The Digital Transformation of Logistics from a Human-Centred Perspective

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and especially warehouses - grew, but also a profound understanding of contexts, concepts and practice-relevant questions. Once again, thank you for the kindness, the freedom and the trust during this exciting time.

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I hope that, in the end, I have contributed to a better understanding of the current developments in logistics. More importantly, I also hope that I supported enterprises to understand the interrelations between the technological developments in logistics and their impacts on the workers and finally that this dissertation also supports the development of better workplaces for workers in logistics.

„Nicht die Wahrheit, in deren Besitz irgendein Mensch ist oder zu sein vermeinet, sondern die aufrichtige Mühe, die er angewandt hat, hinter die Wahrheit zu kommen, macht den Wert des Menschen." G. E. Lessing

Wiesbaden, July 2021

Sven Winkelhaus

Zusammenfassung

Die vorliegende kumulative Dissertation befasst sich mit der digitalen Transformation in der Logistik unter besonderer Berücksichtigung der Auswirkungen des Transformationsprozesses auf die Beschäftigten in dieser Branche. Ziel der kumulativen Dissertation ist es, ein tiefergehendes Verständnis der Entwicklungen zu bekommen, die unter dem Begriff *Logistik 4.0* verstanden werden können und zu untersuchen, welche Auswirkungen dies für die zukünftige Arbeit in der Logistik, insbesondere im Lager, haben wird.

Die kumulative Dissertation besteht aus fünf Artikeln, die in wissenschaftlichen Fachzeitschriften veröffentlicht bzw. eingereicht wurden und kann grob in drei Teile untergliedert werden: Im ersten Teil der kumulativen Dissertation, der aus dem ersten Artikel besteht, wird der inhaltliche Kern, Logistik 4.0, aufbauend auf dem Begriff und der Forschung zum Thema Industrie 4.0 definiert und auf breiter Basis der aktuelle Forschungsstand dargestellt. Dies bildet die inhaltliche und thematische Grundlage für die nachfolgenden Untersuchungen.

Der zweite Teil der kumulativen Dissertation fokussiert auf empirische Grundlagen und einen methodischen Beitrag zur Untersuchung der Menschen-zentrierten Gestaltung der Logistik 4.0, indem zunächst die Auswirkungen der Entwicklung zur Logistik 4.0 auf die Beschäftigten in der Intralogistik, genauer auf ihre Arbeitsplatzmerkmale, untersucht werden. Dies dient dazu, die konkret wahrgenommenen Veränderungen zu erfassen, die Bedeutung des Transformationsprozesses zu verifizieren und den Einfluss seiner technischen Bestandteile auf die Veränderungen der Arbeitsplatzmerkmale zu analysieren. Wenngleich in diesem zweiten Artikel der kumulativen Dissertation deutliche Veränderungen der Arbeitsplatzmerkmale in der Logistik 4.0 aufgezeigt werden konnten, zeigte eine quantitative Analyse von Forschungsarbeiten im dritten Artikel dieser kumulativen Dissertation auf, dass die Forschung sich bei der Gestaltung von Industrie 4.0 auf technische Änderungen fokussiert. Daher wird abschließend im dritten Kapitel ein allgemein anwendbares, theoriebasiertes, systematisches Analysewerkzeug entwickelt, das es ermöglicht, die Auswirkungen der Einführung von Industrie 4.0 und Logistik 4.0 Elementen auf die involvierten Menschen zu untersuchen und die möglichen Folgen für das Gesamtsystem zu antizipieren.

Im abschließenden dritten Teil dieser kumulativen Dissertation erfolgt ein genauerer Blick auf die Auswirkungen der Entwicklung zur Logistik 4.0 auf die Kommissionierung als einen zentralen, zumeist arbeitsintensiven Prozess in der logistischen Kette. In Artikel 4 wird daher zunächst das Feld einer *Kommissionierung 4.0* strukturiert, um darauf aufbauend zu untersuchen, welche technischen und prozessualen Lösungen die Wissenschaft für eine gleichermaßen menschengerechte und ökonomische Kommissionierung unter den sich wandelnden Anforderungen betrachtet hat. Es zeigt sich, dass ein aus ökonomischer und sozialer Perspektive vielversprechendes Kommissioniersystem, die hybride Kommissionierung, bislang kaum untersucht wurde. Dies erfolgt daher im abschließenden fünften Artikel dieser kumulativen Dissertation, in dem ein Beispiel für ein kollaboratives, hybrides Kommissioniersystem untersucht wird, in dem Menschen und autonome Roboter gemeinsam im selben Lagerbereich Aufträge kommissionieren.

Die Artikel greifen zur Untersuchung der Themenschwerpunkte auf verschiedene Methoden unterschiedlicher Disziplinen zurück und stützen sich auf ein breites theoretisches Fundament. Methodisch wird in Artikel 1, der die konzeptionelle Grundlage der Logistik 4.0 behandelt, zunächst ein konzeptioneller Ordnungsrahmen entwickelt, mit dem der Begriff und die Bestandteile des Konzepts Logistik 4.0 abgeleitet werden. Hierbei werden insbesondere zwei Einflussfaktoren berücksichtigt: Neue Anforderungen an die Logistik sowie neue technologische Möglichkeiten. Anschließend wird mittels eines systematischen Literaturüberblicks der aktuelle Stand der Forschung zu Logistik 4.0 strukturiert untersucht. Der Fokus liegt hierbei auf den technologischen Anwendungen in der Logistik und wie diese die Logistik verändern. Auf Basis der gewonnenen Erkenntnisse werden der Ordnungsrahmen zu Logistik 4.0 detailliert und zukünftige Forschungsperspektiven herausgearbeitet – es wird gezeigt, dass die Auswirkungen der Transformation auf menschliche Faktoren nur in geringem Maße in der analysierten Literatur diskutiert wurden.

Im methodischen Fokus von Artikel 2 der vorliegenden kumulativen Dissertation steht daher die Durchführung und Auswertung von teil-strukturierten Interviews, die mit Beschäftigten aus sieben Unternehmen geführt wurden, um die Ausprägungen und Zusammenhänge zwischen Arbeitsplatzmerkmalen und der Intralogistik 4.0-Reife zu untersuchen. Auf der Grundlage des Work Design Questionnaire wurden die Interviews in Bezug auf 21 Arbeitsplatzmerkmale mit 16 Angestellten in der Intralogistik geführt und zusätzlich die Intralogistik 4.0 Reife der Arbeitsplätze bewertet. Die Ergebnisse zeigen, dass Logistik 4.0 signifikanten Einfluss auf die Arbeitsplatzmerkmale hat und die Effekte sowohl positiv als auch negativ in Bezug auf Arbeitszufriedenheit und Motivation sein können. Im Wesentlichen ist die Art und Intensität des Einflusses in den zumeist manuellen Prozessen abhängig von der Art der genutzten Technologien, Automatisierung oder Digitalisierung.

In Artikel 3 wird zunächst eine quantitative Inhaltsanalyse durchgeführt, in der die Themenschwerpunkte bisheriger Forschung zu Industrie 4.0 nachgewiesen werden. Die Ergebnisse zeigen, dass zwar unterschiedliche Rollen von Menschen identifiziert werden, menschliche Faktoren im Vergleich zu technischen Faktoren jedoch eine deutlich untergeordnete Rolle in der Forschung erhalten. Anschließend wird auf Basis von fünf Theorie-Bausteinen ein methodisches Vorgehensmodell zur Analyse der Einflüsse von Industrie 4.0-induzierten Änderungen auf ein bestehendes Arbeitssystems abgeleitet. Anhand zweier Beispiele wird die Methodik veranschaulicht und die Praxistauglichkeit exemplarisch aufgezeigt.

Artikel 4 und 5 fokussieren daraufhin den Kommissionierprozess im Zusammenhang mit Logistik 4.0 und untersuchen zunächst in Artikel 4 mittels eines konzeptionellen Ordnungsrahmens und eines systematischen Literaturüberblicks den aktuellen Stand der Forschung in diesem Bereich. Der Ordnungsrahmen unterscheidet nach substituierenden technischen Systemen im Kommissionierprozess und unterstützenden Technologien und stuft diese qualitativ basierend auf dem Grad der Automatisierung ab. Darauf aufbauend werden vier verschiedene Kommissioniersysteme klassifiziert und drei von ihnen in einem systematischen Literaturüberblick analysiert. Die Ergebnisse zeigen eine deutliche Unterrepräsentierung hybrider Kommissioniersysteme, obwohl diese aus einer soziotechnischen Perspektive vielversprechende Möglichkeiten bieten.

Hierauf aufbauend wird in Artikel 5 ein hybrides Kommissioniersystem bestehend aus menschlichen Kommissionierern und Kommissionierrobotern, die innerhalb eines Arbeitsbereichs kommissionieren, abgeleitet, das aufbauend auf den ökonomischen und sozialen Zielen vielversprechend erscheint. In einer agentenbasierten Simulationsstudie – die besonders geeignet ist um das Verhalten eines Systems basierend auf den Interaktionen verschiedener Akteure aufgrund individueller Verhaltensregeln zu analysieren - werden die Interaktion der technischen und menschlichen Teilsysteme untersucht und der Einfluss von Routenstrategien genauer betrachtet. In einer kritischen Diskussion der Annahmen des idealisierten Systems der Simulationsstudie wird aufgezeigt, dass hybride Systeme vielversprechende Ergebnisse für reale Anwendungen darstellen und geeignet sind, sowohl die Systemeffizienz, als auch die Arbeit der menschlichen Kommissionierer zu verbessern.

Abstract

This cumulative dissertation deals with the digital transformation in logistics focusing on the effects of the transformation process on the employees in this industry. The aim of this cumulative dissertation is to gain a deeper understanding of the developments that can be understood by the term Logistics 4.0 and to examine what impact this will have on future work in logistics, especially in warehouses.

The cumulative dissertation consists of five articles published in or submitted to scientific journals and can be roughly divided into three parts: In the first part of the cumulative dissertation, which consists of the first article, the core concept, Logistics 4.0, is defined based on the term and research on the topic of Industry 4.0 and the current state of research related to Logistics 4.0 is presented. This forms the substantive and thematic basis for the subsequent research.

The second part of the cumulative dissertation focuses on an empirical research foundation and a methodological contribution to the investigation of the human-centred design of Logistics 4.0. First, the effects of the development towards Logistics 4.0 on employees, especially on their work characteristics, are examined with a focus on intralogistics tasks; this serves to capture the changes perceived by employees, to verify the significance of the transformation process and to analyse the influence of its technical components on the changes in work characteristics. Although the second article of this cumulative dissertation is able to show changes in work characteristics in Logistics 4.0, a quantitative analysis of research articles presented in the third article of this cumulative dissertation proves that research focused on technical changes in the design of Industry 4.0. Therefore, the third article develops a generally applicable, theory-based, systematic analysis tool that makes it possible to examine the effects of the introduction of Industry 4.0 and Logistics 4.0 elements on the humans involved and to anticipate the possible consequences for the overall system.

In the third part of this cumulative dissertation, a closer look is taken at the impact of the development towards Logistics 4.0 on order picking as a central, labour-intensive process step in logistics. Therefore, Article 4 first structures the field of Order Picking 4.0 to analyse which technical and process-related solutions have been investigated in research for a human-friendly and economic order picking process. It turns out that a promising order picking system from an economic and social perspective, called hybrid order picking, is

evidently under-researched. To contribute to closing this research gap, the fifth article of this cumulative dissertation examines an example of a collaborative, hybrid picking system in which humans and robots perform order picking tasks in a shared workspace.

The articles draw on various methods from different disciplines to examine the main topics and rely on a broad theoretical foundation. Methodologically, Article 1, which deals with the conceptual basis of Logistics 4.0, first develops a conceptual framework from which the term and the components of the Logistics 4.0 concept are derived. Two main impact factors are focused on: New demands on logistics as well as new technological opportunities. Subsequently, the current state of research on Logistics 4.0 is examined in a systematic literature review. The focus is on technological applications in logistics and how they change logistics operations. On the basis of the insights gained, the conceptual framework of Logistics 4.0 is detailed and future research perspectives are elaborated - it is shown that the impact of the transformation towards Logistics 4.0 on human factors has been discussed only to a limited extent in the literature analysed.

Thus, the methodological focus of Article 2 of this cumulative dissertation is on conducting and analysing semi-structured interviews with intralogistics employees from seven companies in order to investigate interrelations between work characteristics and the Intralogistics 4.0 maturity. Based on the theoretical foundation of the Work Design Questionnaire, the interviews were conducted with 16 employees in intralogistics considering 21 workplace characteristics. Additionally, the Intralogistics 4.0 maturity of the workplaces is assessed. The results show that Logistics 4.0 has a significant impact on the work characteristics and the effects can be both positive and negative in terms of job satisfaction and motivation. In essence, the type and intensity of the impact in the mostly manual processes depend on the type of technologies applied, automation or digital technologies.

In Article 3, this analysis is first complemented carrying out a content analysis of the literature in which the main topics of previous research on Industry 4.0 are analysed. The results show that although different roles of humans are identified, human factors are given a subordinate role in research compared to technical applications. Subsequently, a systems framework for analysing and anticipating the influences of Industry 4.0-induced changes on a work system is derived on the basis of five theoretical building blocks. Two examples are used to illustrate the methodology and to demonstrate its practicality.

Articles 4 and 5 subsequently focus on the order picking process in the context of Logistics 4.0. First, the current state of research in this area is analysed in Article 4 by means of a conceptual framework and a systematic literature review. The framework distinguishes between substituting and supporting technologies and classifies them qualitatively based on the level of automation. Based on this, four different picking systems are classified and analysed in a systematic literature review. The results show a clear under-representation of hybrid order picking systems, although these offer promising possibilities from a sociotechnical perspective.

Based on this, a hybrid order picking system consisting of human order pickers and robot order pickers that pick in a shared workspace is derived in Article 5, which seems promising based on the economic and social goals. In an agent-based simulation − which is especially suitable to analyse the system performance based on interactions between different agents − the interaction of the technical and human subsystems is investigated and the influence of routeing strategies is examined. In a critical discussion of the assumptions of the idealised system of the simulation study, it is shown that hybrid order picking systems offer promising results for real applications and are suitable for improving both the system efficiency and the work of the human order pickers.

Outline

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List of Abbreviations

ABS *Agent-Based Simulation*
AE/BE *American English / British English*
AGV *Automated Guided Vehicle*
AI *Artificial Intelligence*
AR *Augmented Reality*
AS/RS *Automated Storage and Retrieval System*
B2B *Business-to-Business*
B2C *Business-to-Consumer*
BD *Big Data*
BDA *Big Data Analytics*
CA *Content Analysis*
CPPS *Cyber-Physical Production System*
CPS *Cyber-Physical System*
DEMATEL *Decision-Making Trial and Evaluation Laboratory*
DES *Discrete-Event Simulation*
ERP *Enterprise-Resource-Planning*
EU *European Union*
GDP *Gross Domestic Product*
GIS *Geographic Information System*
GZ *Golden Zone*
H *Humans*
HF *Human Factors*
HOPS *Hybrid Order Picking System*
HR-OPS *Human-Reduced Order Picking System*
I *Robot-Incompatible Items*
I4.0 *Industry 4.0*
IoT *Internet of Things*
IT *Information Technology*
LG *Largest Gap Routeing Strategy*
MS *Manufacturing System*
MSD *Musculoskeletal Disorder*
OP *Order Picking*
OP 4.0 *Order Picking 4.0*
OPe4.0 *Operator 4.0*
OPS *Order Picking System*
PRISMA *Preferred Reporting Items for Systematic Reviews and Meta-Analyses*
R *Robots*
Re *Return Routeing Strategy*
RFID *Radio Frequency Identification*
RMFS *Robotic Mobile Fulfilment System*
RO Research Objective
ROI *Return on Investment*
RQ *Research Question*
RU *Recording Unit*
S *S-Shape Routeing Strategy*
SaaS *Software as a Service*
SCM *Supply Chain Management*
STS *Sociotechnical System*
TOE *Technology, Organisation, Environment*
VMI *Vendor Managed Inventory*
VR *Virtual Reality*
WDQ Work Design Questionnaire
WMS *Warehouse Management System*
X *Any Routeing Strategy*

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I. Introduction

Logistics is the sum of activities of enterprises that deal with the transport and storage of goods to make these available for consumption (Lummus et al., 2001). These activities still rely on human work to a large extent. Owing to the current digital transformation of large parts of the economy, logistics is also exposed to a new structural change and the impact of this on human labour is not yet fully foreseeable. In this cumulative dissertation, this change of logistics within what is called the Fourth Industrial Revolution (Culot et al., 2020; Kagermann et al., 2013) is investigated, focusing especially on the impacts on human factors (HF), which is “concerned with the understanding of interactions among humans and other elements of a system [...] design in order to optimize human well-being and overall system performance” (International Ergonomics Association, 2019). Furthermore, this cumulative dissertation takes a specific look at intralogistics and warehousing processes, because in these processes, particularly manual and labour-intensive tasks are carried out, especially order picking (de Koster et al., 2007). Therefore, these tasks are of particular interest in the context of changes brought about by the Fourth Industrial Revolution.

The aim of this cumulative dissertation is thus to gain deeper insights into the developments towards *Logistics 4.0* by answering four overarching research questions:

- *What is Logistics 4.0 and what is the current state of research on Logistics 4.0?*
- *How do the developments towards Logistics 4.0 affect intralogistics employees’ work characteristics?*
- *How can jobs be systematically analysed in the development towards Industry 4.0 and Logistics 4.0?*
- *How is order picking changing in regard to the development towards Logistics 4.0 and what impact does this have on social and economic factors of the order picking process?*

As these research questions show, the main body of this cumulative research process can be divided into three parts, as shown in Figure I-1: Part A of the research body of this cumulative dissertation forms the basis of this research by developing a conceptual foundation of Logistics 4.0 and outlining the changes in logistics systems caused by different push and pull factors in the context of the digital transformation.

Research Design and Scope of the Chapters			Primary Research Question	Methododological Focus
	Section I	Introduction		
Part A	Section II	Article 1: Definition and Conceptualisation of Logistics 4.0	RQ 1: What is Logistics 4.0 and what is the current state of research?	Systematic Literature Review
Part B	Section III	Article 2: Work Characteristics Changes in Logistics 4.0	RQ 2: How do the developments towards Logistics 4.0 affect work characteristics of employees?	Semi-Structured Interviews
	Section IV	Article 3: Human Factors Consideration in Industry 4.0	RQ 3: How can jobs be systematically analysed in the development towards Industry 4.0 and Logistics 4.0?	Content Analysis and Conceptual Framework
Part C	Section V	Article 4: Definition and Conceptualisation of Order Picking 4.0	RQ 4: How is order picking changing in the development towards Logistics 4.0 and what impact does this have on social and economic factors?	Systematic Literature Review
	Section VI	Article 5: Efficiency of a Hybrid Order Picking System		Simulation
	Section VII	Conclusion		

Figure I-1: Research design and structure of this cumulative dissertation.

Part B of the research body of this cumulative dissertation provides an empirical and methodological analysis foundation of these changes. Therefore, it is first empirically investigated which changes on the work characteristics are perceived by employees in the intralogistics domain - which was identified as being especially relevant in the field of logistics - as a result of the development towards Logistics 4.0. The substantial changes identified lead to the question as to whether and to what extent previous research on Industry 4.0 included HF, as the term Industry 4.0 is the predominant term in research on the digital transformation in general industrial contexts. It is found that HF are evidently under-researched. Hence, a theoretically grounded systems framework is developed to support analysing the impacts an Industry 4.0- or Logistics 4.0-induced change of the work system has on human factors and the overall system.

Part C of the research body of this cumulative dissertation narrows down the focus again and provides deeper insights into the order picking process, which was identified as a specific task of interest. As it is a labour-intensive and important process step in logistics (de Koster et al., 2007; Tompkins et al., 2010), considerable research on order picking systems is available (de Koster et al., 2007; Grosse et al., 2017). However, the consequences of the developments towards Logistics 4.0 have not yet been holistically researched, which is tackled in this part. At first, the field of *Order Picking 4.0* is structured and reviewed finding that hybrid order picking systems, in which human order pickers and picking robots work together in a shared workspace to complete the customer orders, are widely neglected in research. Subsequently, a joint manual and automated hybrid order picking system is derived that is promising not only from an economic but also from a HF perspective.

