation and pushing the positive effects on operator performance and well-being to the limits of automation use. Especially with the operator in the control loop suffering periods of underload, the interplay of task design and supporting interfaces must serve to retain purpose of meaningful work. This may require changing the role of the operator, elevating it from a performer of dull, repetitive tasks to an engaged manager of the human-robotic-arm system. This also highlights the transfer to, and appropriate embedding in the work context guided by human factors research. Therefore, future studies should consider the innovative use of feedback in trainings, the impact of automation effects on workload and situational awareness during operations, all of which should be driven by operator acceptance and well-being.

Whatever system will support training and performance of heavy machinery the meaningful integration of the human in the complex control environment will remain the major concern of future work systems. Support and training systems must serve to compensate for the lack of precision and vigilance in human control and learn to benefit from the reasoning and flexibility of the human mind.

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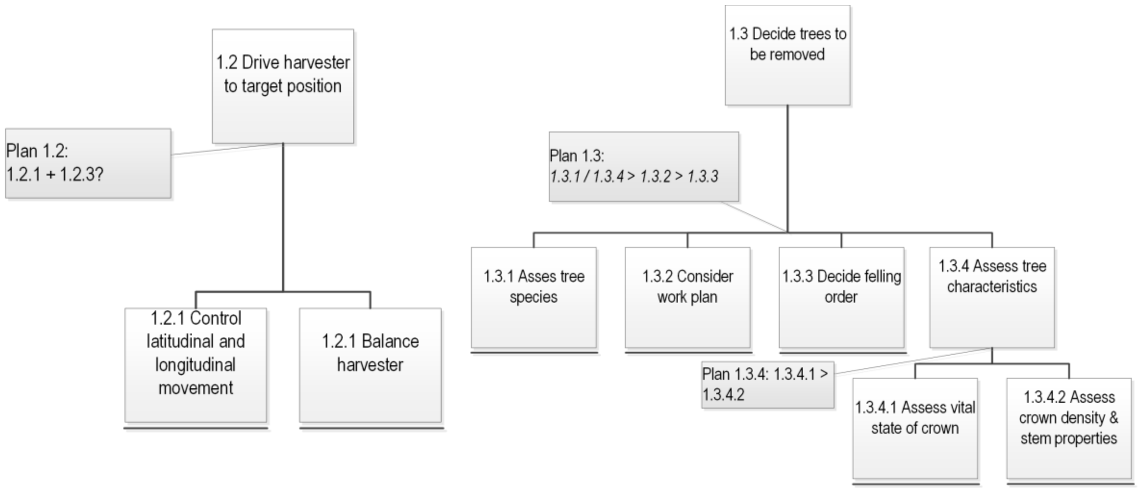
Appendix

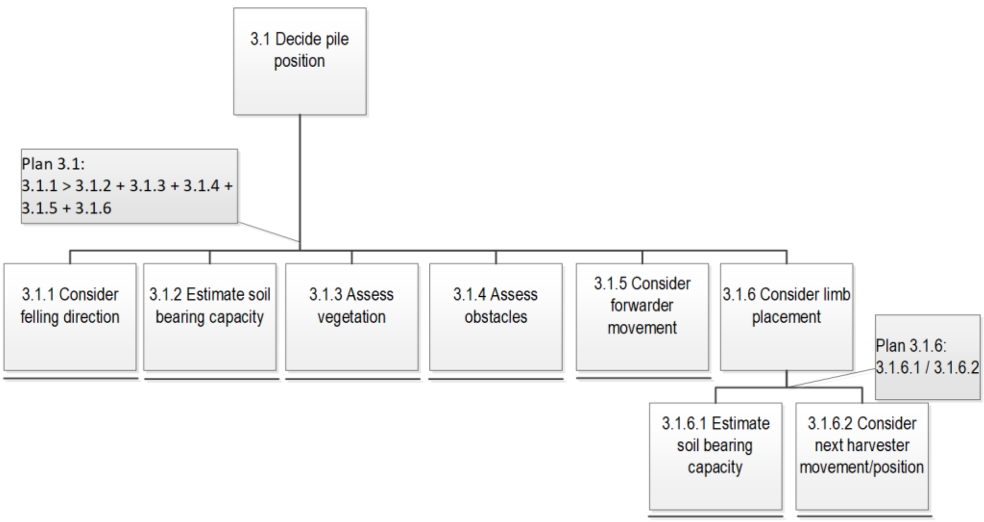
Appendix A

The full complementary presentation of the HTA sub-goals of Chapter 3:



(a) (b)

Figure A1. Displayed subgoals: goal 1.2: Drive harvester to target position (a) and goal 1.3: Decide trees to be removed (b) of goal 1.1: Position harvester of harvester operators in clear-felling operations.