The three parts (A-C) follow the cycle that is shown in Figure I-2, which is based on the sociotechnical perspective: As there is a change of demands and applications within the logistics systems caused by the developments towards Logistics 4.0, there is a simultaneous change in the existing work systems. Following the theory of sociotechnical systems, individual subsystems cannot be optimised separately from each other (Rose et al., 2013; van Eijnatten, 1998). Since logistical systems can be understood as sociotechnical systems, the social and technical subsystems change along with the overall work system. It is therefore not sufficient to exploit the technical possibilities of the digital transformation without also considering the human subsystem in logistics, because this might lead to “phantom profits” (Rose et al., 2013). These arise when the technological impacts on the system are below expectations because the effects of the human subsystem have not been sufficiently considered. The adaptation effects of humans as a result of the work system change lead to indirect system effects that can lead to a change in the planned system results. Accordingly, it is of great importance to understand the effects of the structural change in logistics regarding the developments towards Logistics 4.0. Thereupon, it is possible to derive and implement a jointly optimised sociotechnical system in logistics based on which it is possible to actively manage the changes of the work system.

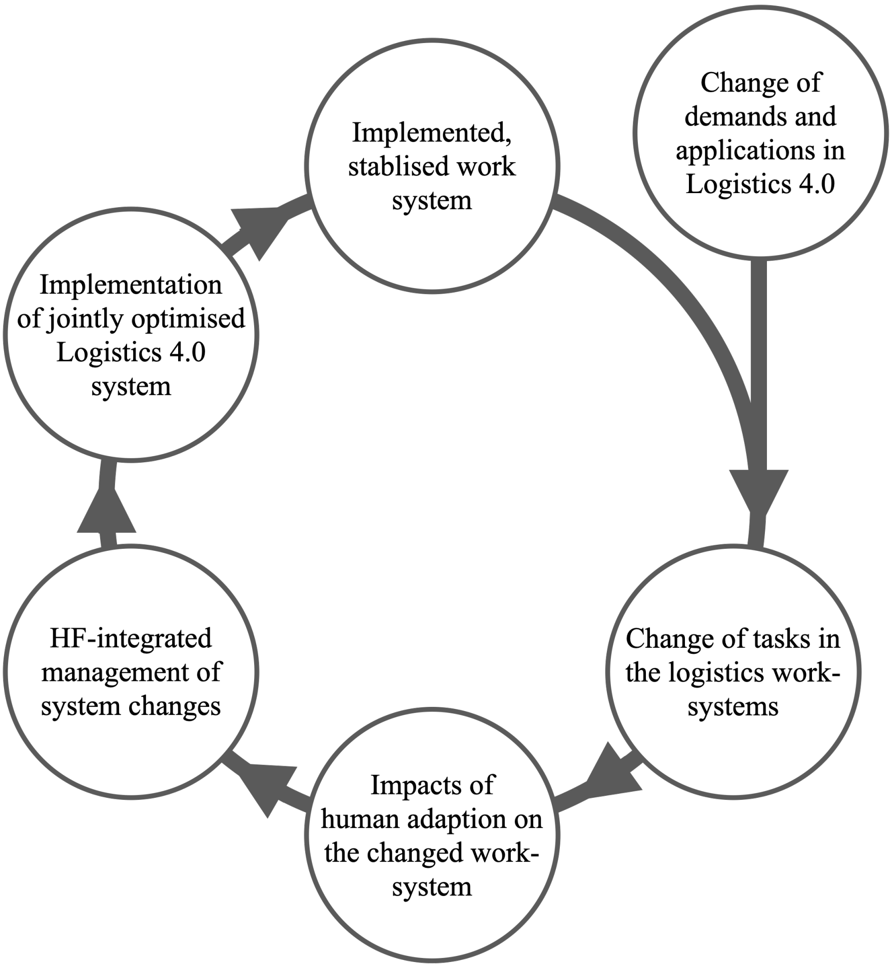

Figure I-2: Theoretical foundation of the dissertation.

The publication status of the five articles included in the three parts of this cumulative dissertation is presented in Table I-1. As can be seen, three articles have already been published while two articles are still under review, all of them in high-quality scientific journals.

Table I-1: Overview of article included in this cumulative dissertation.

Article #	Titel	Authors	Journal	VHB-JOURQUAL 3 Rating	Publication Status
1	Logistics 4.0: A systematic review towards a new logistics system	Winkelhaus, Sven Grosse, Eric H.	International Journal of Production Research	B	Published
2	Job Satisfaction: An explorative study on work characteristics changes of employees in Intralogistics 4.0	Winkelhaus, Sven Grosse, Eric H. Glock, Christoph H.	Journal of Business Logistics	B	2nd Revision Under Review
3	Industry 4.0 and the Human Factor - A Systems Framework and Analysis Methodology for Successful Development	Neumann, Patrick W. Winkelhaus, Sven Grosse, Eric H. Glock, Christoph H.	International Journal of Production Economics	B	Published
4	Towards a Conceptualisation of Order Picking 4.0	Winkelhaus, Sven Grosse, Eric H. Morana, Stefan	Computers & Industrial Engineering	B	Published
5	Hybrid order picking: conceptualisation and simulation of a joint manual and autonomous order picking system	Winkelhaus, Sven Zhang, Minqi Grosse, Eric H. Glock, Christoph H.	Computers & Industrial Engineering	B	Under Review

Part A of this cumulative dissertation consists of **Article 1** that provides an introduction into the research stream on Logistics 4.0. This research stream has gained importance as the business environment of logistics has been changing and setting new demands for fulfilling the targets of logistics. One part of this changing business environment is the advent of Industry 4.0, which enables more customised products for businesses as well as private customers (Kagermann et al., 2013). In addition, the demands on logistics from the private customer sector are increasing: For example, an increasing amount of goods is being distributed via e-commerce and the variety of products is increasing as is the requirement to make products available in ever shorter delivery times, up to same-day delivery (Boysen et al., 2019). Furthermore, sustainability goals gain importance for logistics including a reduction of emissions but also social targets gain importance within this development (Kagermann et al., 2013). On the other side of this development, new technologies are being developed that enable a more efficient, more complicated and more timely operation of logistics on the production side and open up new possibilities in logistics. Applications include the Internet of Things, cyber-physical systems and Big Data analytics (Hofmann and Rüsch, 2017). As a consequence of these complementary streams, research focuses on how to handle the new requirements in logistics. Although being tightly connected to each other, a comprehensive overview of research in logistics that summarises the research on technological developments and possibilities to meet the requirements was missing. Hence, a systematic literature review is performed in Article 1 that focuses on the new technological possibilities in the context of Logistics 4.0 that is conceptually derived before. Based on the systematic literature search strategy, 114 articles are reviewed contained in one of seven technological building blocks. Within each technological building block, articles are discussed as to whether they focus on a domain of logistics, such as distribution logistics, or on a particular logistics task like warehousing. As a result, a conceptual framework of Logistics 4.0 is refined and research opportunities are outlined to open new research perspectives. In this context, empirical research as well as research on human factors is identified as being under-represented in research compared to technological possibilities. By this conceptualisation as well as the systematic review, the article contributes to closing the research gap the development of Industry 4.0 opens in logistics.

In Part B of this cumulative dissertation, **Article 2** pursues the topics identified regarding the research opportunities of Article 1 and provides an empirical insight into the work of intralogistics employees. As the work in logistics changes with new technologies applied in the context of Logistics 4.0, employees' work characteristics change as well. Work characteristics impact employees' motivation and performance as well as their well-being and job satisfaction (Morgeson et al., 2013; Morgeson and Humphrey, 2006). Hence, there are two main reasons why investigating the impacts of Logistics 4.0 on work characteristics is important: First, human well-being is part of the sustainability goals as discussed in regard to the triple bottom line concepts and can be considered valuable in itself (Braccini and Margherita, 2018). Second, work characteristics also impact how humans work within the sociotechnical logistics system and thus impact the system performance (Rose et al., 2013). Not considering human work characteristics can influence the use of technologies and lead to phantom profits. The aim of Article 2 of this cumulative dissertation thus aims at understanding how the Intralogistics 4.0 maturity level impacts work characteristics and which aspects play a major role regarding these impacts. Therefore, 16 semi-structured interviews with intralogistics employees were performed in seven different companies on the basis of a comprehensive work design measure to empirically derive and analyse the impacts Logistics 4.0 has on work characteristics in intralogistics processes. Because a comprehensive overview on the impacts of Logistics 4.0 on work characteristics was missing, this article closes an important research gap.

After the basic topic of Logistics 4.0 was introduced conceptually in the first article of this cumulative dissertation and the perceived status-quo of the influence of Logistics 4.0 on human work in intralogistics was analysed in Article 2, **Article 3** first focuses on the actual state of human factors consideration in research on Logistics 4.0. Based on the identified research opportunity in this field from Article 1 and the empirical findings from Article 2 that mark this research gap as relevant, Article 3 thus complements the verification of the research gap in this cumulative dissertation. A content analysis of the literature dealing with Industry 4.0 was conducted for this purpose. In a content analysis, representative words for specific topics are defined as recording units (Krippendorff, 2013) and their occurrence in the sample is measured. The aim of this first part of Article 3 is – again in the context of the sociotechnical systems theory – to show to what extent human factors are taken into account in research on Industry 4.0, especially in relation to technical aspects. Together with the results of Article 2, the neglection of human factors consideration is evident and the importance of transformative knowledge for enterprises to consider these aspects is emphasised. Hence, the second part of Article 3 goes beyond the prior articles by focusing more strongly on the derivation of a systems framework to enable the theory-driven, systematic analysis of human impacts of the introduction of technological Industry 4.0 elements to support the active management of these developments. The aim of this second part of Article 3 is thus to close a research gap on how to consider technological impacts on human factors, on the production system and lastly also on financial figures of the enterprise.

Article 4 introduces Part C of this cumulative dissertation. In this article, the focus shifts from an overall perspective on Logistics 4.0 and Industry 4.0 to the order picking process. The order picking process is of high interest in research, because it is still labour-intensive and capital-intensive to automate (de Koster et al., 2007). Research articles, for example, focus on optimising the order picking process by providing routeing, batching, storage assignment and zoning strategies. Additionally, technical solutions are being analysed in the literature (see, e.g. Azadeh et al., 2019; Glock et al., 2021). However, on a broader conceptual level, classifications that provide an overview on order picking from a technological and processual point of view were missing. Hence, research was missing the link between technology usage, process design and outcomes. This gap is addressed in Article 4 of this cumulative dissertation by providing a framework of Order Picking 4.0 grounded on substituting and supporting technologies and different levels of automation. Following, a systematic literature review of Order Picking 4.0 systems is performed and research opportunities are highlighted. Especially the investigation of hybrid order picking systems, in which human order pickers and automation technologies cooperate or collaborate to perform the order picking process in a shared workspace, seems valuable from a sociotechnical perspective, but research on these order picking systems is still scarce.

Hence, **Article 5** explores this topic further. In this article, an in-depth investigation of hybrid order picking systems is provided, pursuing the research opportunities identified in Article 4. The aim is to close the research gap on hybrid order picking systems and to contribute to a comprehensive understanding of the possibilities and impacts of a collaborative hybrid order picking system applying autonomous order picking robots. Since the literature only provides a few examples for hybrid order picking systems and real-world applications are still scarce, an instance of a hybrid order picking system is derived and investigated in an agent-based simulation study. With this simulation study, Article 5 contributes to closing the research gap on hybrid order picking systems by investigating interrelations between collaborating highly automated and manual order picking systems in a shared workspace. The investigated hybrid order picking system is designed to meet HF requirements. Besides investigating the interrelations between the human and the automated order picking system, the article especially focuses on economic factors and which effects lead to hybrid order picking systems being preferable to purely manual or purely automatic order picking systems. To evaluate the practicality of these results, the assumptions made throughout the idealised agent-based simulation study are discussed critically.

Overall, this cumulative dissertation enhances the literature on Logistics 4.0 with two systematic literature reviews and conceptualisations of major concepts relevant for the future development of logistics (Article 1 and Article 4), a content analysis of the literature on Industry 4.0 and an analysis framework for the development towards Industry 4.0 and Logistics 4.0 (Article 3), a status-quo investigation based on an interview study on Logistics 4.0 impacts on work characteristics (Article 2) and a simulation study that provides new insights into hybrid order picking systems (Article 5). Owing to the dynamic developments businesses are currently facing, research on these developments is also of great importance for enterprises. Hence, besides the scientific contribution of the articles, this cumulative dissertation is also important from a practical and managerial point of view.

PART A - FOUNDATIONS OF LOGISTICS 4.0

II. [Article 1] Logistics 4.0: a systematic review towards a new logistics system[1]

Authors: Winkelhaus, Sven; Grosse, Eric H.

Enterprises are confronted with new customer requirements and challenged by global competition leading to fundamental changes of today's industry. Against this background, at present Industry 4.0 is the main concept of dealing with these challenges in manufacturing. Lacking a comparable covering concept in logistics, this study aims to stringently unify diverse approaches in research to a Logistics 4.0-framework in order to generate a new picture of the state of logistics research. In this article, a comprehensive framework of Logistics 4.0 is developed.

First, the term Logistics 4.0 is defined and then a systematic literature review of 114 articles on Logistics 4.0 is performed. The resulting framework combines external triggers, main technological innovations, impacts of human interactions and logistics tasks. Existing solutions that support Logistics 4.0 are summarised according to the technologies: Internet of Things, cyber-physical systems, Big Data, cloud computing, mobile-based systems, social media-based systems and further technologies. Managerial implications are outlined and open research issues are examined. For researchers, this review offers the possibility to unify and expand existing solutions and to identify links and interfaces that are still needed. As for managerial implications, this framework can be used to identify future strategies and technologies to fulfil certain logistics tasks, but also to develop new technological solutions for current and future demands.

Keywords:

Logistics; Industry 4.0, Smart, Internet of Things, Big Data, Systematic Literature Review

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[1] This article has been published as Sven Winkelhaus and Eric H. Grosse (2020): Logistics 4.0: a systematic review towards a new logistics system. International Journal of Production Research 58, 18-43. DOI: 10.1080/00207543.2019.1612964. This article has been slightly adapted for use in this dissertation, for example to ensure consistent spelling.

1. Introduction

Industrial production and logistics fulfil customer demands. Since those change over time, production paradigms also change. With the current turn towards more individual products, new ways of production and logistics are needed to avoid an increase of costs and competitive disadvantages on global markets (Hofmann and Rüsch, 2017; Weyer et al., 2015). Therefore, this study aims to develop a comprehensive framework for Logistics 4.0 to meet these challenges.

In this study, the focus is put on the role of logistics in the development towards individualisation, as logistics is of high importance for the overall economy. Logistics is the "planning, implementing and controlling efficient, effective flow and storage of goods and services from the beginning point of external origin to the company and from the company to the point of consumption for the purpose of confirming to customer requirements" (Lummus et al., 2001). In 2015, nearly 1.19 million enterprises could be recorded in the transportation and storage service sector for the 28 EU countries, employing nearly 11 million people with 556 billion EUR value added (Eurostat European Commission, 2018). Similarly, Ruan et al. (2012) figured out that the total social logistics costs in Europe and the USA were as high as 10% of GDP compared to 17.8% in China in 2011.

In addition to these economic indicators, different studies showed that logistics networks co-determine customer satisfaction or dissatisfaction, high or low productivity, even business success or failure by means of adding "place utility" (Islam et al., 2013). For example, Tracey (1998) as well as Davis-Sramek et al. (2008) figured out that logistics influences customer service and satisfaction, since its main drivers – for instance price, quality, variety and delivery speed – are impacted by logistics. Hence, logistics has a marketing and a production character at the same time (Kent and Flint, 1997). Tracey (1998) concluded, "manufacturing firms that do not specifically develop and benefit from logistics efficiency will inevitably find themselves handicapped competitively". Logistics and supply chain management (SCM) are not defined generally consistent and are not mutually exclusive (Ballou, 2007; Lummus and Vokurka, 1999). According to the council of supply chain management professionals, SCM is "the planning and management of all activities involved in sourcing and procurement, conversion and all logistics management activities" (Council of Supply Chain Management Professionals, 2013). Hence, logistics is one part of SCM. Nevertheless, SCM especially "includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers and customers" (Council of Supply Chain Management Professionals, 2013). Thus, SCM is distinguished from logistics hereinafter as activities of general coordination among partners in a supply chain without a focus on the hands-on activities of logistics tasks, and not in the scope of this review.

Although manufacturing and logistics have gained maturity over the last decades, saturated markets and new customer demands put pressure on logistics systems, turning them from complicated to complex ones (Bauernhansl, 2014). Important drivers are shortening product lifecycles, globalisation of markets, demographic change and customer demands to offer individualised products, also accompanied by sustainability aspects (Jubiz-Diaz et al., 2019; Kagermann et al., 2013; Lasi et al., 2014). These drivers form a dynamic and challenging environment for enterprises, which, in manufacturing, can be addressed with Industry 4.0. Since an according covering concept is still missing in logistics, this study aims at answering the following research questions (RQ) that arise in the development of logistics systems towards the fulfilment of individualised customer demands and Industry 4.0:

- *RQ 1: Which characteristics should be included in a covering concept of Logistics 4.0?*
- *RQ 2: What is the state of knowledge in Logistics 4.0 research?*
- *RQ 3: Which aspects of Logistics 4.0 are currently under-represented but promising to fulfil the requirements of these systems?*

The theoretical foundations of Industry 4.0 are provided in Section 2. The term Logistics 4.0 is introduced and a deductive framework of Logistics 4.0 is derived in Section 3. A systematic literature review is performed to answer the research questions. Section 4 provides insights from previously published, related literature reviews and presents the methodology for the systematic literature review employed in this study. The review is conducted in Section 5. In Section 6, key results are discussed according to the framework elements highlighting the research streams and a research agenda is outlined in comparison to the derived concept of Logistics 4.0. Finally, the limitations of this study are discussed in Section 7 and the study is concluded.

2. Theoretical foundations of Industry 4.0

The buzzword Industry 4.0 was raised in 2011 and has gained significant attention since then. About four years later, the Scopus database already showed more publications with the keyword “Industry 4.0” than for earlier emerged concepts of alternative manufacturing systems (MS) (Bi et al., 2008; Kuehnle, 2007; Mehrsai et al., 2013; Monostori, 2014; Sanchez and Nagi, 2010), which is shown in Figure II-1.

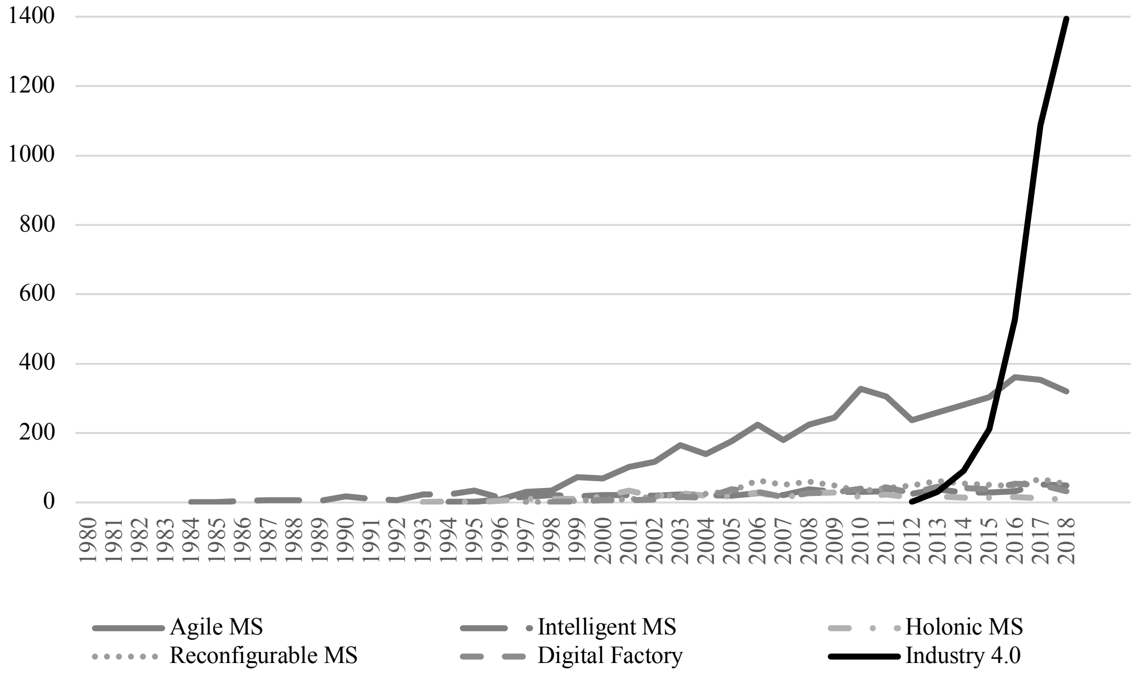

Figure II-1: Number of publications for different keywords related to smart manufacturing over time.

This trend in the manufacturing literature hints at the need for a concept providing a conclusive way of answering to the derived demands. In Industry 4.0, three aspects can be distinguished: a paradigmatic one, a technological one and one related to sustainability. On the paradigmatic side, Industry 4.0 fulfils the mass customisation production paradigm (Kagermann et al., 2013), combining the scale effects of mass production with the scope effect of individualised products requiring flexibility and decentralisation (Barman and Canizares, 2015; Duguay et al., 1997; Lasi et al., 2014). On the technological side, mainly new information technologies are considered, addressing the rising complexity (Lu, 2017).

Hence, Industry 4.0 is related to the digital transformation. A third aspect of Industry 4.0 relates to the integration of humans and the environment for future industrial systems, thus calling for sustainability (Kagermann et al., 2013). Besides new human-technology interactions, Kagermann et al. (2013) originally emphasised the need of a supportive organisation of work to meet the requirements of employees for work-life-balance, lifelong learning and higher degrees of autonomy due to the change of work characteristics as well as the need for activities dealing with the demographic change and resource efficient production.

Following, definitions focusing on a certain technology lack abstraction. Combining the aspects derived by Kagermann et al. (2013) and Hofmann and Rüsch (2017), a possible definition of Industry 4.0 is: *The vision of a highly integrated smart factory, in which individual goods are produced sustainably in a mass production manner to fulfil customer demands in a global competition*. The main technological building blocks that are considered as essential for the vision of Industry 4.0 are cyber-physical systems (CPS) and the Internet of Things (IoT) (Buer et al., 2018; Hofmann and Rüsch, 2017; Liao et al., 2017).

In the IoT, physical entities are able to generate and share information, often based on radio-frequency identification (RFID) (Grüninger et al., 2010; Ustundag, 2010). Hence, the IoT can be seen as the basis for many applications related to Industry 4.0 (Gunes et al., 2014). In 2016, already more than 17 billion devices have been connected via the IoT and the amount is expected to reach 30 billion devices in 2020 (Statista, 2016). CPS are able to generate and use information in the cyber-sphere and use actuators to affect the physical world (Lee, 2006; Lee et al., 2015). Multiple interacting CPS in manufacturing can build cyber-physical production systems (CPPS) (Seitz and Nyhuis, 2015) and cyber-physical production networks (Mladineo et al., 2016). Moreover, Big Data (BD) is often used as an underlying tool of Industry 4.0 due to the huge amount of data generated (Lu, 2017). Technological drivers with a narrower focus are e.g. augmented reality (Hofmann and Rüsch, 2017), blockchain technologies (Kamble et al., 2019) and additive manufacturing, which also relies on 3D model data (Hofmann and Rüsch, 2017; Li et al., 2016). For a more in-depth discussion of Industry 4.0 in general we refer to the recent reviews of Liao et al. (2017) and Xu et al. (2018).

However, a sole focus on manufacturing falls short. Especially in global markets, efficient logistics is a key aspect for companies to stay competitive and is essential to reach the target of delivering mass customised high-quality products sustainably (Gunasekaran and Ngai, 2012; Hofmann and Rüsch, 2017; Kagermann et al., 2013). Hence, Industry 4.0 offers manifold opportunities for logistics systems to adopt to the new environment.

3. Theoretical derivation of Logistics 4.0

To handle today's global logistics systems of a multitude of product variants, different methods have been derived e.g. postponement or modularisation (Costantino et al., 2014). However, it is questionable whether todays logistics systems will be able to handle even more complex systems like a one-off item production (Windt et al., 2008) – especially without an increase of cost or decrease of quality. In this case, the business-environment requires dynamic and customer-oriented adaption to new demands and new ways might be necessary to achieve the goals of logistics. Logistics real-time visibility becomes more important to be able to react on sudden changes (Kache and Seuring, 2017). Hence, following the assumption that Industry 4.0 realises mass customisation, an according system Logistics 4.0 is needed, as manufacturing systems fail if the link between manufacturers and customers is fragile – be it B2B, B2C or internal.

3.1. Definition of Logistics 4.0

In the literature, only few articles referred to the term Logistics 4.0. Strandhagen et al. (2017) described Logistics 4.0 according to five characteristics: real-time Big Data analytics (BDA), for example for optimised routeing, reduced storage requirement due to new manufacturing techniques, autonomous robots with tracking and decision systems leading to optimised inventory control, information exchange in real time avoiding e.g. bullwhip effects and no information disruption due to smart items. In contrast, Barreto et al. (2017) referred to the combination of using logistics with the innovations and applications added by CPS. Additionally, Timm and Lorig (2015) described Logistics 4.0 as the transformation from hardware-oriented logistics to software-oriented logistics.

To derive a common and general understanding of Logistics 4.0 synthesising the existing definitions of logistics, Industry 4.0 and Logistics 4.0, we distinguish three aspects:

- (1) The implications of the changing production paradigm to mass customisation (Gunasekaran and Ngai, 2012; Kuehnle, 2007) on logistics.
- (2) The changes of logistics processes caused by the use of new digital technologies, e.g. IoT and CPS.
- (3) The importance of humans that are considered in their roles as employees, customers and other stakeholders also accompanied by environmental changes.

Based on these aspects, we define Logistics 4.0 as:

Logistics 4.0 is the logistical system that enables the sustainable satisfaction of individualised customer demands without an increase in costs and supports this development in industry and trade using digital technologies.

The phrase “4.0” is used instead of, e.g. “smart”, since it is a versioning-analogy of the software industry and directs to the digital technologies that are in the centre of the Fourth Industrial Revolution (Lasi et al., 2014). Nevertheless, since technological lifecycles might be shorter than the underlying paradigm of Logistics 4.0 lasts, it is not based on one specific technology.

3.2. Conceptual framework of Logistics 4.0

Figure II-2 shows the conceptual framework of Logistics 4.0 adopted from the technology, organisation, environment (TOE) framework, which was originally developed for a comprehensive analysis of technology adoption (Oliviera and Martins, 2011). The Logistics 4.0 framework consists of three dimensions:

(1) The first dimension is the external one, consisting of the paradigmatic changes triggered by customer demands of individualised high-quality products, the developments of Industry 4.0 and the related aspects of globalisation and sustainability (Hofmann and Rüsch, 2017; Kagermann et al., 2013; Lasi et al., 2014). Moreover, this dimension includes the changes in societies e.g. towards new work-life balances. These new demands could be considered as a pull-perspective to “4.0”-systems (Lasi et al., 2014).

(2) The second dimension is the technological one. It consists of the technological building blocks of the developments enabling the paradigmatic change practically leading to the change from traditional logistics systems to Logistics 4.0. It mainly consists of the main technological drivers of Industry 4.0 but is not limited to these, e.g. the digital transformation offers additional technologies of relevance such as BD, cloud computing or social media applications (Probst et al., 2017). This dimension can be considered as a push-perspective towards “4.0”-systems (Lasi et al., 2014).

(3) The third dimension focuses on logistics. Three aspects are distinguished: tasks, domains and human factors. Tasks incorporate management activities (Islam et al., 2013) and execution activities (Gudehus and Kotzab, 2009). These activities can be separated into

four domains following the direction of material flows: supply logistics, intra/production logistics, distribution logistics and reverse logistics (Gudehus and Kotzab, 2009). Third, logistics is influenced by humans, their knowledge and capabilities. Human factors, like physical limits and psycho-social interactions as well as human decisions and motivation influence logistics quality and efficiency. It is expected that humans will not be substituted in Logistics 4.0 by machines, but their work is influenced and supported by new technologies and human-machine cooperation (Kagermann et al., 2013). Additionally, humans are important impact factors concerning the benefit of new technologies, since they decide about adoption or rejection according to the perceived costs and benefits (Tu, 2018).

As shown in Figure II-2, Logistics 4.0 is the outcome of the interaction of the three dimensions and enables the realisation and integration of all elements. For example, the external changes trigger the use of new technologies to fulfil new demands on the one hand, and on the other hand, new technologies might enable the fulfilment or trigger the occurrence of new demands. External changes could lead to a change of logistics tasks since shifts in the way logistics is performed as well as the importance and functioning of different domains might occur with a different load. Similarly, technological developments interact with logistics tasks and human factors.

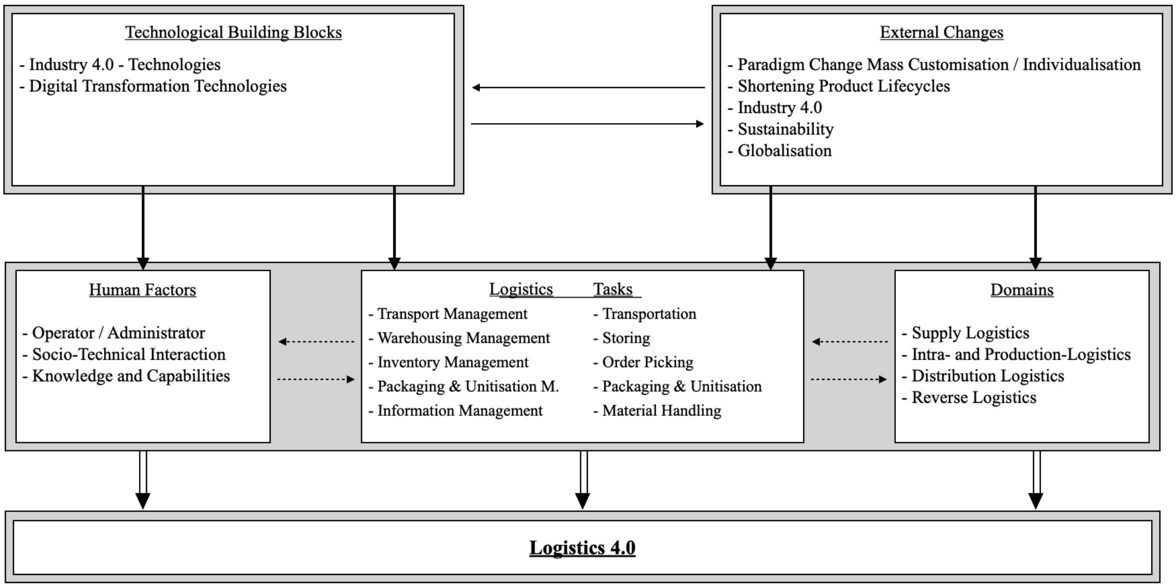

Figure II-2: Conceptual framework of Logistics 4.0.

This deductively developed framework has inductively been refined considering the results of the literature review to provide a more precise picture of the current status and the characteristics of Logistics 4.0 (see Sections 5 and 6).

4. Methodology

In the following, an overview of published literature review articles in related research fields is presented to highlight the contribution of this study. Then, the methodology of our literature search and sample generation is presented to guarantee scientific standards of reliability, validity and objectivity.

4.1. Insights from previous literature reviews

Seven literature reviews could be identified that are related to the topic, four of these are narrative ones and three are systematic reviews.

Wang et al. (2018b) provided a survey of ubiquitous manufacturing and offered insights to logistics systems finding especially the additional application of BD and the automation of shopfloor logistics as future trends of ubiquitous computing. Goudos et al. (2017) reviewed enabling technologies of the IoT and examined important technologies for logistics applications like RFID, cloud computing and agent-based systems, which are systems aiming at a defined target autonomously by interacting with their environment. Focusing on BD in SCM, Zhong et al. (2016b) conducted a review focusing on challenges and opportunities, whereas Addo-Tenkorang and Helo (2016) aimed at the development of a framework for BD and IoT applications in operations and SCM according to BD characteristics.

As for the systematic ones, Lamba and Singh (2017) reviewed BD in the fields of manufacturing, procurement and logistics focusing on volume, velocity and variety. Wang et al. (2016) reviewed the literature on supply chain analytics, which is the combination of BDA and SCM to develop a maturity framework. Ben-Daya et al. (2017) conducted a network analysis on the IoT in SCM and concluded that most studies are of conceptual character within food and manufacturing supply chains.

Table II-1: Comparison of related systematic literature reviews.

Authors Year	**Wang et al., 2018b**	**Goudos et al., 2017**	**Zhong et al., 2016b**	**Addo-Tenkorang and Helo, 2016**	**Lamba and Singh, 2017**	**Wang et al., 2016**	**Ben-Daya et al., 2017**
Focus	Ubiquitous Manufacturing	Internet of Things	Big Data and SCM	Big Data and Oper- ations & SCM	Big Data and Oper- ations & SCM	Big Data and Logistics & SCM	Internet of Things and SCM
Method	Narrative review	Narrative review	Narrative review	Narrative review	Systematic literature review	Systematic literature review	Systematic literature review / biblio- metric analysis
Sample overlap (Review of Section 5)	6%	1%	3%	2%	0%	0%	8%

Table II-1 summarises the differences of the existing literature reviews with regard to topic and methodology and highlights the sample overlap of these reviews with the review at hand. Hence, this study contributes to the existing literature by:

- (1) Starting from the paradigmatic change and reviewing the outcomes for logistics regardless of which emerging digital technology is used, whereas existing reviews applied a technological starting point, especially BD;
- (2) Focusing on logistics tasks, not on SCM or operations management in general.
- (3) Providing a review of literature that has not been considered in a secondary study, since the sample overlap is always less than 8% and even the total overlap of this study with all literature reviews described above is less than 13%.

4.2. Literature search and selection strategy

A literature review helps structuring a topic of research, identifies research gaps and contributes to theory development (Seuring and Gold, 2012). Therefore, literature reviews should employ “a systematic, explicit and reproducible method” (Fink, 2005) to identify and analyse the body of literature (Seuring and Müller, 2008). Usually, a sample is derived for analysing a conclusive part of the whole body of published literature. To guarantee a stringent, systematic and transparent literature search and selection procedure, we followed the suggestions made by Tranfield et al. (2003) and Krippendorff (2013) for systematic literature reviews and sample generation. The sample was generated in five steps:

(1) *Definition of keywords*: Based on the conceptual framework derived in Section 3, a set of keywords was defined that basically distinguish a text for inclusion or exclusion from the sample (Krippendorff, 2013). Within the study, the keywords belong to one of two groups that are displayed in Table II-2: Logistics-related keywords and terms related to "4.0"-systems according to the theoretical foundations. We do not refer to "transport" as a single keyword, because transportation itself is a dynamic field of research, often related to infrastructural and legal issues that are not within the scope of this review. Only articles containing at least one keyword of both groups in the title, abstract or list of keywords were included. The databases Scopus and Business Source Premiere were searched for these keyword combinations, resulting in more than 15.000 initial results.

Table II-2: Sample keywords related to logistics and "4.0".

Logistics-related	**4.0-related**		
*Logistics	4.0	IoT	Cobots
Material handling	Smart	Internet of Services	Collaborative robot
Storing	Mass customisation	Cyber-physical	Augmented reality
Order picking	Individualisation	Cybersecurity	Virtual reality
Warehous*	Human-machine	Blockchain	Big data
Unitising	Assisted operator	Social media	Cloud
Packaging	Adaptive workplace	Mobile services	Exoskeleton
Transport* management	Internet of things	Autonomous robot	Gamification
Inventory management			

(2) *Refinement*: The refinement process only included peer reviewed English journal articles. We further identified six subject areas as relevant: "Computer Science", "Engineering", "Economics", "Management", "Social Science" and "Decision Science" leading to 1919 results.

(3) *Inclusion and exclusion criteria*: Irrelevant articles were identified by reading the title, abstracts and keywords. Articles were read completely in this stage, if no clear decision was possible. Moreover, every decision was double-checked to avoid inconsistent classifications. An article was seen as irrelevant, for example, if it describes a technological development without applying it in logistics. To keep the review focused, logistics was limited to the context of industrial systems and non-perishable goods, e.g. in the automobile industry. Thus, articles dealing with blood supply chain, food supply chain, emergency logistics or

the logistics of vending machines were not within the scope of this review. 334 articles remained in the sample after this step.

(4) *Second refinement*: All articles were read completely and irrelevant ones were excluded subject to the defined inclusion and exclusion criteria. After this step, 108 articles remained.

(5) *Snowball search*: A backward snowball-search in the references of the relevant articles was carried out to search for further relevant articles. 6 new articles were found in this step and added to the sample, so 114 articles remained in the final sample.

4.3. Descriptive results

The articles' distribution over time is shown in Figure II-3. As can be seen, Logistics 4.0 has gained more attention over the past years, indicating the rising importance of the investigated approaches. In 2018, the decrease is caused by a reduction of time, not of attention in research, thus following the trend of research on Industry 4.0 shown in Figure II-1. Moreover, the technologies used could be divided into seven main categories: (5.1) IoT-based systems, (5.2) cyber-physical applications and autonomous robotics, (5.3) Big Data applications, (5.4) cloud-enabled systems (5.5) mobile-based systems (5.6) social media-based applications and (5.7) other technologies related to the paradigm. The contribution of articles over time according to these seven dimensions is shown in Figure II-3, too.

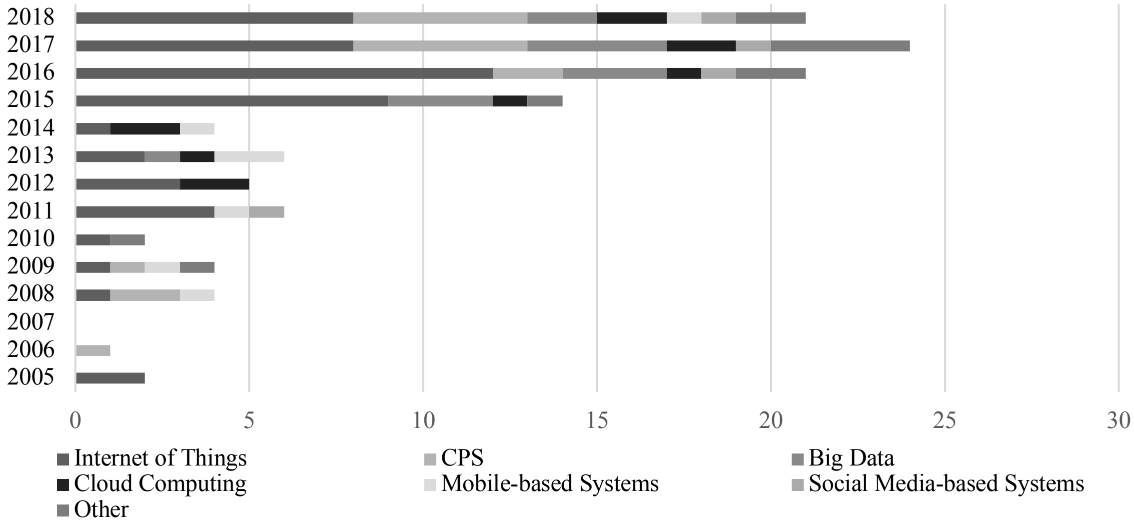

Figure II-3: Contribution of articles over time and technology.

Moreover, as summarised in Table II-3, there is a wide-spread contribution of articles over diverse journals. Journals with three or more contributions are listed in Table II-3. It can be summarised that the most contributing journal is the *International Journal of Production Research,* and that research on Logistics 4.0 has been published in journals with different scope, be it operations management, information technology, or logistics. This emphasises the interdisciplinary character of Logistics 4.0.

Table II-3: Number of articles per journal.

Journal name	**Number of articles**
International Journal of Production Research	6
International Journal of Production Economics	4
The International Journal of Logistics Management	4
Computers in Industry	4
IEEE Transactions on Industrial Informatics	3
Industrial Management & Data Systems	3
The International Journal of Advanced Manufacturing Technology	3
International Journal of Physical Distribution & Logistics Management	3
Procedia Manufacturing	3
Others	81
	114

Analysing the distribution of keywords of the sample as shown in Figure II-4, it can be seen that IoT as well as RFID have an outstanding importance. Logistics as a keyword is only on third position. Moreover, although BD was searched explicitly in the databases, it has only one-quarter of the hits of RFID, which was not searched explicitly. This is remarkable, because there are numerous literature reviews on BD, but only a few that consider the IoT and RFID within logistics.