(a)

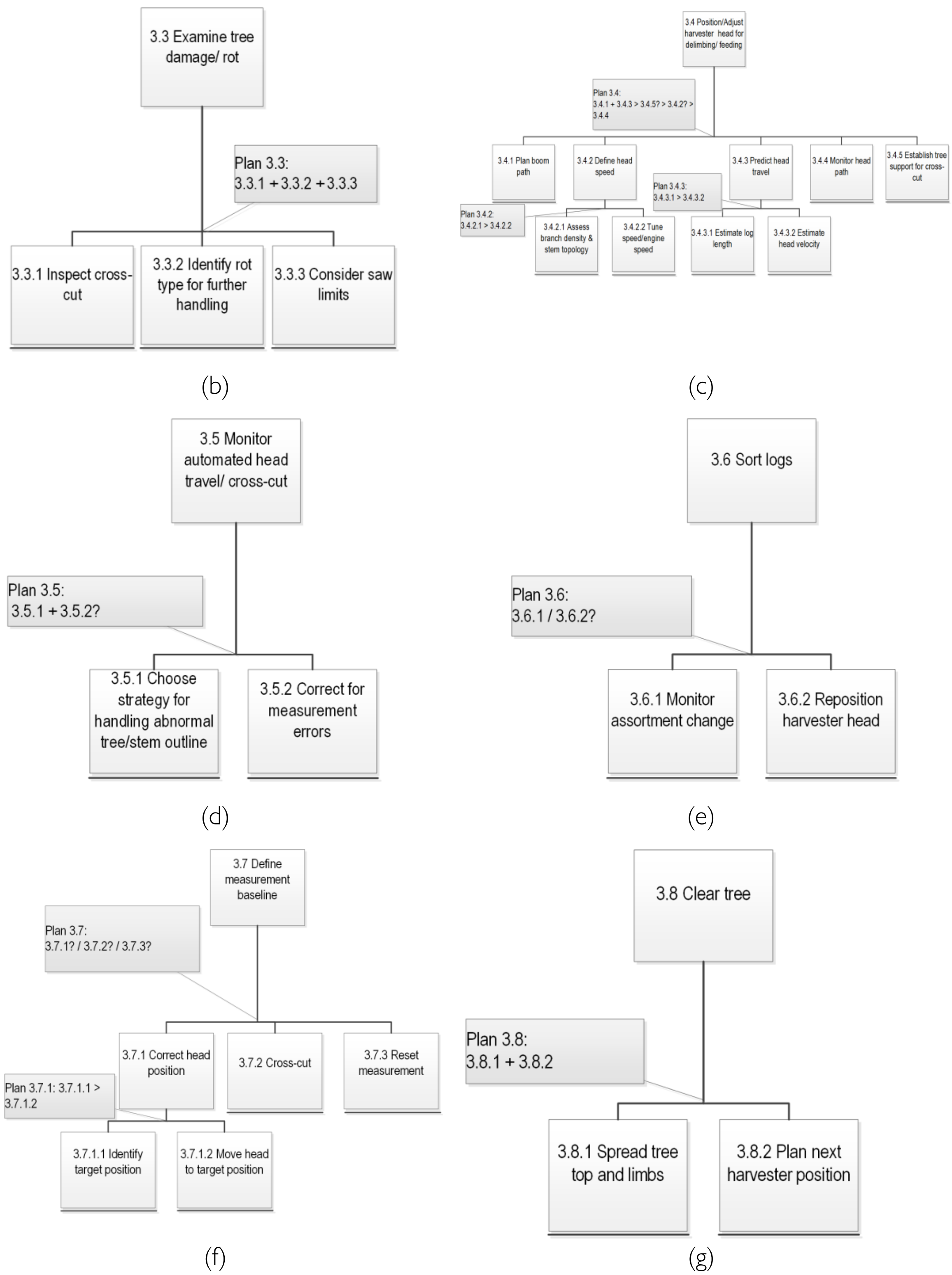


Figure A2. Displayed subgoals 3.1: Decide pile position (a), 3.3: Examine tree damage/rot (b), 3.4: Position/adjust harvester head for delimbing (c), 3.5: Monitor automated head travel and cross-cut (d), 3.6: Sort logs (e), 3.7: Define measurement baseline (f), and 3.8: Clear tree (g) of goal 3: Process tree in clear-felling operations.