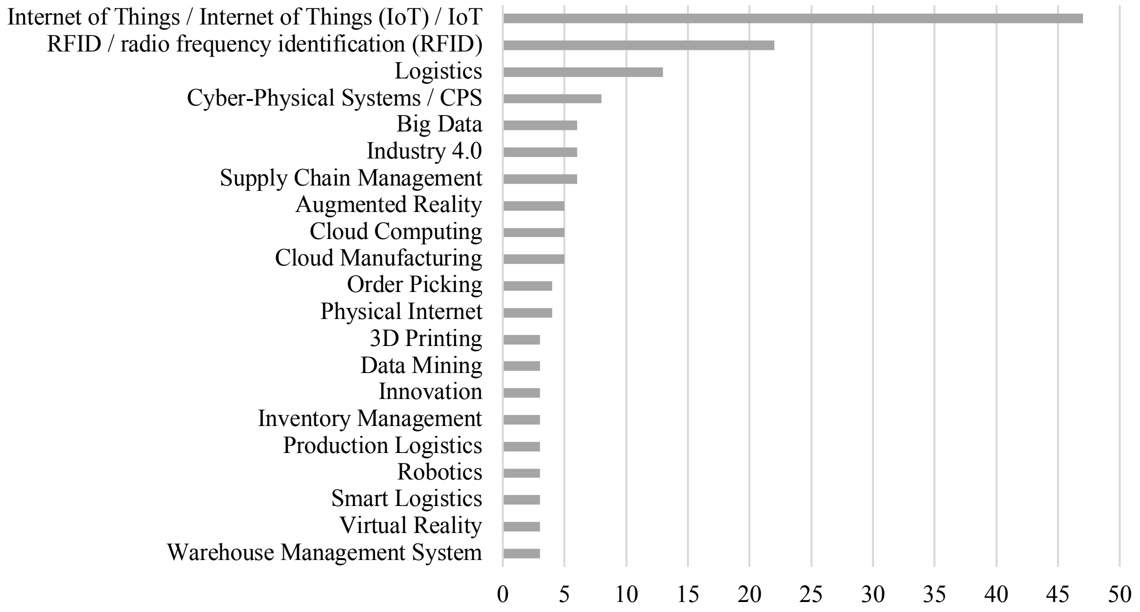

Figure II-4: Number of most mentioned keywords in the sample.

5. Literature review

To guarantee a structured review, the framework developed in Section 3 is used for classifying and discussing the sample. Due to the evidence of different technologies for Logistics 4.0, the technological category is chosen to structure the review. If several of the relevant technologies are included in one article, the articles are presented in the technological category which is assessed as the most relevant one. Additionally, Table II-4 summarises contributions according to the focused tasks and Table II-5 according to the focused domains.

5.1. IoT

The IoT enables the information generation and transmission of objects to a central or decentral system and goes beyond “simple” identification, often related to and enabled by RFID technology. The IoT as defined by Gubbi et al. (2013) is the “interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications.” With 45% of the sampled articles, the IoT is the main application of Logistics 4.0.

Table II-4: Contributions in the sample concerning tasks of logistics.

Classification criteria	Number	References
Information Management	14	Liu and Sun (2012), Papert and Pflaum (2017), Zhu (2018), Meroni et al. (2018), Gu and Liu (2013), Thürer et al. (2016), Langer et al. (2006), Zhong et al. (2015a), Zhong et al. (2015b), Zhong et al. (2016a), Kong et al. (2015), Gao et al. (2018), Bhattacharjya et al. (2016), Bhattacharjya et al. (2018)
Transportation and Transport Management	12	Stefansson and Lumsden (2008), Kim et al. (2015), Lang et al. (2011), Sallez et al. (2016), Schuhmacher et al. (2017), Zhang et al. (2016), McKelvey et al. (2009), Hopkins and Hawking (2018), Boon and van Wee (2017), Zhou et al. (2018), Alves et al. (2009), Yuen et al. (2010)
Warehousing, Packaging and Warehouse Management	25	Xu (2014), Semunab et al. (2016), Kim and Park (2016), Lee et al. (2017), Zhou et al. (2017), Ramakrishnan et al. (2016), Reaidy et al. (2015), Pan et al. (2015), Culler and Long (2016), Semwal et al. (2017), Zheng and Wu (2017), Bertsimas et al. (2016), Nagorny et al. (2012), Alwadi et al. (2017), Gupta and Jones (2014), Reif and Walch (2008), Reif and Günthner (2009), Schwerdtfeger et al. (2011), Cirulis and Ginters (2013), Ginters and Martin-Gutierrez (2013), Krajcovic et al. (2014), Mathaba et al. (2011), Mathaba et al. (2017), Szafir et al. (2017), Kembro et al. (2017)
Material Handling	8	Kousi et al. (2018), Zhang et al. (2018a), Zhang et al. (2018b), Wahrmann et al. (2017), Wan et al. (2018), Overmeyer et al. (2016), Toxiri et al. (2018), Naruoka et al. (2016)
General Contributions	23	Sun (2012), Twist (2005), Gładysz (2015), Geng and He (2016), Tadejko (2015), Gong and Liu (2013), Chen and Zhao (2018), Ganzha et al. (2017), Qu et al. (2015), Bremer (2015), Yam et al. (2005), Kim et al. (2017), Simske (2011), Wang et al. (2018a), Barreto et al. (2017), Hofmann and Rüsch (2017), Wasesa et al. (2017), Brandau and Tolujevs (2013), Kim (2017), Frazzon et al. (2015), Chen et al. (2014), Tiejun (2012), Gromovs and Lammi (2017)

5.1.1. IoT systems

Dealing with the IoT, either the objects themselves or packages and the periphery can provide “smartness” to objects. The former case is investigated in this subsection, the latter case in the next subsection.

On the way towards Logistics 4.0, opportunities and threats of the IoT were investigated in general. Therefore, Friedewald and Raabe (2011) conceptualised ubiquitous computing as an evolutionary step towards the IoT to examine possible technological influences in transportation logistics and other industries. Potential opportunities were examined especially according to automated information flows, more efficient internal processes, enhanced cooperation with partners and the enabled development to all-round service providers. Additionally, Atzori et al. (2010) provided a conceptual investigation of the IoT technologically and applicational, finding opportunities in logistics for efficiency and responsiveness due to real-time information processing.

Table II-5: Contributions in the sample concerning domains of logistics.

Classification criteria	Number	References
Supply Logistics	6	Qiu et al. (2015), Liu and Sun (2011), Yerpude and Singhal (2017), Pan et al. (2015), Wycisk et al. (2008), Zheng and Wu (2017)
Intra- and Production Logistics	20	Twist (2005), Kartnig et al. (2012), Tu et al. (2018a), Qu et al. (2017), Mahmud (2017), Nopper and ten Hompel (2009), Lin and Yang (2018), Schuhmacher et al. (2017), Windt et al. (2008), Pujo et al. (2016), Kousi et al. (2018), Zhang et al. (2018a), Zhang et al. (2018b), Tu et al. (2018b), Zhong et al. (2015a), Zhong et al. (2015b), Zhong et al. (2016a), Li et al. (2013), Kong et al. (2015), Qu et al. (2016)
Distribution	16	Yu (2016), Gan (2015), Xu (2014), Hu et al. (2016), Wu (2018), Zhu (2018), Zhang et al. (2016), Lee (2017), Liu and Wang (2016), Yang et al. (2017), Leung et al. (2018), Gao et al. (2018), Bhattacharjya et al. (2016), Bhattacharjya et al. (2018), Boon and van Wee (2017), Zhou et al. (2018)
Reverse Logistics	2	Gu and Liu (2013), Thürer et al. (2016)
General Contributions	11	Friedewald and Raabe (2011), Atzori et al. (2010), Hsu and Yeh (2017), Tu (2018), Hwang et al. (2016), Geng and He (2016), Barreto et al. (2017), Wen et al. (2018), Angeleanu (2015), Lai et al. (2018), Alberti-Alhtaybat et al. (2019)

Since there are possible benefits and application fields of the IoT in logistics, the adoption of the IoT is important. Therefore, Hsu and Yeh (2017) applied the TOE model and the DEMATEL method to investigate the IoT adoption intention in logistics. Evaluations with an expert group revealed that IT expertise, top management support, government policy, competitive pressure and security issues to be the most important influences. In addition, Tu (2018) found out in a questionnaire based investigation that the IoT adoption intention in logistics is based on the perceived benefits, costs and external pressure.

Beside the adoption intention, the IoTs diffusion is relevant. Hence, Hwang et al. (2016), performed a cluster-analysis of business cases for the IoT-diffusion in different value configuration models. In the value configuration cluster "intelligent inventory transport model", logistics was considered most often.

Deepening these findings and figuring out possible influences of the IoT for logistics applications in general, the following studies show the importance of visibility and possible outcomes for efficiency and accuracy improvements in logistics. Sun (2012) investigated RFID for the IoT in logistics and especially emphasised two benefits: improved visibility of goods on data-level and reduced errors based on e.g. inventory inaccuracies. Additionally, Twist (2005) conceptually investigated the impact of RFID technologies on logistics facilities finding productivity improvements, although imperfect read rates, system's costs and security issues are discussed as major barriers. Nevertheless, both studies forecasted possibilities for a decrease of labour costs due to RFID-enabled automatised identification and information provision. Since the IoT grounds on RFID, Gładysz (2015) developed a decision support model to investigate the role of RFID in manufacturing companies. Due to a lack of analysis methods, the RFID technology assessment method was proposed to identify, decide, design and evaluate RFID-based improvements of logistics processes. Moreover, Geng and He (2016) derived a concept of the IoT in logistics processes and outlined innovation possibilities for transportation, warehousing, sales and production logistics. Furthermore, in a conceptual investigation of logistics applications, Tadejko (2015) found visibility, warehouse management and fleet management as improvable with the IoT. Nevertheless, also challenges in the areas of security, standardisation and data handling and on technology, network and application level were examined.

Beside opportunities of the IoT for the whole logistics process, several authors provided more focused investigations of the IoT. On a systems level, Gong and Liu (2013) developed a conceptual model for the integration of logistics resources making real world logistics systems more robust. The IoT was therefore applied as a sensing part and a neural network as a cognitive part. A conceptual model for a logistics automation management system based on the IoT and RFID was provided by Chen and Zhao (2018) aiming for accurate and efficient information flows. To avoid the collision of RFID tags, which could deteriorate accuracy, anti-collision algorithms were applied. With a focus on ontologies in the IoT, Ganzha et al. (2017) provided a conceptual investigation to facilitate the inter-operability of heterogenous IoT platforms, finding a lack of ontologies covering a broad spectrum of logistics prohibiting wide interoperability. Further, Qu et al. (2015) presented a framework for information processing on the IoT. The framework is based on different ontologies enabling the system for IoT transactions. Tests in a third-party logistics case study revealed efficiency improvements by constructing and executing the IoT transactions automatically.

According to different domains, supply logistics was focused by Qiu et al. (2015), who provided a conceptual model for supply hubs in industrial parks applying the IoT for optimised physical asset and service sharing. Thereupon, research opportunities were derived, e.g. in the dimensions of IoT infrastructure standardisation and security, business models and decision models. In addition, two articles focused on vendor managed inventory (VMI). Liu and Sun (2011) developed a model for information management for VMI for automobile manufacturers. Analysing the information flows, the usage of RFID-based IoT was examined. On this basis, Yerpude and Singhal (2017) provided a conceptual framework for the improvement of VMI with the IoT, finding possible outcomes in higher inventory turns. Additionally, both articles figured out that the utilisation of the IoT in VMI activities supports the transparency, agility and efficiency by real-time and bidirectional information flows.

Introducing the research on the IoT in intra-and production-logistics, Kartnig et al. (2012) provided a conceptual work identifying current mega-trends like globalisation, sustainability and individualisation as important for intra-logistics. It was derived that high efficiency, environmental conscious ("green") logistics and the IoT will influence logistics most. Focusing on production logistics systems, Tu et al. (2018a) developed a unified framework for the adoption of the IoT. The model consists of three layers in a top-down synthesis including object, process and ontology models. Additionally, Qu et al. (2017) conducted a system dynamics-based simulation study to investigate internal and external production logistics. Findings revealed that the overall optimum of the IoT control scheme for production logistics is not equal to the superposition of local optima for internal and external production logistics. Adding an IT-perspective, Mahmud (2017) conceptually investigated the usage of ERP-based possibilities and the IoT in production logistics. Results like improved efficiency and decision-making processes were found, just as the necessity of collaboration to implement the IoT in logistics. Additionally, in a simulation study, Nopper and ten Hompel (2009) analysed how IoT-based information quantity influences throughput time and capacity utilisation of a conveyor system. It was found that simple but robust control strategies might be preferred for realistic systems. Supporting the implementation, Lin and Yang (2018) provided a model for an intelligent computing system based on the IoT and fog computing as distributed computing resources. The model aimed at minimising the installation costs of such devices by varying the locations, which was verified in a simulation study.

In distribution processes, especially transportation tasks are relevant for enterprises. Hence, two articles investigated new tracking and monitoring systems using RFID and GIS systems. Yu (2016) developed a system based on IoT and GIS and stated improvements of accuracy and rapidity of logistics planning. Gan (2015) similarly developed a model for logistics management based on the IoT and GIS and exemplified it in the tobacco industry. Both systems aim to identify errors and minimise failures.

In e-commerce logistics, opportunities of the IoT were broadly investigated. In a conceptual study, Xu (2014) focused on inventory, logistics management and payment. The authors concluded that applications of the IoT, like intelligent transportation and warehouse management, improve competitiveness of e-commerce, although challenges in the technology's maturity and missing standards still exist. Additionally, Hu et al. (2016) investigated the effect of logistics services quality on customer satisfaction level in online shopping empirically showing that the IoT has the potential to enable customised logistics services and hence promote customer satisfaction levels. Moreover, Wu (2018) provided a framework for an IoT and agent-based decision support system in e-commerce. With this system, information could be acquired, automatically processed and utilised supporting varied decisions like resource allocation, order release times or process management.

Focusing on certain tasks in logistics like information management, warehousing or inventory management instead of an application field, several articles were found, which are discussed briefly hereinafter.

Investigating the value of shared information, Liu and Sun (2012) proposed an IoT-based model for collaborative planning, forecasting and replenishment. The information flow of inbound logistics of automotive manufacturers was investigated and optimised according to real-time information integration. Papert and Pflaum (2017) developed an IoT business ecosystem model for logistics service providers aiming for information integration. In this model, a solution integrator realises the combination of subsystems to complete IoT services. Further, Zhu (2018) derived a method for cooperative logistics delivery scheduling across companies applying BD, cloud computing and especially the IoT. The study aimed for improved fulfilment of customer requirements according to cost, speed and security.

Meroni et al. (2018) derived a conceptual model for decentralised compliance monitoring using the Extended Guard-Stage-Milestone notation. The authors stated that the IoT could be used to enable monitoring and information management within multiple business process management systems, which was illustrated in a logistics case.

Information management is also important in reverse logistics due to the spatially and temporally distribution of logistics activities. Hence, Gu and Liu (2013) developed a conceptual model for information management in a closed-loop logistic system based on the IoT pointing out constraints in the realisation, i.e. economic, management, data security and technological issues. Moreover, Thürer et al. (2016) investigated the feasibility of Kanban-systems for solid-waste collection as an inventory control problem. The authors developed a concept applying the IoT to manage geographical distribution and the amount of collection points.

Focusing on the IoT in transportation management, Stefansson and Lumsden (2008) investigated a smart transportation management system based on case studies. Smart goods, vehicles and infrastructure lead to better visibility and information accessibility revealing opportunities in time savings in warehouse and transportation tasks and communications with customers. Kim et al. (2015) also studied transportation and warehouse management using the IoT and developed a smart integrated multiple tracking system for logistics companies, integrating materials, personnel and inventory, improving accuracy and reliability by reducing location errors.

Several authors focused in particular on the improvement of inventory and warehouse management tasks, generally enabled by RFID. Semunab et al. (2016) developed an experimentally tested framework for RFID readers combined with the IoT for warehouse management to locate and track objects inside a building. Additionally, Kim and Park (2016) derived a conceptual model applying the IoT in warehouse management systems (WMSs). Expanding this to a low-volume, high-mix scenario, Lee et al. (2017) derived a framework for an IoT-based WMS including a system to select the most suitable order picking method which was tested in a case study. Additionally, Zhou et al. (2017) developed a numerically tested model where beside inventory also storage equipment is tracked and traced. By this, location and capacity decisions could be made dynamically. Reaidy et al. (2015) developed a conceptual model for city hubs as decentral controlled collaborative warehouses based on the IoT and agents and examined different scenarios for the allocation of resources. In contrast to such RFID-based systems, Ramakrishnan et al. (2016) performed a case study focusing on inventory management on shopfloor level based on IoT-beacons. These articles on warehousing tasks found improvement systems that were verified either conceptually or in a case study finding efficiency and information availability and accuracy leading to e.g. reduced stocks, costs or errors and improved order picking and inventory management.

Incorporating humans into these considerations, Bremer (2015) focused on the impact of IoT on human factors in logistics. Two scenarios for future development could be identified: a scenario with expert system tools for qualified skilled workers and a scenario for lower autonomy of skilled workers involved with automated tasks.

Summarising the findings of this subsection, the IoT is considered as a main driver of Logistics 4.0, influencing all tasks of logistics as well as incoming, internal, outgoing and even reverse flows of material. Most articles reported opportunities and threats as well as possible applications of IoT in logistics. Moreover, technological developments were provided and first works also started to incorporate human factors. Hence, the IoT shows evident importance for the management of future logistics systems due to its ability to provide visibility and enabling autonomy.

5.1.2. Peripheral IoT systems

Some authors applied the IoT in the periphery or packaging of objects. Especially packaging – itself an aspect of logistics functions – is an important enabler of such IoT systems, providing information generation and transmission infrastructure.

Smart packaging consists of sensing and communication applications, e.g. RFID or temperature sensors. Aiming for a theoretical foundation, Yam et al. (2005) developed a definition and conceptual framework of smart packaging, based on RFID and different sensors, e.g. time-temperature indicators. Thereafter, applications and a research roadmap that includes decision support systems were outlined. Similarly, Kim et al. (2017) derived a conceptual structure of smart packaging functions and technologies and highlighted current challenges in practice, especially due to regulation issues and implementation costs. Additionally, Simske (2011) provided a categorisation of smart packaging focusing especially on hybrid packaging solutions, which could consist of printed information, sensors and manufactured parts and thus enable efficient workflows e.g. through a better supply chain visibility. Expanding these approaches, Wang et al. (2018a) developed and successfully tested a RFID application experimentally, where the backscatter communication of passive RFID tags is used for testing the packages internal status without destruction of the package, which could reveal abnormal changes, e.g. breakage.

Concerning the use of smart packaging, containers and boxes, five applications could be found. Lang et al. (2011) developed an experimentally tested smart container which allows decentralised decision-making in transport management using sensor data. Accordingly, Sallez et al. (2016) provided a framework for active intelligent containers that are able to take decisions and tested it in a simulation study for a grouping strategy for optimised loading. Aiming at improved inventory control, Pan et al. (2015) conducted a simulation study for supply networks including smart containers and smart hubs, finding that simple inventory management strategies, e.g. where the source of replenishment is the nearest hub with sufficient inventory, lead to reduced costs and allow lower inventory levels. Moreover, Schuhmacher et al. (2017) developed a model for a smart bin combined with conveyor modules that enable so-called self-execution-systems supporting improved material flows in production enterprises. Additionally, Zhang et al. (2016) developed a model for a smart box that communicates with a cloud to design a sustainable product service system for distribution. It uses a real-time, information-based optimisation method to assign orders to containers. A simulation case study shows positive outcomes on loading rate and distribution distances.

As can be seen, the literature on peripheral IoT systems stresses the importance of the improved information generation and provision for logistics tasks and showed varied fields of application. The extensions of decentralised decision-making and algorithm implementation point towards the importance of these systems for the development of CPS.

5.2. Cyber-Physical systems

CPS widen the IoT-approach by using the information to directly act in the physical world and thus are often decentral systems. CPS can be defined according to Lee (2008) as "integrations of computation with physical processes. Embedded computers and networks monitor and control the physical processes, usually with feedback loops where physical processes affect computations and vice versa." Following, CPS can be applied to several logistics tasks. 14% of the articles in the sample are classified in this category.

Barreto et al. (2017) conceptually investigated smart logistics systems focusing on CPS and outlined examples in the tasks of resource planning, warehousing and transportation systems and information security that were contrasted with challenges for logistics e.g. visibility and integrity control. Moreover, Wen et al. (2018) derived several areas in logistics that could be supported by autonomous swarm robotics, e.g. efficient transportation or green logistics. The authors highlighted the existing challenges, including communication and safety issues as well as object recognition.

More specific contributions were provided by Hofmann and Rüsch (2017), who provided a theoretical case analysis and expert interviews concerning Industry 4.0 implications on Just-in-Time/Just-in-Sequence and cross-company Kanban systems. Opportunities of using

CPS and IoT were outlined regarding decentralisation and efficiency. Focusing on agent-based systems, Langer et al. (2006) developed a framework for distributed knowledge management for decentral autonomous logistics processes in an open network. A case study revealed that the system contributes to knowledge management in multi-agent systems. Additionally, Wasesa et al. (2017) provided a conceptual model of agent-based systems. In three case studies in transportation, freight forwarding and warehousing, the impacts on logistics performance parameters like coordination, agility and informational performance were derived.

In the domain of incoming material flows, Wycisk et al. (2008) analysed smart parts supply networks as complex adaptive systems, referring to smart parts as components of material, equipment or even transportation systems. The authors outlined how negative effects like the bullwhip effect, could be tackled with such decentral controlled smart parts.

Concerning the intra-logistics domain, Windt et al. (2008) built a conceptual model of autonomous production logistics processes. The authors outlined that higher degrees of autonomous control according to a developed criteria catalogue support goal achievement in logistics, although too much decentralisation could lead to obstructive chaotic systems. Additionally, Pujo et al. (2016) developed a conceptual model for an instance of cyber-physical production systems, called wireless holon networks. A new control system was applied without the need for a hierarchical decision structure, which was tested experimentally in the case of the internal logistics of a job shop for efficiency and flexibility. Moreover, Kousi et al. (2018) developed a prototype for internal material supply consisting of mobile assistant units, an execution control layer and a decision layer, also responsible for scheduling. The system was tested in a simulation case study of the automotive industry. Additionally, Zhang et al. (2018b) developed a model to improve the material handling efficiency of production logistics by applying automated guided vehicles (AGVs) as cyber-physical systems, which are able to perform different strategies, i.e. following, overtaking and collision avoidance. A simulation revealed improvements of efficiency and road utilisation. Furthermore, Zhang et al. (2018a) proposed a framework for CPS-based smart production logistics systems aiming for self-organisation, where resources can respond to changes adaptively and collaboratively. A simulation study of the proposed system revealed positive influences on manufacturing time and energy consumption but also an increase of costs. Moreover, Tu et al. (2018b) developed a CPS architecture including the IoT, using a design research approach. The proposed architecture was tested in an emulation experiment finding improvements especially in labour costs and efficiency in a production logistics context compared to barcode-based systems.

According to transportation, McKelvey et al. (2009) developed an electronic auction market model for smart parts logistics by using a stock market model for efficient transport based on the idea of complex adaptive logistics systems. Hence, smart parts were able to bid for their best routeing.

Focusing on warehouse and material handling tasks of CPS, Culler and Long (2016) developed a smart materials warehouse with CPS. Autonomous AGV were extended with technologies like a Kinect camera, thus enabling transportation and warehouse activities. Additionally, Semwal et al. (2017) developed a model for the ordering of task executions of multiple agent-based CPS in warehouses. The problem was solved by mobile agents leading to a decentral, scalable solution, which was tested experimentally. Lastly, Wahrmann et al. (2017) provided a framework for autonomous and flexible robotics for material handling in logistics. Elements for object recognition, environment and error handling were combined among others, enabling pick and place tasks in logistics in previously unknown scenarios.

Deriving the main outcomes of the articles discussed in this subsection, CPS are applied in numerous contexts and are based on the IoT and software agents. By this, the authors also provided important insights in autonomous control strategies. Moreover, the sample showed a focus on intra-logistics tasks.

5.3. Big Data-based systems

Within a logistics process, mass of data can be generated, e.g. with the IoT and utilised especially with BD approaches. BD "consists of extensive datasets – primarily in the characteristics of volume, variety, velocity, and/or variability – that require a scalable architecture for efficient storage, manipulation, and analysis" (National Institute of Standards and Technology, 2015). BD in logistics can be used to optimise, control and forecast systems' behaviour. 12% of the sample relate to BD-based systems.

Investigating the adoption intention of BDA in logistics, Lai et al. (2018) conducted a survey using the TOE model and the innovation diffusion theory, figuring out that especially top management support, the perceived benefits and environmental impacts like the adoption of BDA by competitors or government policies, influence the BDA adoption. Accordingly, Alberti-Alhtaybat et al. (2019) provided a case study of a global logistics enterprise business model. It is exemplary shown how the enterprise deals with disruptive technologies such as BDA aiming for customised services, optimised routes and resources, or improved decision-making.

Providing concepts of BD-systems, Brandau and Tolujevs (2013) developed a conceptual model for the analysis of logistics state data to find irregularities and their causes in four steps: problem understanding, data understanding, data preparation and data analysis, which were illustrated in the case example of a freight airport. For further development and adoption, Kim (2017) developed a conceptual model and provided prototypes for the design and implementation of an open source platform for IoT-generated BD processing in logistics. A cloud computing platform was applied for utilisation, analysis, storage and collection of the data. Additionally, Frazzon et al. (2015) developed a conceptual model for BDA based on cyber-physical logistics systems leading to customised BD modules that can be applied to different specific logistics tasks. The model works reactively and proactively, aiming to support decision-making processes.

In the domain of spare parts supply logistics, Zheng and Wu (2017) developed a smart inventory management system. Applying IoT and BDA, the developed model forecasts the demand of spare parts and ordering of contingent spare parts according to the expected costs.

Concentrating on production-logistics, BD applications were investigated. First, Zhong et al. (2015a) provided an experimentally tested framework for the utilisation of BD, generated by RFID; the framework uses RFID cuboids, a way of information representation, and enables the usage of the gained information for prediction and analysis functions. Zhong et al. (2015b) proposed a related framework for BDA where data is collected from RFID-enabled smart manufacturing objects and analysed with BDA tools for decision-making and prediction. Additionally, Zhong et al. (2016a) developed a model for visualisation of RFID-based data sets in a cloud manufacturing environment, which was tested in a case study. The generated information can be used to visualise logistics trajectory and hence, ease the understanding of complex data to support decision-making processes like scheduling and inventory management tasks.

According to outgoing flows of material, Lee (2017) developed a genetic algorithm and BDA-based model to predict future shipping necessities. A case study revealed that all factors in the anticipatory shipping problem like travelling time and transportation costs should be optimised simultaneously to prevent negative outcomes. Additionally, Liu and Wang (2016) developed a mathematical model to allocate orders to functional logistics service providers using BD. Aiming for customer satisfaction the model predicts customer needs, which was tested in a numerical analysis finding improvements according to the included cost and service level parameters.

Focusing on transportation management, Hopkins and Hawking (2018) performed a case study on BD and IoT in the context of managerial and administrative tasks of a logistics enterprise, e.g. according to routeing, maintenance planning and safety issues finding improvement opportunities like fatigue management for driver safety or predictive maintenance.

Concerning warehousing activities, Bertsimas et al. (2016) developed a model for inventory predictions, supporting inventory management decisions using web-based BD. The derived model was applied in a case study of a multimedia distributor.

Concluding this subsection, BD plays an important role in the developments of Logistics 4.0. BDA enable the utilisation of huge amounts of data. Applications in several fields showed improvement opportunities especially for management activities, including forecasting, decision-making, service levels and safety.

5.4. Cloud-based systems

Emphasising the importance of cloud computing for Logistics 4.0, 10% of the sample could be identified in this category. Cloud computing "is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (National Institute of Standards and Technology, 2011). Hence, clouds can be seen as data and information hubs, providing infrastructure, platform or software services (SaaS).

Providing structures of cloud-based systems in logistics, Chen et al. (2014) derived a reference framework combining cloud computing enabled SaaS and the IoT for logistics management. In a case study, the framework was tested according to the web server performance and the equipment performance. Tiejun (2012) proposed a method for value chain analysis in smart logistics, consisting of production, information and financial flows.

The process could be analysed with the developed method aiming for optimised process integration.

Moreover, Li et al. (2013) developed a conceptual model for the virtualisation of logistics resources in a cloud logistics approach and a platform for the logistics service selection in logistics centres using quality of service constraints and particle swarm optimisation, which was tested as efficiently in a simulation study. Additionally, Kong et al. (2015) developed an architecture of a cloud platform for an auction logistics centre, which was used for adaptive planning and control tasks with IoT-enabled real time data flows. Results of a case study showed that the processed data supports the effectiveness and efficiency of various decision-making processes in planning and coordination tasks.

In production-logistics, Qu et al. (2016) developed a framework expanding the cloud manufacturing approach by synchronisation of an IoT-enabled production environment and a cloud-supported resource management. The authors applied the concept in a case study finding improvements to the delivery rate and inventory levels, among others.

Focusing on distribution tasks, Yang et al. (2017) developed an architecture of a cloud platform for intelligent logistics management. By this, information-based cloud services were enabled to support logistics tasks such as navigation and scheduling. In addition, the order fulfilment process in e-commerce was investigated by Leung et al. (2018), who developed an architecture for a cloud-based order pre-processing system. This system groups the pending orders for optimised fulfilment using a genetic algorithm, finding shortened throughput times in a case study.

Concerning warehousing tasks, Nagorny et al. (2012) developed a service-oriented automation architecture for distributed manufacturing environments. Virtualised physical resources were managed using cloud technology leading to an intelligent warehouse application, which e.g. exposes its storage functionalities as services. Accordingly, Alwadi et al. (2017) conducted a conceptual investigation of concepts of cloud and RFID technology for inventory management including anti-collision algorithms for RFID detection and outlined the possibilities of such systems like automatic object localisation. In addition, Gupta and Jones (2014) developed a framework for cloud-based WMS in connection with RFID tagged inventory. Related to the order picking activities, the authors compared the cloud-based “Mobile RFID WMS”-order picking with other order picking methods and found high initial investment costs but greater savings per year.

Additionally, Wan et al. (2018) developed an architecture for load balanced and context-aware robotics material handling based on cloud technology and the IoT. In a simulation study, the authors found performance improvements of the proposed system regarding energy efficiency and cost-savings compared to the one-time on-demand delivery approach which is common in industry.

As can be derived, cloud computing expands the possibilities of IoT with a more service-based perspective and enables flexibility due to dynamic resource provision to handle the huge amount of data generated in the IoT, which is also important according to BD applications and for information management in distributed systems.

5.5. Mobile-based systems

Most applications of mobile-based systems relate to the direct support of the operator with an intuitive information provision. According to Siau and Shen (2003), mobile services' core is "about delivering the right information to the right place at the right time. This flexibility of mobile services is made possible by the convergence of the internet and wireless technologies" (Siau and Shen, 2003). Key drivers of mobile services are: mobility, reachability, localisation and personalisation (Siau and Shen, 2003). 6% of the articles in the sample are in this category.

Gao et al. (2018) developed a logistics information framework with a special focus on information-safety and privacy protection based on mobile devices in the so-called Logistics-IoT. The scheme was developed for information security e.g. against couriers with malicious mobile devices and tested as feasible and efficient.

Related to warehousing tasks, augmented reality (AR) was specifically investigated. In this regard, Reif and Walch (2008) and Reif and Günthner (2009) experimentally investigated AR systems based on head-mounted displays to meet rising customer demands. During a first session of experiments other order picking methods performed better whereas later experiments revealed improvements concerning efficiency and quality. Accordingly, a development process of an AR order picking system with six test series was summarised by Schwerdtfeger et al. (2011) finding that the visualisation and the used head-mounted-displays were important factors for the usefulness of AR in order picking. Similarly, Cirulis and Ginters (2013) theoretically analysed the usage of AR in warehouse logistics.

Improvement possibilities in order picking operations according to error reduction and efficiency improvements were exemplified, whereas Ginters and Martin-Gutierrez (2013) derived a conceptual model to enrich the AR system with RFID. The proposed AR-RFID system supports workers identifying the correct item aiming for lower error rates. Additionally, Krajcovic et al. (2014) provided a conceptual model how to implement AR in order picking and calls for deeper integration between AR systems with WMS and RFID-systems. The process model described in six steps how an AR support system could be set up.

Summing up, mobile-based systems deal with human-machine interaction especially for the provision of information. Hence, in our literature sample, AR applications were applied most often in the warehouse activities context.

5.6. Social media-based systems

This section reviews applications of social media-based systems in Logistics 4.0. Social media as defined by Obar and Wildman (2015) consists of four characteristics: (1) Internet-based applications, (2) user-generated content (3) user-specific profiles for apps of social media services and (4) the development of social networks online of individuals and/or groups. Social media can be used for interaction between customers and companies as well as internal information transmission. Only 3.5% of the articles in the sample belong to this category.

Concerning interaction possibilities, Bhattacharjya et al. (2016) as well as Bhattacharjya et al. (2018) provided a data analysis to explore the communication of logistics service providers and retailers with customers on Twitter. Investigations whether and how Twitter could be used to solve delivery problems revealed that Twitter could be applied to bridge communication gaps to the customers, although publicly discussed service issues should be tracked carefully to prevent reputational consequences.

Within information transmission, Mathaba et al. (2011) developed a conceptual model for using RFID-enabled IoT and Web 2.0 tools to improve inventory management. Thus, the authors applied twitter for reporting of inventory events like errors and misplaced goods detected by RFID, which was extended and prototyped by Mathaba et al. (2017) based on a retail-store scenario. Although it was feasible, effective scalability could not be guaranteed due to the amount of data in real life applications.

In conclusion, twitter plays an important role as a social media channel that is applied to logistics tasks as it is a prototype for social media-based information transmission between sender and receiver.

5.7. Other technologies

Articles in this section deal with technologies in the context of Logistics 4.0 that have not been described yet. Examples are articles on blockchain technology, additive manufacturing and advanced human-machine interactions.

Dealing with possible outcomes of new technologies for logistics, Angeleanu (2015) performed a conceptual investigation of additive manufacturing, cloud logistics and anticipatory logistics, among others and found reduced costs, increased efficiency and reduced capital expenditure as possible outcomes. Additionally, Gromovs and Lammi (2017) provided a conceptual study to investigate the impacts of technologies like blockchain, IoT and 3D printing on logistics education, stating that there is a need for the adoption of these new technologies in education programmes.

Focusing especially on additive manufacturing, Boon and van Wee (2017) developed a conceptual model for influences of 3D printing on logistics based on expert interviews. The model contains several dimensions that were impacted like consumer requirements, cost factors in transportation and discusses issues like spare parts inventory. Additionally, Zhou et al. (2018) developed an analytical model to incorporate logistics tasks in the scheduling objective function of distributed manufacturing systems of 3D-printing services. Tests in a case study showed improvements of the average latest task delivery time compared to other scheduling models.

Concerning human–technology interaction, control and support systems can be considered. Concerning control systems, Overmeyer et al. (2016) experimentally investigated speech and gesture control of AGV and incorporated cognitive workload as an impact factor for adaptive speech control. Furthermore, Szafir et al. (2017) conducted an experimental study to explore the collaboration between operators and flying robots in logistics inventory control. Based on a set of three prototypes, the study examined key factors for efficiency improvement, e.g. interactive timelines for task planning. Regarding support systems, Toxiri et al. (2018) presented an experimental study developing an exoskeleton. The study revealed that due to an active back support, the compression forces of the lumbar spine of logistics workers could be reduced up to 35%. Similarly, Naruoka et al. (2016) developed an exoskeleton device for knee support. By this, logistics workers were supported in the material handling activities preventing lower back strain.

Additionally, virtual realities (VR) might support humans in understanding and simulating complex situations. In the domain of transportation, Alves et al. (2009) provided a conceptual model for a discrete-event-simulation to improve transportation networks. Since transportation networks are expensive to change, the developed simulation system supports operators in decision-making by applying a VR 3D visualisation of the simulation. Also applying VR, Yuen et al. (2010) developed a prototype full-immersive VR simulator for forklift truck drivers. This simulator could be used for training warehouse truck drivers, since dangerous situations during work could be simulated and thus avoided.

Last, Kembro et al. (2017) performed multiple case studies to figure out the possibilities of network video technology for the improvement of warehouse activities, e.g. in visual goods tracking. The barriers to implement this technology are an uncertain ROI and a lack of integration with other systems.

6. Discussion

In this section, key aspects of Logistics 4.0 are derived from the literature and future research opportunities are deduced based on the results of the review and discussed in detail.

6.1. Key aspects of Logistics 4.0

The review on Logistics 4.0 revealed six key aspects according to the dimensions of the framework. The framework is refined according to these findings as shown in Figure II-5.

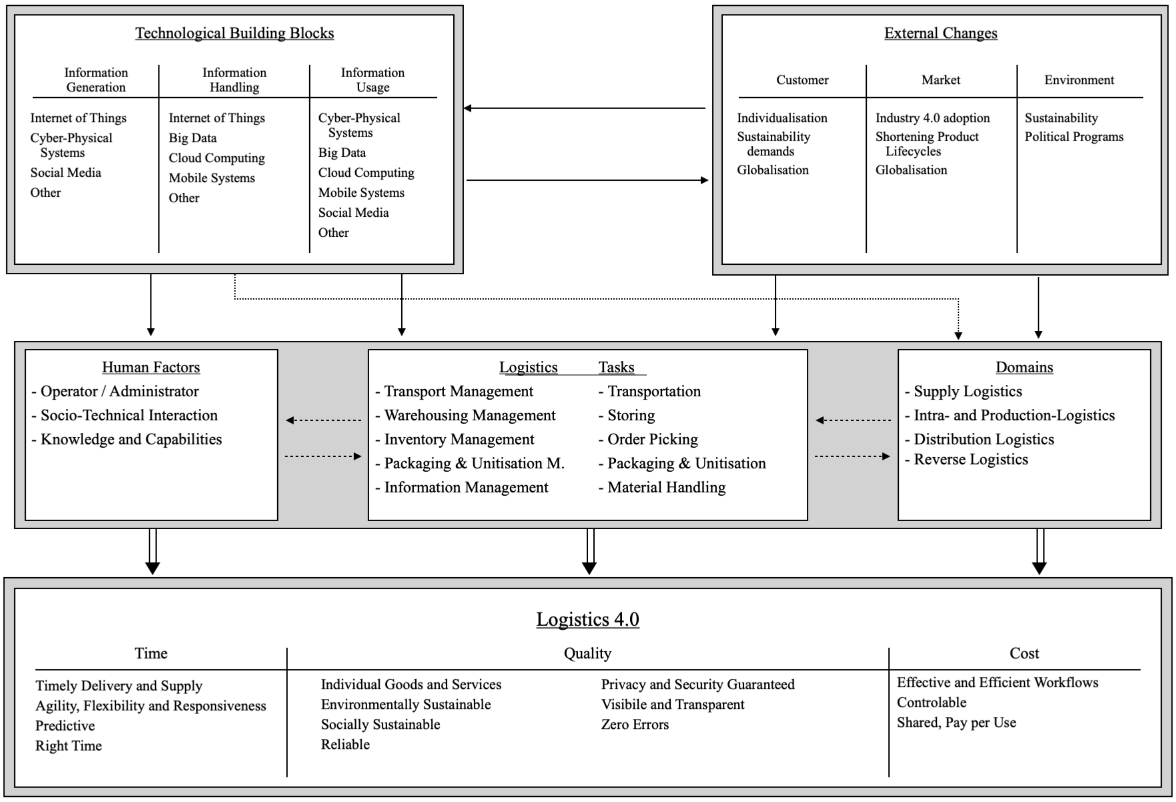

Figure II-5: Inductively refined framework of Logistics 4.0.

(1) From the descriptive results, it could be figured out that research on Logistics 4.0 systems has gained attention over time. Our literature review hints at reasons for this development containing articles that explicitly examine external triggers, e.g. according to current social and individual trends. Numerous systems were developed to enable efficient, flexible and individual services to support customer satisfaction. These findings support the assumption that external changes trigger the Logistics 4.0 evolvement, with causes to be grouped into three categories: customer-triggered, competition-triggered and environment-triggered. The sample also reveals that political programmes are relevant in these developments.

(2) Information is at the centre of all technologies examined in this study. The technologies can thus be grouped into three subcategories: (a) technologies to generate information, (b) technologies to handle information and (c) technologies to use information.

(2a) Generating information enables visibility, which is necessary to plan and control spatially and temporally distributed, complex systems. The IoT as the main application is deeply connected to RFID although the sample also revealed alternative technologies. Until today, physical flows and information flows are often handled separately or media discontinuities disrupt the process leading to inefficiencies. Hence, the IoT enables visibility and thus supports most activities of logistics either directly, e.g. planning and control tasks, or indirectly, e.g. packaging and order picking by providing possibilities like quality control.

(2b) Handling the huge amount of data that is generated by IoT is challenging but necessary to gain managerial decision support. As the previous reviews, the keyword analysis and the content analysis of the sample show, BD is a vital field of research focusing on the handling of mass data and the examination of information out of this data. In this context, the sample hints at two principles for data and information handling: central, e.g. via cloud computing, and decentral, e.g. in autonomous systems. Moreover, blockchain technology could be used for transaction handling.