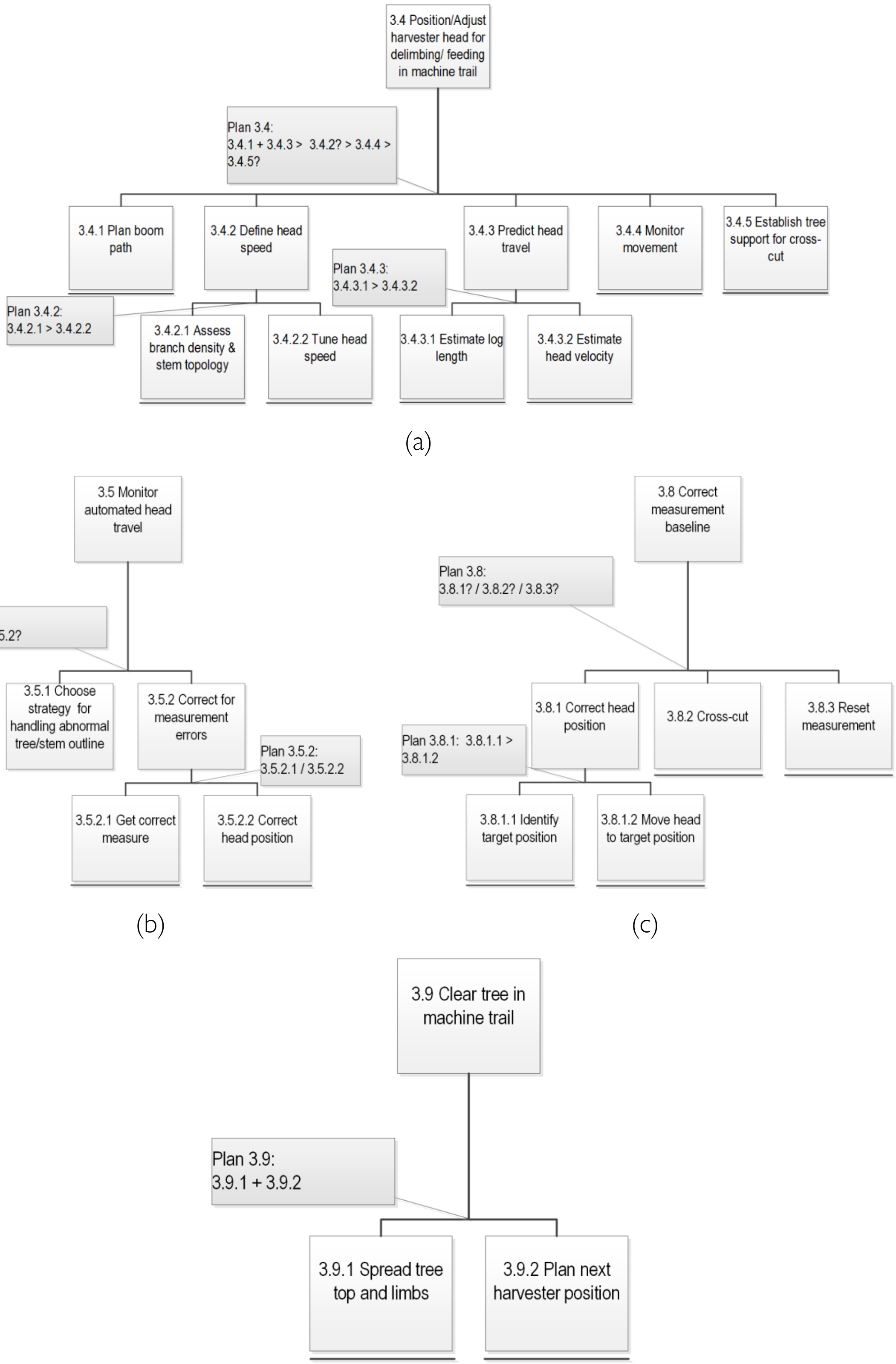


Figure A3. Displayed subgoals 3.4: Position/adjust harvester head for delimbing/feeding in machine trail (a), 3.5: Monitor automated head travel (b), 3.8: Correct measurement baseline (c), 3.9: Clear tree (d) in machine trail that are different in stand thinning compared to clear felling of goal 3: Process tree in stand-thinning operations.

Appendix B

List of publications in this dissertation.

Publication 1

Hartsch, F.*; Dreger, F.A.*; Englund, M.; Hoffart, E.; Rinkenauer, G.; Wagner, T.; Jaeger, D. Positive and Negative Work Practices of Forest Machine Operators: Interviews and Literature Analysis. *Forests* 2022, *13*(12), 2153; https://doi.org/10.3390/f13122153. *Note. Joint first authorship.

Publication 2

Dreger, F.A.; Englund, M.; Hartsch, F.; Wagner, T.; Jaeger, D.; Björheden, R.; Rinkenauer, G. Hierarchical Task Analysis (HTA) for Application Research on Operator Work Practices and the Design of Training and Support Systems for Forestry Harvester. *Forests* 2023, *14*(2), 424. https://doi.org/10.3390/f14020424

Publication 3

Dreger, F.A., Chuang, L.L., & Rinkenauer, G. (Accepted for Publication). Analysis of learning the bimanual control of (tele)operating joint space controlled robotic arms with 4 degrees of freedom using the two-timescales power law of learning. *Ergonomics, 2023*.

Publication 4

Dreger, F.A., Chuang, L.L., & Rinkenauer, G. (Under Review). Comparing Operator learning, Performance, Cognitive Load, and Trajectories of End-Effector and Joint-Controlled Robotic Arms for Support System Design. *IEEE Transactions on Human Machine Systems*, 2023.

Publication 5

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Felix Alexander Dreger