(2c) The information gathered can be used in different ways. Three principles seem to be conclusive according to Logistics 4.0: First, in executing tasks, the information can be used by the systems themselves, e.g. in CPS that might perform tasks autonomously. Second, in complex planning tasks, the information can be used by humans to support todays systems and decision-making processes, e.g. by using BD to optimise inventory levels or to support workers with augmented reality. Hence, roles of humans in such systems can change from an operator to an administrator role. The third possibility of information usage can be seen in the "XaaS" approach meaning that almost everything could be provided as a service. For the provision, selection, usage and control of services, information is necessary.

(3) The sample shows varied impacts on task execution in logistics. Warehousing and warehouse management tasks were found most often in the sample followed by information management tasks. Although this differentiation is not mutually exclusive it hints at the different foci in the sample. Since warehousing is still labour-intensive, considering warehousing as one of the pioneering tasks is conclusive. Moreover, although transportation was not considered as a keyword, several contributions could be found according to transportation and transportation management too. Lastly, it was found that material handling was also considered without further consideration of other tasks. It was for example related to exoskeletons. Hence, nearly all tasks in logistics systems can be transformed in Logistics 4.0 systems since they could be found within the sample.

(4) Accordingly, great influence of Logistics 4.0 on intralogistics was found, since most articles in the sample belong to this dimension, which might be due to the relation to Industry 4.0. Nevertheless, articles according to all domains of logistics were considered in the

sample emphasising the importance of the transformation of tasks in every direction of material flows. The sample also hints at an influence of external triggers and technological developments on these dimensions, too, since e.g. the possibility of predictive shipping changes the way distribution logistics is performed.

(5) With regard to human involvement in the development towards Logistics 4.0, two views can be distinguished. On the one hand, some articles dealt with inherent influences of people, e.g. according to the adoption intention. On the other hand, some articles put the worker in the centre of the research, e.g. when developing exoskeleton support systems for material handling tasks or human-machine interfaces. In many cases human work is enhanced, e.g. when applying VR, AR and exoskeletons. This supports the proposition that humans will probably not be replaced by technical systems, but will be supported in their work.

(6) The objectives of articles in the sample are often operational ones like improved efficiency of a certain process, improved responsiveness, customised services and process visibility. These objectives are in line with the idea of mass customisation since efficiency is needed to avoid an increase of cost and responsiveness is needed to react to customer demands. Thus, the objectives of Logistics 4.0 articles can be structured according to the dimensions of (a) time, represented by responsiveness or shortened throughput times, (b) quality, shown by customised processes and a reduction of errors, and (c) cost, relying on efficiency improvements and pay-per-use services and resources.

These key findings underline that Logistics 4.0 does not replace systems like lean logistics, but supplements and improves them where inefficiencies arise or managing becomes too complex. Integrated products, services, processes, technologies and even organisations and networks could be supported during the whole lifecycle. Quality could be improved and products and services match customer requirements better. Employees could be supported to perform the work more efficiently, ergonomically and motivated, and workers shortage could be prevented. In contrast, several barriers could be identified, as for example, a lack of standardisation of technologies and uncertainties about economic values and costs hinder the implementation. Moreover, regulatory uncertainties and infrastructure issues were addressed within the sample. From a human perspective, especially skills and knowledge were addressed as possible barriers. Hence, possible research opportunities are derived in the following to address these issues and further develop the vision of Logistics 4.0.

6.2. Research opportunities

Although the sample revealed manifold contributions to Logistics 4.0, some aspects that were outlined in the theoretical derivation of Logistics 4.0 are still missing in the literature. Hence, research opportunities are subsequently outlined according to the framework:

(1) Concerning external developments, it was found that only a few articles address these driving forces systematically. Hence, a more comprehensive examination of the influences of driving forces could be valuable to understand the needs of different sectors and societies, e.g. according to demographic change and ageing workforce.

(2) On a technological level it was outlined that the IoT is dominant in research. Hence, further research is required especially to deepen the knowledge about less considered applications of technologies like blockchain, AR and VR or social media and according to the integration of additional technologies not found within the sample. This might lead to further applications in Logistics 4.0 contributing to manage complex systems, increase resource efficiency or improve human work conditions. For example, gamification approaches could be investigated according to the potential to support workers in preventing errors and improve motivation. Concerning the technology acceptance, further studies could provide insights into success factors.

Although many technologies are already considered in the literature, the economic assessment is scarce. Thus, the economic examination of new technologies is difficult to assess for companies and future research could provide valuable guidelines for this.

(3) Beside the tasks that were found most often in the sample, i.e. warehousing and information management, other specific tasks of logistics, like packaging or truck loading, are less investigated. The influences of the changing tasks could have an influence on the organisational structure, since some jobs might have less importance and others will gain importance in the development of Logistics 4.0, which is yet not considered within the literature. Hence, the emerging organisational structures within Logistics 4.0 systems could be investigated. The interrelations and feedbacks into existing production systems might be an interesting research field. For example, possible interferences between lean systems and "4.0" systems might be found within different divisions of one company raising the question how a logistics system should be designed in that case. From a practitioners' perspective, this might also lead to the need for advanced methods for planning and organisation.

Providing a methodological toolbox to guarantee a structured implementation seems to be valuable.

(4) Concerning the domains of logistics, reverse logistics is under-represented within the sample and could be focused in more depth, especially in the context of resource efficiency. From a broader context, an economic perspective was missing, too. Potential new business models are also not assessed in depth. For example, Logistics-as-a-Service or dynamic cooperation between companies might gain more importance, as well as pay-per-use systems. Which necessities this might have and how traditional businesses can be transformed could be researched in more depth.

(5) Human Factors could only be found in focus of a few studies within the sample like in technology acceptance models. Although mentioned in many contexts within the articles, the human-centric view was not discussed intensively. Hence, although some technological possibilities are valuable to ease the work of humans, human capabilities are supported to fit the system instead of changing systems according to humans. Research providing a system design perspective on these issues could reveal insights into how Logistics 4.0 could be designed from a human-centric point of view. This is in line with worker shortage and the demographic changes and the consequences for logistics systems. These interrelations, however, could not be found intensively within the literature. Interesting research opportunities are, e.g. studying which skills will gain importance and how human learning can be supported in these systems as well as how the transformation of work can be developed to fit the capabilities of the employees.

(6) From a methodological perspective, it became apparent that most of the contributions are conceptual and theoretical works, which supports the finding that Logistics 4.0 is a relatively young field of research. Thus, empirically validating the theoretical contributions is necessary. Especially concerning the incorporation of human factors, mixed methods approaches would be valuable to gain insights into a theoretically grounded and validated picture of reality.

7. Conclusion

This study explored three research questions: According to the first research question, it was shown, that mass customisation and associated trends like sustainability lead to a rising complexity and higher demands on logistics systems. Managing this complexity needs other planning and controlling mechanisms than available today. Based on this evaluation, the term Logistics 4.0 was defined.

Hereupon main research streams and patterns of Logistics 4.0 systems were addressed. Answering the second research question, a systematic literature review was conducted leading to a comprehensive framework for Logistics 4.0. With this framework, it was derived which Logistics 4.0 systems already exist and where further research is required answering the third research question.

For researchers, this review offers important insights. The review and the created framework provide a picture of the state of the art of research on Logistics 4.0. The review is grounded on the assumption that new logistics systems are not an end in themselves, but a necessary element of future production and trade networks. The research also considers research related to Industry 4.0 and thus provides a comprehensive foundation for future works. On the other hand, this review offers insights into possibilities to enhance existing logistics systems, integrate Industry 4.0 applications and improve technological solutions. Moreover, this review exposes the importance of humans in the developments of Logistics 4.0. Based on the results of the review, promising research opportunities were highlighted.

For practitioners, this review shows various examples of technologies that can be adapted and combined to improve logistics according to the dimensions of cost, time and quality, e.g. optimising service quality or reducing errors even in more complex environments. Moreover, Logistics 4.0 offers approaches of how to deal with challenges according to skills shortage in logistics, for example. Beside a user’s perspective, this review offers insights for producers of these applications, too, evaluating which technologies and services are seen as relevant in research. Thus, this review supports knowledge transfer. Furthermore, technologies and applications that were not considered can be investigated as being new offerings on the market.

Despite its contribution, this study has its limitations. Only peer-reviewed English journal articles were considered according to the mentioned keywords. Furthermore, we referred to primary logistics tasks and not on SCM, although there is some overlap in research on logistics and SCM. Moreover, only articles in the scope of industry and trade were considered as relevant.

Finally, there is a wide consensus of the phrase “4.0” in production research, but it seems that logistics did not adopt this phrase systematically and although there is a rising amount of scientific literature dealing with Industry 4.0, logistics has not been addressed systematically. This review might provide a baseline to interlink works in the area of smart logistics systems and aims to encourage future research in this direction.

PART B – CONSIDERATION OF HUMAN FACTORS IN LOGISTICS 4.0 AND INDUSTRY 4.0

III. [Article 2] Job satisfaction: an explorative study on work characteristics changes of employees in Intralogistics 4.0[2]

Authors: Winkelhaus, Sven; Grosse, Eric H.; Glock, Christoph H.

The increasing trend toward digitalisation in logistics poses a significant managerial challenge, particularly by fundamentally changing the traditional, manual workplaces in intralogistics. Although intralogistics processes have, in some cases, already been automated or are supported by smart technologies, humans remain an inevitable part of future intralogistics but with changing work characteristics. This study aims to examine the influences of the transition towards Intralogistics 4.0 on work characteristics of intralogistics employees.

First, a systematic literature review on work characteristics and job satisfaction in a broader Logistics 4.0 context was conducted. Thereafter, a qualitative, explorative methodology was employed to examine the perception of work characteristics that impact job outcomes such as job satisfaction, motivation and performance at different Intralogistics 4.0 maturity levels. The results of semi-structured interviews conducted across seven companies demonstrated the significant, heterogeneous changes of work characteristics related to the type of technology applied in Intralogistics 4.0.

Our findings indicate that the development towards Intralogistics 4.0-implemented workplaces does not have a simple or predefined impact on humans; instead, the individual design is relevant and can improve the workplaces with more opportunities for satisfying and motivating jobs.

Keywords:

Industry 4.0, Logistics 4.0, Intralogistics 4.0, Job Characteristics, Job Satisfaction, Qualitative interview, Systematic literature review, Intralogistics 4.0 maturity

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[2] This article has been submitted as Sven Winkelhaus, Eric H. Grosse and Christoph H. Glock (2021): Job Satisfaction: An explorative study on work characteristics changes of employees in Intralogistics 4.0. Journal of Business Logistics. It is currently in its second revision under review. This article has been slightly adapted for use in this dissertation, for example to ensure consistent spelling.

1. Introduction

The digital transformation that involves the utilisation of digital technologies in all spheres of life has a great influence on the society and the economy as a whole (Holmström et al., 2019; Kagermann et al., 2013; Leyh et al., 2016; Reis et al., 2018). This trend presents new challenges to organisations for satisfying the changing and individualised customer demands using smart industrial technologies. Specifically, logistics companies perceive this digital transformation as a main driver of future business success and more importantly, logistics also codetermines the outcome of this digital transformation in industry and trade because the efficiency and quality of logistics affect customer satisfaction and overall company performance (Cichosz et al., 2020; Davis-Sramek et al., 2008; Springinklee and Wallenburg, 2012). In this context, the World Economic Forum estimates that the digital transformation has a value at stake in the logistics sector of US$ 1.5 trillion by 2025 (World Economic Forum, 2016). Despite this evident potential, a recent survey has shown that 79% of the participants classified the digital transformation in logistics as a major challenge (Rohleder, 2019). Logistics companies themselves are significantly influenced by this digital transformation through incorporation of new technologies such as Big Data, artificial intelligence (AI) and CPSs also in intralogistics processes (Cichosz et al., 2020; Hofmann and Rüsch, 2017).

The share of manual work is still high in intralogistics. In the United States, for example, more than 1.4 million employees worked in the storage and warehousing sector in March 2021, with 1.26 million of these as production and non-supervisory employees (U.S. Bureau of Labor Statistics, 2021). In intralogistics, activities such as internal transportation, packaging, storing, or order picking have traditionally been performed manually with limited technical support (Michel, 2016, 2019). Major changes are expected in this specific domain owing to the multitude of possibilities for supporting or automating these tasks (Winkelhaus and Grosse, 2020a). In particular, intralogistics (and here especially warehousing) is currently seen as the area of logistics that may benefit the most from digitalisation and automation (Rohleder 2019). The use of AGVs, for example, will transform intralogistics transportation tasks. Besides automation technologies that enable physical tasks to be performed without human involvement (Fasth-Berglund and Stahre, 2013), digital technologies, that encompass both tangible equipment such as computers and mobile devices as well as intangible goods such as software and the internet (Ibem and Laryea, 2014), further improve the capabilities of automation technologies: “Like automation, the goal of system autonomy is to achieve tasks with little or no human intervention […] Whereas previous generations of automation have typically employed logic-based programming, today’s system autonomy efforts are leveraging computational intelligence and learning algorithms to better adapt to unanticipated and changing situations” (Endsley, 2017). This technological trend is part of *Logistics 4.0,* with Intralogistics 4.0 as a subdomain of this concept that this paper aims to investigate (Madsen, 2019; Winkelhaus and Grosse, 2020a).

Although business processes can change significantly in this development, numerous researchers have concluded that human workers will remain an integral part of future logistics workplaces (Erol et al., 2016; Kadir et al., 2019; Kagermann et al., 2013) and codetermine the companies’ productivity (Klumpp and Zijm, 2019). Therefore, human workers constitute an inevitable and a vital part in this progress with significant influence on the future production and outcomes of logistics systems (Kagermann et al., 2013).

Changing intralogistics work transforms work characteristics as well, which affects the employees’ perceptions of their workplaces. As work characteristics and job satisfaction are interrelated (Morris and Venkatesh, 2010), job satisfaction is impacted in Intralogistics 4.0 owing to the substitution, limitation, support, or change of tasks performed by humans (Bremer, 2015). Besides, job satisfaction is also related to individual work outcomes such as turnover intention, motivation, performance and organisational commitment (Ang and Slaughter, 2001; Autry and Daugherty, 2003; Loher et al., 1985; Morris and Venkatesh, 2010). In addition to the influence on these outcomes, job satisfaction can be considered as a value in itself also because it contributes to the concept of social sustainability (Morris and Venkatesh, 2010; Oermann and Weinert, 2014), which is widely discussed in a broader logistics context (Carter and Washispack, 2018; Castillo et al., 2018; Grosse et al., 2015; Klumpp and Zijm, 2019). Thus, investigating the factors in the emerging (Intra-)Logistics 4.0 that impact job satisfaction in intralogistics poses an interesting field of research.

However, little is known about the impact of Intralogistics 4.0 on manual workplaces in this field despite its economic importance, the high share of manual human work and the expected effects of Intralogistics 4.0 on human work in this sector. Earlier research noted that the changing roles of workers often remain inexplicably unaddressed in the entire Industry 4.0 domain (Kadir et al., 2019; Winkelhaus and Grosse, 2020a), and only first conceptual studies highlight the need for examination and make initial contributions (Cimini et al., 2021; Neumann et al., 2021). Therefore, this study investigates the relationship between the developments of Intralogistics 4.0 and the characteristics of intralogistics workplaces. For this reason, the Intralogistics 4.0 maturity is relevant as a tool for benchmarking and comparing different expressions of this development, i.e. the kind and depth of technology usage. Thereby, our study aims to answer the following *RQs*:

- *RQ 1: How do work characteristics of intralogistics employees change with different Intralogistics 4.0 maturity levels?*
- *RQ 2: What are the effects of digital technologies as compared to automation technologies on work characteristics of different Intralogistics 4.0 maturity levels and what are the driving and inhibiting mechanisms behind this?*
- *RQ 3: How does the Intralogistics 4.0 maturity level impact job satisfaction in intralogistics?*
- *RQ 4: How can practitioners anticipate the development toward Intralogistics 4.0 in designing future intralogistics workplaces?*

To answer these *RQs*, two methods are applied: A systematic literature review is performed (part 1) with the aim of understanding the state of knowledge within the researched topic, verifying the research gap and deducing theoretical insights. The results of part 1 are reflected in light of a qualitative, explorative study applying semi-structured interviews to compare work characteristics of workplaces with different levels of Intralogistics 4.0 maturity (part 2).

Applying this qualitative approach has three main reasons. First, Intralogistics 4.0 is an emerging phenomenon facilitated through the digital transformation and its vital impacts on work characteristics are still underexplored (Körner et al., 2019). A qualitative method facilitates to inductively expand, transfer and verify existing hypotheses and concepts (Fawcett et al., 2014; Gioia et al., 2012; Stank et al., 2017). Second, the current study considers a complex interaction within this emerging phenomenon and attempts to comprehend these relationships (Fawcett et al., 2014), such as the impacts of technology usage on the work characteristics. Third, this study aims to understand the worker's perspective without predetermination, which is difficult to achieve if quantitative methods, including questionnaires, are applied (Grosse et al., 2016), or on a theoretical level as in previous studies. Thus, a qualitative method is appropriate to answer the *RQs*. In this view, this work contributes towards the development of a middle-range-theory.

The remainder of the article is structured as follows: the subsequent section provides the theoretical foundations of the study; this is followed by a review of the relevant literature on the changes in work characteristics and job satisfaction in (Intra-)Logistics 4.0 and Industry 4.0 as a basis for the further analysis. Thereafter, the research methodology used for data collection and evaluation is detailed. Then, the results of the data assessment are presented to answer *RQ* 1. Subsequently, the obtained data are synthesised to answer *RQ* 2 and *RQ* 3 by analysing the impacts of technology provision and usage on work characteristics and respective mechanisms behind these impacts. The results are discussed from a managerial perspective, making them applicable for the design of future workplaces for answering *RQ* 4. The last section summarises the study, discusses its limitations and presents an outlook on future research.

2. Foundations of the study

This section describes three constructs within the scope of the study: a) work characteristics and job satisfaction in general, b) work characteristics and job satisfaction in logistics and c) Logistics 4.0 and Intralogistics 4.0 maturity.

2.1 Work characteristics and job satisfaction in general

Job satisfaction has a cognitive and an affective aspect (Fisher, 2010) and can be described analogously to an early definition of Locke (1976) as a positive emotional state resulting from the appraisal of one’s job experiences (Tietjen and Myers, 1998; Yousef, 2016). Various models have attempted to explain the relation between job design and job satisfaction (Fisher, 2010; Limbu et al., 2014) differentiating between an individual, a group and an organisational level. The “Job Characteristics Model” (Hackman and Oldham, 1975) outlines relations between job design and personal outcomes; in particular, it hypothesises a relation between job characteristics and job satisfaction (Hackman and Oldham, 1975) and has frequently been studied in the literature (see the reviews of Boonzaier et al. (2001) or

Loher et al. (1985)). We therefore evaluated it as particularly relevant for answering the *RQs* on work characteristics that change within Intralogistics 4.0 and their impacts on job satisfaction. The job diagnostic survey, developed by Hackman and Oldham (1974) based on their "Job Characteristics Model", includes five main characteristics of the job: (1) skill variety, (2) task significance, (3) task identity, (4) autonomy and (5) feedback. These characteristics contribute to critical psychological states. The first three characteristics contribute to "experienced meaningfulness of work", the fourth to "experienced responsibility for outcomes of the work" and the fifth to "knowledge of the actual results of the work", all impacting job satisfaction. Moderating effects suggested in the model such as "personal growth need strength" and context satisfaction factors such as payment and job security (Hackman and Oldham, 1975) were found to have no moderating influence on the personal outcomes or critical psychological states (Tiegs et al., 1992). In several studies, the job diagnostic survey was adopted for further analysis, for example to evaluate moderating effects of IT implementation on the relation between job characteristics and job satisfaction (see. e.g. Morris and Venkatesh, 2010).

Theoretically expanding the research of Hackman and Oldham (1975), Morgeson and Humphrey (2006) created a more comprehensive survey, referred to as the "Work Design Questionnaire" (WDQ), that facilitates the assessment of the work characteristics that contribute to job satisfaction. The authors referred to the terms "work characteristics" and "work design" in contrast to "job characteristics" and "job design", because "work" focuses on a broader context of the job and its environment (Morgeson and Humphrey, 2006). In the following, we use the broader term "work characteristics" as introduced by Morgeson and Humphrey (2006), although the term "job characteristics" is used more frequently in the literature referring to the "Job Characteristics Model" of Hackman and Oldham (1975) (Morgeson and Humphrey, 2006). The category "task characteristics" included in their survey is similar to the characteristics developed by Hackman and Oldham (1975). Apart from this, Morgeson and Humphrey (2006) included additional categories in the WDQ: "knowledge characteristics", comprising items related to problem solving and skill variety for example; "social characteristics", covering, for example, interactions outside the company and interdependence; and "contextual characteristics" that enlist physical demands and equipment usage among others (Morgeson and Humphrey, 2006). Thus, the WDQ enables a comprehensive analysis of job satisfaction in the digital transformation, as these extensions include a higher number of different work characteristics. The category system developed by Morgeson and Humphrey (2006), shown in Figure III-1, has a strong relation to job satisfaction and related concepts of intrinsic motivation. The proposed system is used as a starting point for developing qualitative interview questions in this study because we do not question the general relationship between work characteristics and job satisfaction; instead, the aim of the current study is to provide answers on how the qualitative how and why of the transformations impact job satisfaction and not the quantitative how many (Fawcett et al., 2014; Stank et al., 2017). The questionnaire was replaced with an open form of interview questions to answer the *RQs*; the method is outlined in more detail in the methodology section.

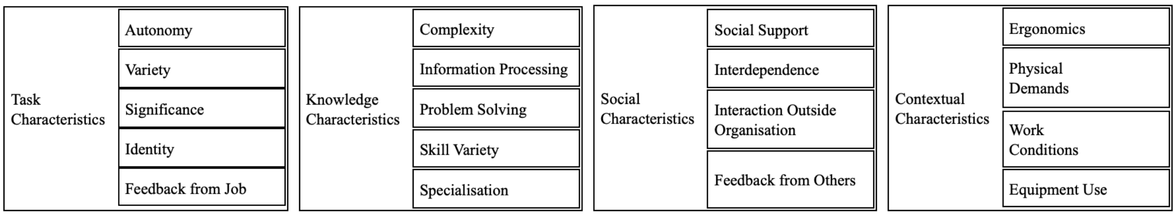

Figure III-1: Work characteristics that may influence job satisfaction.

2.2 Work characteristics and job satisfaction in logistics

Despite the high relevance of work characteristics for job satisfaction, performance, turnover intentions and several other job outcomes, only a few works have addressed this topic in a logistics context. As reviewed by Maloni et al. (2017), most related studies primarily focused on specific professions such as truck drivers or warehouse employees (Min, 2007) or measured job satisfaction without determining the driving factors and inhibitors (Maloni et al., 2017). Nonetheless, some studies determined the impacts of certain work characteristics including contextual factors, such as job security and pay, on the workers' perceptions of logistics and supply chain workplaces. These studies reported that certain organisational concepts such as lean production (de Haan et al., 2012) and the workforce level (Maloni et al., 2017) play key roles in the job satisfaction of logistics employees. Moreover, supervisors can contribute toward job satisfaction by providing coaching (Ellinger et al., 2005) or by influencing possible work–family conflicts in logistics

(Maloni et al., 2019). Furthermore, employer-sponsored training can positively impact workforce productivity and job satisfaction in logistics (Chhetri et al., 2018).

In summary, most studies either do not examine the driving factors of job satisfaction, or they focus only on a few aspects such as autonomy or task identity (de Haan et al., 2012) or context factors like payment (Min, 2007). In addition, the identified studies did not focus on the application and impact of technologies on work characteristics and job satisfaction and are therefore not suitable to provide a broad theoretical basis for this work. Hence, a detailed investigation of these impacts is necessary because the continuing digital transformation of the logistics sector questions current knowledge and understanding.

2.3 Logistics 4.0 and Intralogistics 4.0 maturity

The concept of Logistics 4.0 originates from Industry 4.0, which was initially coined as an overarching term for several developments in the context of the digital transformation in the industrial sector (Kagermann et al., 2013). Industry 4.0 incorporates two major aspects: a paradigmatic aspect that considers the changes toward individualised products, globalisation and shortening lifecycles; and the technological aspect that considers the incorporation of CPSs, Internet of Things, Big Data, AI or cloud-based systems (Hofmann and Rüsch, 2017; Lasi et al., 2014).

Both aspects also influence the logistics and intralogistics sphere (Min et al., 2019) through, for example, the implementation of smart goods (Holmqvist and Stefansson, 2006), the application of AI for planning and advanced robotics (Klumpp, 2018), or the realisation of mass customisation (Christopher and Ryals, 2014). For the purpose of our research, we adopt the definition of Winkelhaus and Grosse (2020a) and define Logistics 4.0 as follows: "Logistics 4.0 is the logistical system that enables the sustainable satisfaction of individualised customer demands without an increase in costs and supports this development in industry and trade using digital technologies". This definition incorporates the concept of sustainability, which calls to integrate economic, ecological as well as social targets (Brockhaus et al., 2013). We refer to Intralogistics 4.0 as being all parts of Logistics 4.0 that are concerned with intralogistics processes.

The importance of humans in this industrial development has already been emphasised in the seminal report on Industry 4.0 by Kagermann et al. (2013), where the inclusion of humans in different roles is a key aspect in the identified eight priority areas for action (Neumann et al., 2021); this supports the hypothesis that humans will remain an important element of Intralogistics 4.0 systems. Additionally, research on the Operator 4.0 manifests clear evidence that a substitution of workers by machines is not expected in most areas (see, e.g. Cimini et al., 2021; Guerin et al., 2019; Romero et al., 2016a; Ruppert et al., 2018).

Based on the distinction between automation technologies that can replace physical tasks and digital technologies that can replace cognitive tasks (Endsley, 2017), we differentiate between four effects of Intralogistics 4.0 technologies (see Figure III-2): 1) digital technologies can substitute cognitive tasks such as administration; this can be termed cognitive automation (Choe et al., 2015; Schumacher et al., 2016). Warehouse management systems and, for example, implemented AI technologies are examples for this kind of technologies that ease or automate cognitive tasks. 2) Automation technologies allow the substitution of physical tasks such as order picking, loading, transportation or material handling with the help of CPSs, AGVs or collaborative robots. 3) Digital technologies and automation technologies further improve one another. First, digital technologies enable the progression of automation technologies to autonomous technologies (Monostori, 2014). Simple automation technologies such as conveyor belts are replaced by more advanced and flexible systems such as smart AGVs. Second, sensor-based systems successively generate data for further improvement of digital technologies. Thus, these more advanced automation technologies can automate further physical tasks. 4) Besides a possible substitution, digital and automation technologies can also support human operators in different ways. As digital technologies cannot perform physical tasks, they can support human operators in performing these tasks, for example, by providing information, guiding the operator, or giving feedback on task performance. In contrast to that, automation technologies cannot perform cognitive tasks of operators, but support these, for example, by only presenting one product at a time in front of a machine, which trivialises (cognitive) searching and identifying tasks.

Both digital and automation technologies are an integral part of Intralogistics 4.0, where, beside the complete substitution, three developments for workplaces are possible: a) trivialisation of tasks that are not automatable owing to the replacement of prior manual tasks by advanced systems (Waschull et al., 2020), b) enlargement of tasks, where the share of repetitive (automatable) tasks is reduced and additional, more diverse tasks are added to the work and c) enrichment of tasks with the requirement of qualified employees for more difficult tasks (Waschull et al., 2020). We therefore expect significant changes in future intralogistics workplaces.

As Intralogistics 4.0 can be driven by diverse technologies and impact different processes in different ways in each company, maturity models can provide a basis for benchmarking, as-is assessments and for the further development of intralogistics in light of the company's strategy (Asdecker and Felch, 2018; Krowas and Riedel, 2019). In a maturity model, the degree to which a certain target state is achieved is generally expressed by consecutive maturity levels (Krowas and Riedel, 2019). In the study at hand, this target state is called Intralogistics 4.0. In the work at hand, we use a maturity model that was specifically developed for the logistics and intralogistics domain to evaluate and compare different levels of technology usage en route to Intralogistics 4.0.

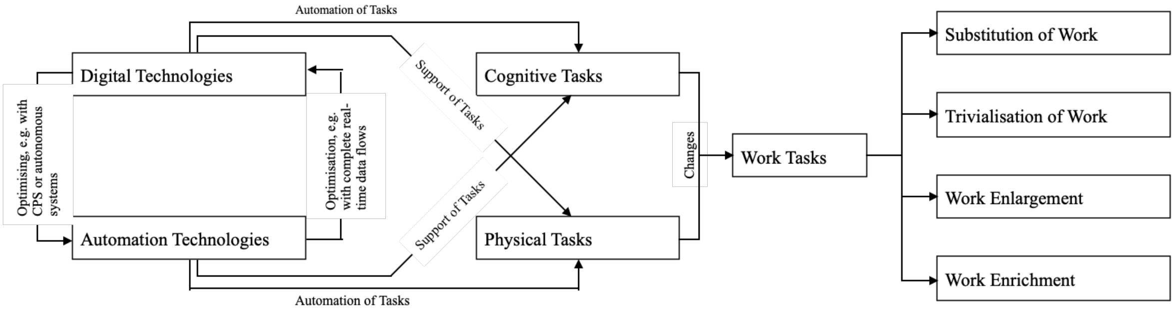

Figure III-2: Interactions between digital and automation technologies possibly influencing work tasks.

To select a suitable maturity model for the study at hand, a systematic literature review was conducted. Using the search string ("Industry 4.0" maturity model) in the title, abstract and list of keywords in the Web of Science database, 49 journal articles and proceeding papers were identified. We evaluated these papers for a detailed development and discussion of a maturity model that was suitable for our research and thus reduced the set of relevant papers to 22. In a second refinement step, we limited our review to articles that explicitly incorporated logistics or supply chains, leading to three articles of relevance: Asdecker and Felch (2018); Leyh et al. (2017); and Sternad et al. (2018).

The model of Asdecker and Felch (2018) is of major importance for the assessment of the Intralogistics 4.0 maturity later in this article, as it includes a detailed description of the different maturity levels and focuses on technology-improved processes instead of, e.g. management and culture issues as well as intellectual capital (Krowas and Riedel, 2019) – although these are also important. We further identified a maturity model for Intralogistics 4.0 (Krowas and Riedel, 2019) that can be applied to extend the model of Asdecker and Felch (2018), even though no full documentation is available.

Overall, five development stages were identified that consider characteristics from Level 1 for companies or workplaces that are not Intralogistics 4.0 mature up to level 5 for highest Intralogistics 4.0 maturity of companies or workplaces. For the study at hand, it is important that both digital and automation technologies are considered relevant as these are integral parts of CPSs that are part of the technological core of Industry 4.0, Logistics 4.0 and Intralogistics 4.0. For example, the levels of automation identified range from manual, mechanically supported, mechanised and automated to autonomous processes (Krowas and Riedel, 2019). Relevant process steps include intralogistics transportation, storing and order picking.

Before the qualitative study is performed, part 1 of the study that grounds on a systematic evaluation of the literature is carried out to support the validity of the subsequent empirical study.

3. Literature review on work characteristics and job satisfaction in Industry 4.0 and Logistics 4.0

According to Munn et al. (2018), we decided to perform a systematic literature review and not a scoping review as “scoping reviews do not aim to produce a critically appraised and synthesised result”. This section describes the methodology and results of the systematic literature review that was performed for the following reasons: First, it is necessary to assess the state of knowledge in our study’s research field, and there is a need to point out the research gap addressed in this work in detail. Apart from this, the results of the review imply possible relationships between technologies, work characteristics and job satisfaction (albeit in different contexts), which supports the preparation of the interviews. Lastly, the results that emerged from the qualitative study can be interpreted and reflected in light of the state of knowledge, which supports drawing theoretical implications. The transparent and reproducible method of sample derivation (Fink, 2005) employed by a systematic literature review enables us to identify publication patterns and gaps in existing research (Seuring and Gold, 2012; Tranfield et al., 2003). The literature review also considers insights from research on IT systems to examine the development path of the digital transformation, which is strongly related to the emerging Intralogistics 4.0 systems.

3.1 Review methodology

The literature sample was generated in five steps following the suggestions of Krippendorff (2013) and Carter and Washispack (2018):

(1) We first developed a search string that considered two keyword groups shown in Table III-1 based on the theoretical background described in the prior section. Group A includes "job characteristic", "work characteristic" and "job satisfaction" as keywords, whereas Group B comprises terms generally related to the digital transformation to additionally cover possibly relevant studies from other sectors where the term Industry 4.0 is not commonly used. We did not use keywords related to specific domains (e.g. "logistics" or "supply chain"), as this may narrow the search with risks of missing important references. Each article identified during the search should contain at least one keyword from both groups. The keywords were searched across all fields in the database "Web of Science Core Collection", which was chosen because this database contains a comprehensive amount of multidisciplinary, high quality journals. The keyword search yielded an initial sample consisting of 364 studies.

Table III-1: Keywords used in the database search.

Group A	Group B
Job Characteristic	Digital Transformation
Work Characteristic	Industry 4.0
Job Satisfaction	Logistics 4.0
	Automation
	Information System
	Information Technology
	Human–Machine

(2) The sample was refined using the exclusion/inclusion (E/I) criteria shown in Table III-2 that were structurally adapted from Liao et al. (2017). In the first refinement step, we selected only peer-reviewed English journal articles to guarantee a high scientific standard of the publications. 313 of the initial search results remained post refining in this step.

Table III-2: Inclusion and exclusion criteria of the systematic review.

E/I	Criteria	Criteria Explanation
Exclusion	Search engine reason	The article is not written in English, or it was not published in a peer-reviewed journal
	Non-related	The article is not an academic article (e.g. editorials or newspapers) The keywords are related to another topic due to homonyms
	Loosely related	The keywords only appear in the references The article generally concerns the topic of relevance but in a sector or domain that is structurally different, such as public sectors or marketing tasks The article uses keywords of a category only in a quotation, example, or in the research outlook/future directions without investigating it
Inclusion	Partially related	The article concerns the intersection of categories at least in a part/section of the article The article addresses the topic without using the keywords but synonyms
	Closely related	The article concerns keywords of both categories in depth and majorly focuses on the topic of interest

(3) Thereafter, the title, abstract and keywords were read and analysed for relevance by two coders. In case of unclear classifications, the articles were discussed to reach consensus. This process did, however, not result in significant deviations from the initial assessment. Articles remained in the sample in case no clear decision could be derived from the information to ensure that no relevant article was excluded. Thirty-nine articles remained in the sample at the end of this process step.

(4) The articles were read completely and those not focusing on the selected primary topics (e.g. work characteristics) were excluded from the sample. The literature sample consisted of 22 articles at the end of this step.

(5) A backward snowball-search conducted on the references resulted in two additional articles, leading to a final sample size of 24 articles. The analysis results of the sample are described briefly to examine the state of knowledge, highlight the research gap and allow the transfer of knowledge from associated research.

3.2 Results of the review

The results of the review are briefly summarised in Table III-3. Three types of models were identified in the literature sample: 1) Technology Acceptance Models, 2) Job-Demands-Resource/Job-Demand Job-Control Models and 3) Job Characteristics Models. Most studies focused on the implementation phases of IT systems instead of stabilised conditions. Digital technologies such as the internet and IT systems, automation technologies and CPSs that can be viewed as integrations of digital and automation technologies (Lee, 2008) impact work characteristics relevant for job satisfaction. The findings of the review thus point towards possible impacts and mechanisms that are relevant for work characteristics changes (e.g. perceived complexity) also in intralogistics. In addition, the review also hints at conceptual differences between the effects of automation and digitalisation on work characteristics. Key takeaways from the literature analysis relevant for the study at hand can be summarised as follows:

- *Automation leads to deskilling for shopfloor employees (de Witte and Steijn 2000).*
- *During IT system implementation, perceived process complexity and rigidity increase, and autonomy, skill variety and feedback are moderated by the implementation.*
- *Conceptually, digitalisation and especially automation are expected to increase task complexity, which increases knowledge needs and skill variety and reduces the autonomy for low- and medium-skilled jobs.*

Although organisational aspects are considered in various publications, these studies mostly focus on the implementation phase and are thus not addressed in the research at hand, which instead focuses on stabilised systems.

Table III-3: Summary of key findings of the systematic literature review.

#	Article	Methodology	Core findings related to work characteristics/ job satisfaction
1	Bailey (2000)	Survey	External factors, such as conflicts with supervisors, are predictors of work-group productivity, and internal factors, such as internal conflicts, can more accurately predict job satisfaction than factors such as autonomy, which has a low predictive value.
2	Bala (2013)	Longitudinal Study	The implementation of an IT system (supply chain management system) has an effect on perceived process rigidity and process complexity, which has a negative impact on job outcomes such as satisfaction.

3	Bala and Venkatesh (2013)	Longitudinal Study	The implementation of an IT system (ERP system) and the perceived technology characteristics impact perceived process complexity, rigidity and radicalness that have an impact on perceived job demands, job control and job satisfaction.
4	Bala and Venkatesh (2016)	Longitudinal Study	The employees can perceive an IT system implementation as an opportunity or a threat; the resulting technology adaption behaviors have an impact on their job satisfaction.
5	Brah and Ying Lim (2006)	Survey	High-technology logistics firms perform better than low-technology logistics firms, and it is hypothesised that technology usage has the potential to enrich jobs and that it can positively drive job satisfaction.
6	Carlson et al. (2017)	Survey	Turnover intentions are impacted by job satisfaction and organisational commitment that vary upon influences of technology-based job autonomy, overload and monitoring on job engagement and tension.
7	Castellacci and Viñas-Bardolet (2019)	Analysis of Survey Data	The use of the internet positively affects job satisfaction by improving factors related to social interactions and autonomy. Less positive effects are observed for blue-collar workers.
8	de Witte and Steijn (2000)	Analysis of Survey Data	Jobs with a higher degree of automation have different effects on blue-collar, white-collar and professional employees; for blue-collar employees, a deskilling due to internal differentiation can be observed, which impacts job satisfaction but not because of decreasing autonomy or complexity.
9	Elias et al. (2012)	Analysis of Survey Data	Age moderates the attitude towards technology and has effects on intrinsic and extrinsic motivation. The moderating effect of age on job satisfaction is less pronounced.
10	Hannola et al. (2018)	Conceptual	There are four kinds of digitally facilitated knowledge management processes for production workers that contribute toward job satisfaction and efficiency.
11	Korunka and Vitouch (1999)	Longitudinal Study	The effects of an IT system implementation on stress and satisfaction mainly depend on the context of change and the implementation management.
12	Kwahk and Lee (2008)	Survey	The behavioral intention of using an IT system (ERP system) is indirectly impacted by the readiness for change, which is influenced by personal factors such as organisational commitment.
13	Mariani et al. (2013)	Survey	Providing training opportunities impacts the employees’ acceptance of an IT system as well as job satisfaction.
14	Martin and Omrani (2014)	Analysis of Survey Data	The use of the internet affects job attitudes positively and thus increases job satisfaction, which is impacted by changes in accessing knowledge and social interaction.
15	Mitchell et al. (2012)	Survey	Organisational support has a positive influence on employees’ attitudes and behavioral reactions toward new IT systems.
16	Morris and Venkatesh (2010)	Longitudinal Study	The implementation of an IT system (ERP system) moderates the effects of autonomy, skill variety and feedback on job satisfaction but does not moderate the effects of task significance and task identity on job satisfaction.
17	Navimipour et al. (2018)	Survey	The organisational performance is influenced by IT-related factors such as ease of use; further, it is impacted by organisational culture including job characteristics and employees’ satisfaction.
18	Ötting and Maier (2018)	Vignette Study	The employees’ behaviors and attitudes, including job satisfaction, are impacted by procedural justice in work-related decisions, independently of the decision agent (human or computer).
19	Salanova et al. (2004)	Survey	The type of an IT system implementation has a significant impact on the employees’ cognitive well-being including job satisfaction.
20	Schwarzmüller et al. (2018)	Expert Survey	Work design and leadership are changed through digitalisation, for example, by setting higher job demands for employees, increased technologisation and changes of communication and collaboration.
21	Seppälä (2004)	Interviews and Survey	The role of white-collar employees in production industry changes, also based on advanced IT systems, leading to changed job characteristics such as variety and autonomy.
22	Sykes (2015)	Longitudinal Study	During the implementation of an IT system (ERP system), traditional support structures and peer-advice impact employees’ perceived system satisfaction, job stress and job satisfaction.
23	Venkatesh et al. (2010)	Longitudinal Study and Interviews	The implementation of IT systems and communication technology systems enriches jobs and improves job characteristics; however, the effects on job satisfaction depend on contextual forces that are also related to the characteristics of industrial sectors in India and possibly other developing countries.
24	Waschull et al. (2020)	Conceptual	Depending on the task to be performed, the application of CPSs can create new human tasks or substitute them, resulting in enriched, simplified and substituted jobs; this subsequently changes the job characteristics such as autonomy, complexity and skill requirements.

The results of the literature review also reveal the gaps in the existing literature: First, there are only few studies that examined the influences of digitalisation on work characteristics in a broader context. Most studies conducted to date focused on the implementation phase and only on one specific technology, in most cases a comprehensive IT system like an ERP system. Second, most studies did not focus on shop-floor workers who might operate with less complex IT systems. Third, the intersection between automation technologies and digital technologies were not considered in depth in the literature, although effects of physical automation and cognitive automation are probably relevant. Fourth, although intralogistics fulfils important tasks in most companies, the literature did not focus on intralogistics and only few papers explored the overall logistics sector. The study of Bala (2013) is the only research identified in the sample that focused on the logistics sector and investigated the effects of technology usage, i.e. the implementation of a supply chain management IT system particularly on work characteristics and job satisfaction. Overall, there is a clear research gap on how the digital transformation impacts work characteristics and, subsequently, job satisfaction in intralogistics. We address this research gap in the following.

4. Research design and methodology

A qualitative approach was chosen to explore the *RQs* for three reasons: 1) to unearth new knowledge in an under-researched area, 2) to identify interrelations and draw conclusions from complex interactions of factors and mechanisms and 3) to understand the workers' situation without predetermination. Binder and Edwards (2010) argued that qualitative methods are still infrequently applied in operations management, for example compared to social sciences. We follow the argumentation of Gioia et al. (2012), who stated that examining new or questioning existing constructs "requires an approach that captures concepts relevant to the human organizational experience in terms that are adequate at the level of meaning of the people living that experience and adequate at the level of scientific theorizing about that experience."

4.1 Data collection process

The literature discusses a broad portfolio of qualitative research methods for generating data, such as observations or structured interviews (Phellas et al., 2011). Semi-structured interviewing was considered suitable for the current study as it allows an analysis of perceived causal relations, helps gaining insights into the perceived reality and facilitates the assessment of an interviewee's perception (Tanskanen et al., 2015; Venkatesh et al., 2010). In addition, interviewees and interviewers have more freedom to focus on aspects of relevance and previously unknown situations, as compared to structured interviews. Therefore, semi-structured interviews are suitable for analysing emerging phenomena. This study followed four major steps in conducting the semi-structured interviews at the companies with a cross-organisational approach.

(1) The cases and interview partners were selected from intralogistics workers as the focal group for the investigation. The research principle of "maximum heterogeneity" was followed for case selection, such that the cases varied in relevant key dimensions as much as possible (Suri, 2011). Key dimensions considered here include attributes that could influence work characteristics, such as different work environments (normal temperature as well as cold storages), company size, industrial sector, as well as Intralogistics 4.0 maturity that will be described below in more detail. A further limitation within this selection process was that the interviewees should be working for the company for at least one year so they have the necessary knowledge regarding the work. A description of the interview cases is presented in Table III-4. The interviewees worked in warehouses, but also in pre- and post-processing steps, e.g. receiving and truck-loading. The sample contains companies from five different sectors and varies from completely manual intralogistics processes to highly technology-supported processes. All cases included in the study were placed in Germany to control for location-based effects (Anand et al., 2007).

Table III-4: Description of cases.

Case	Position of Interviewee	Industry	Company Size[3]
Case 1.1	Order Picking	Wholesale	Medium
Case 1.2	Order Picking	Wholesale	Medium
Case 2.1	Order Processing	Production	Medium - Large
Case 2.2	Receiving	Production	Medium - Large
Case 3.1	Order Picking	Production & Trade	Medium
Case 3.2	Order Picking	Production & Trade	Medium
Case 4.1	Storekeeping	Publisher	Small
Case 4.2	Receiving	Publisher	Small
Case 5.1	Storekeeping	Food	Large
Case 5.2	Order Picking	Food	Large
Case 6.1	Order Picking	Manufacturing	Medium
Case 6.2	Storekeeping	Manufacturing	Medium
Case 6.3	Packing	Manufacturing	Medium
Case 7.1	Loading / Storekeeping	Food	Large
Case 7.2	Loading / Storekeeping	Food	Large
Case 7.3	Storekeeping / Disposition	Food	Large

(2) Second, an interview guide was prepared following the suggestions of Grosse et al. (2016). The interview guide was split into four sections: the first section contained initial questions to gain information about the subject's job title, work history (time in this company and job) and typical work processes. Second, the interview guide contained core questions referring to the focus of the research—work characteristics related to personal outcomes like job satisfaction. Questions were prepared based on the five work characteristics proposed by Hackman and Oldham (1975), which were enriched by the additional characteristics introduced by Morgeson and Humphrey (2006) for allowing a broader view of the topic. The reflection of the results of the literature review indicated possible influences of technologies on the extended work characteristics that were not addressed by Hackman and Oldham, such as "Social Support" or "Equipment Use". Every work characteristic construct shown in Figure III-1 was addressed within the core questions. All core questions were prepared in an open-ended style and the interview was conducted as a dialogue to avoid preconception. Consequently, longer answers and explanations were favoured for gaining deeper insights. For instance, a typical question would read: "Could you please tell me about the physical

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[3] Estimated company size in respect of the EU definition (2003/361/EG) on small- and medium-sized enterprises (small companies: <50 employees, <10 million euro annual turnover; medium-sized companies: <250 employees, <50 million euro annual turnover; above this, it is a large company).

load you have to handle during your work?” As the interviews were conducted in German, we applied the vocabulary of a validated German version of the WDQ for referring to work characteristics in the interview questions to avoid language biases (Stegmann et al., 2010). In the third section, the focus shifted to understand the employees’ expectations regarding more Intralogistics 4.0 mature workplaces. As the interviewees did not receive additional information from the interviewer about possible technologies that might be used in their companies in the future, they were just able to respond based on their own state of knowledge. In the last section, the interview guide was closed with an open question, where the subjects had the opportunity to focus on topics that had not been addressed yet.

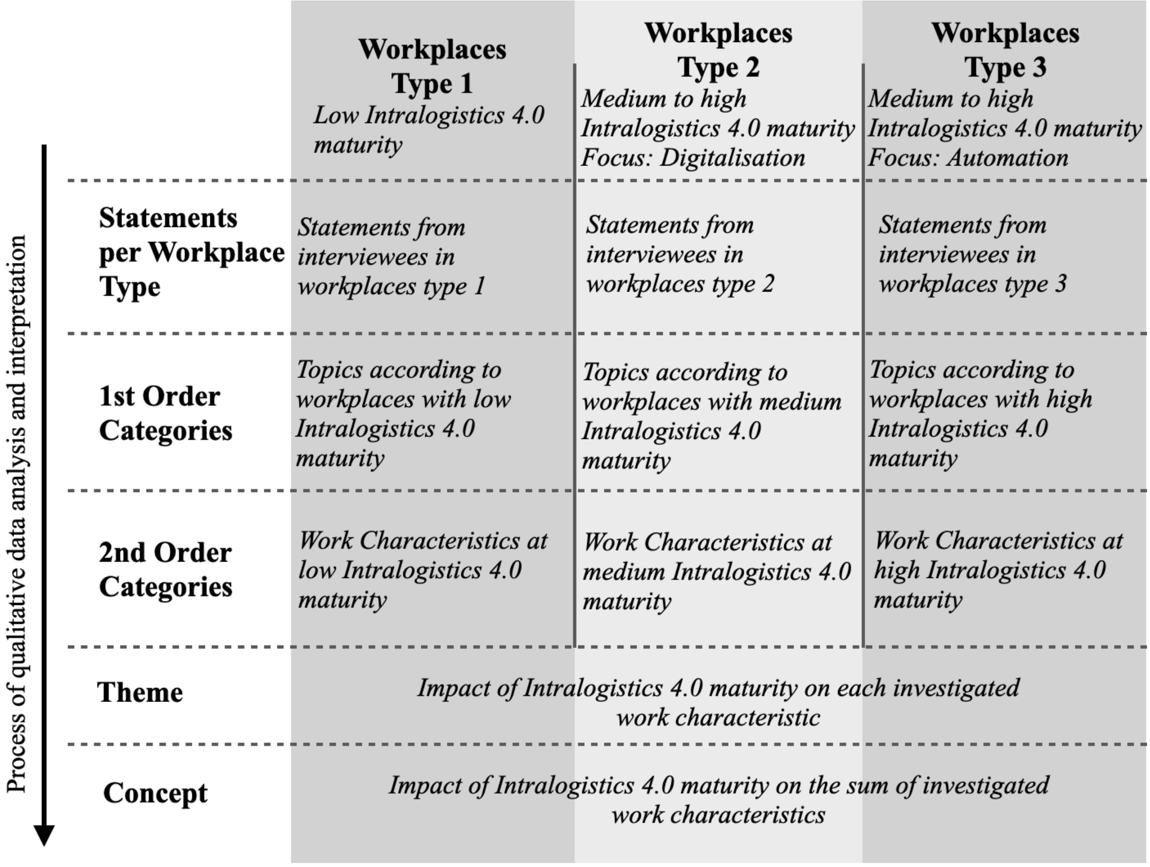
(3) Third, the interviews were conducted by the same researcher to avoid bias and were based on the suggestions of Grosse et al. (2016). The interviews took place between March and September 2019, where each interview was audio recorded in agreement with the managing directors, interviewees and the workers’ councils following data privacy guidelines. Each interview required 20–30 min. No major issues could be observed during the interviews, for instance, concerning understandability of the questions or meaning of the technical terms. Overall, 16 interviews were conducted, and 132 pages of transcripts were analysed.

(4) The fourth step included the preparation of the analysis with the transcription of interview recordings. We followed the recommendations of Mayring (2014) and Gioia et al. (2012) during coding and data analysis to ensure reliability and validity. The method of Gioia et al. (2012) suggests to derive first-order categories that are mainly informant-centric and second-order categories that are obtained based on the former as researcher-centric ones. The approach is more descriptive in its aim (Sodero et al., 2019) and enables us to systematically describe the relations between Intralogistics 4.0 and work characteristics. Thus, it is adequate for the study at hand by “translating” between the experiences of knowledgeable agents (the interviewees) and the researchers’ constructs (Gioia et al., 2012; Sodero et al., 2019). Based on this methodology, the current study applied a data analysis and interpretation that followed the five steps shown in Table III-5. First, the transcripts were coded, and the first-order categories were derived. Thereafter, these categories were consolidated and abstracted to form second-order categories that fit with the work characteristics identified earlier. Until this step, the analysis focused on workplaces of a comparable type that is based on the estimated Intralogistics 4.0 maturity level and its

technological driver that will be described subsequently in more detail. These steps enabled us to answer *RQ* 1. Based on these second order categories of different workplace types, and thus of different kinds of Intralogistics 4.0 maturity, the impacts of the Intralogistics 4.0 maturity on the work characteristics were analysed for every workplace characteristic. This consolidation of second-order categories, based on the structuring dimensions of the WDQ, was necessary to examine the impacts of Intralogistics 4.0 on work characteristics relevant for job satisfaction. After consolidating the work characteristics, the conclusions were derived to understand the impacts of Intralogistics 4.0 on job satisfaction.

The analysis described above was verified for inter-coder-reliability. Therefore, the interviews were coded by two coders and the coding-results were assessed for consistency. Slight differences were identified during the comparison but could be solved through discussions among the coders.

Table III-5: Steps of qualitative data analysis and interpretation.



Process of qualitative data analysis and interpretation

	Workplaces Type 1 *Low Intralogistics 4.0 maturity*	**Workplaces Type 2** *Medium to high Intralogistics 4.0 maturity* *Focus: Digitalisation*	**Workplaces Type 3** *Medium to high Intralogistics 4.0 maturity* *Focus: Automation*
Statements per Workplace Type	*Statements from interviewees in workplaces type 1*	*Statements from interviewees in workplaces type 2*	*Statements from interviewees in workplaces type 3*
1st Order Categories	*Topics according to workplaces with low Intralogistics 4.0 maturity*	*Topics according to workplaces with medium Intralogistics 4.0 maturity*	*Topics according to workplaces with high Intralogistics 4.0 maturity*
2nd Order Categories	*Work Characteristics at low Intralogistics 4.0 maturity*	*Work Characteristics at medium Intralogistics 4.0 maturity*	*Work Characteristics at high Intralogistics 4.0 maturity*
Theme	*Impact of Intralogistics 4.0 maturity on each investigated work characteristic*		
Concept	*Impact of Intralogistics 4.0 maturity on the sum of investigated work characteristics*		

4.2 Intralogistics 4.0 maturity of the cases

The Intralogistics 4.0 maturity of the case workplaces was estimated according to the described maturity models of Asdecker and Felch (2018) and Krowas and Riedel (2019) grounding on the interviews. The flow of information and the digital and automation technologies used were taken into consideration. Four cases were identified to fit to the lowest Level 1, five to Level 2, five to Level 3 and two to Level 4. Given that the application of advanced digital and automation technologies in intralogistics is limited (see, e.g. Napolitano (2012) or Michel (2016)), examples for Level 5 intralogistics activities are still scarce and our results are thus plausible. In contrast to this, Level 1 processes are still common in intralogistics and it might be questioned whether this mostly analogue and manual process can be considered as being a first step towards Intralogistics 4.0 (Zeller et al., 2018).

In a detailed examination of the Intralogistics 4.0 maturity levels of the cases, we determined which categories of technologies – digital technologies or automation technologies – seemed to be drivers of the (high or low) Intralogistics 4.0 maturity level. In doing so, we found that the interview cases that we assigned to the five maturity levels can be categorised into three workplace types. These workplace types are: 1) workplaces with a low level of Intralogistics 4.0 maturity, where the work tasks were performed manually and (nearly) without the support of digital and automation technologies (Cases 4.1, 4.2, 6.1, 6.2). Within these workplaces, for example, only paper-based pick lists and hand pallet trucks were used as support technologies. 2) Workplaces with a medium to high level of Intralogistics 4.0 maturity and driven by digital technologies and only a limited use of automation technologies in their processes. Technologies used are e.g. pick-by-voice and put-to-light systems, barcode scanners, warehouse management systems as well as simple conveyor belts (Cases 1.1, 1.2, 2.1, 2.2, 5.1, 5.2, 6.2, 7.2). 3) Workplaces with a medium to high level of Intralogistics 4.0 maturity and driven by automation technologies in their processes and medium to high level of digital technologies (Cases 3.1, 3.2, 7.1, 7.2). Technologies used are e.g. automated storage and retrieval systems (AS/RS), warehouse management systems and barcode scanners. A theoretically possible workplace type 4) with a high level of Intralogistics 4.0 maturity driven by automation technologies without the support of digital technologies was not found within the sample. Also referring to Figure III-2, automation technologies and digital technologies can benefit from each other, but digital technologies can also work without automation technology while automation technology requires digital technologies like sensors, controllers and IT-systems (e.g. warehouse managements systems) in most cases. Hence, we can expect that automation technologies will not be found without comparable levels of digital technologies.

As the answers of the interviewees from these three workplace types were mostly homogenous with only slight individual differences and the type and extent of technology usage was comparable, we ground the analysis of the cases on the three workplace types.

5. Results

The interviews demonstrated that significant differences in the work characteristics of the intralogistics workplaces exist.

The main descriptive interview results consolidated in the 2nd order categories of the analysis are presented in Table III-6 to Table III-10; in addition, exemplary citations following the recommendation of Gioia et al. (2012) are provided in quotations ("…").

Table III-6: Descriptive results of the interviews on task characteristics.

Character-istics		**Jobs with low Intralogistics 4.0 maturity and no automation** **(Workplace type 1)**	**Jobs with medium or high Intralogistics 4.0 maturity and low degree of automation** **(Workplace type 2)**	**Jobs with medium or high Intralogistics 4.0 maturity and high degree of automation** **(Workplace type 3)**
Task Characteristics	**Autonomy**	perceived as not high but important; decision-making autonomy mostly in enlarged elements; work scheduling autonomy higher than in other workplaces, for example, owing to self-organisation of work; work scheduling autonomy and handling of different enriched and enlarged tasks perceived as demanding; no autonomy in work methods;	perceived as not high but important; decision-making and scheduling autonomy mostly reduced to enriched and enlarged elements, but also not high; within the main process, work scheduling autonomy perceived as reduced owing to, for example, put-to-light or pick-by-voice systems; no autonomy in work methods;	perceived as very low with medium importance; decision-making and scheduling autonomy not provided even in fault situations owing to fixed and prepared pipeline of work tasks and complex changes of the order and correction procedures; no autonomy in work methods;
	Variety	perceived as repetitive but not monotonous; opportunity of enlargement of tasks positively accepted and perceived on a medium level, for example, by supporting colleagues;	perceived as repetitive but not monotonous; opportunity of enlargement and enrichment of tasks positively accepted and perceived as high, for example, data management or quality checks;	perceived no task variety; no actions even in fault situations allowed; reduction of order picking task to the picking procedure; "Good work is high, frequent work"; "The aim of my work is to pick as many items as possible";

Significance	perceived mid to high importance of the job driven by holistic process understanding; impact on customer and company emphasised beside personal consequences;	perceived mid to high importance of the job driven by holistic process understanding; impact on customer and company emphasised beside personal consequences;	perceived low importance of the job; reduction of significance on a personal level; not the process but the worktime perceived as the end of a work process;
Identity	perceived complete and defined task; division of labour with less strict distinction; support of accompanying tasks and more holistic view on work;	perceived complete and defined task; work enlargement and enrichment enabled holistic view on work task and interdependencies;	very limited work task, perceived as very monotonous; “Actually nowadays everything is so automated that the human is nothing else than a part of a machine”;
Feedback	neither administrative nor working tasks perceived as delivering feedback from the job; feedback emphasised as being important but missing; feedback only received in failure events involving the customer;	administrative and manual tasks perceived as delivering only little feedback from the job; feedback emphasised as being important but rare, at best, for example, the calculated quantities fit exactly; most feedback received in failure events involving the customer;	tasks not perceived as delivering feedback from the job; checks of correct task performance used even in failure events; limited personal feedback; “If there is a fail and you do not know where it happened, they tell you about it, but also that you do not have to think about it”;

As can be seen, the task characteristics varied significantly between the three workplace types identified. A high Intralogistics 4.0 maturity with a widespread use of automation technology negatively impacted the task characteristics. This was mainly caused by the high process rigour and limitation of tasks for the employees who, for instance, perceived themselves as “part of a machine.” Instead, high Intralogistics 4.0 maturities levels combined with a low degree of automation have only minor impacts on the assessment of task characteristics; however, the intralogistics process was impacted by the maturity level. This indicates that the change in the process kept the personal outcomes comparable. For instance, the task identity was perceived as high in workplaces with lower Intralogistics 4.0 maturity because the employees had to perform several tasks, coordinate themselves and support their colleagues whenever necessary, thus gaining an impression of every task performed. In workplaces with high Intralogistics 4.0 maturity but a low degree of automation, processes were standardised and the division of labour initially limited the range of tasks; however, additional tasks were performed owing to faster processes. Therefore, the range of tasks remained comparable, but the cause was different.

Table III-7: Descriptive results of the interviews on knowledge characteristics.

Character-istics		Jobs with low Intralogistics 4.0 maturity and no automation (Workplace type 1)	Jobs with medium or high Intralogistics 4.0 maturity and low degree of automation (Workplace type 2)	Jobs with medium or high Intralogistics 4.0 maturity and high degree of automation (Workplace type 3)
Knowledge Characteristics	**Complexity**	perceived as low to medium; additional information about work items (e.g. products and components) emphasised as necessary; complexity added by enriched and enlarged task organisation, not by the task itself; “Organisation, that is of course also a big part”	perceived low to medium complexity; information about the systems seen as necessary; usefulness of technologies individually perceived diverse; complexity mainly added by enriched and enlarged tasks that were more complex compared to other tasks, for example, order picking; higher demand in administrative tasks;	complexity not mentioned in the interviews; “Cognitive demands are very low, because you have your monotonous movement the whole time”;
	Information Processing	perceived as important; a lot of information had to be processed; tasks perceived as a permanent data exchange and check; perceived medium to high cognitive demands because of repetitive tasks but necessary cautiousness;	perceived as important; a lot of information had to be processed especially for enriched and enlarged tasks; tasks perceived as a permanent but more intuitive data exchange; processing and often checked by, for example, scans; “In earlier times, we worked with a list with all the items. Tick everything, pack everything, manually. The new system is a big advantage”; perceived medium to low cognitive demands owing to necessary cautiousness but demanding interaction with, for example, pick-by-voice technology;	Perceived as easy and not very important; permanent checks of correct information processing; only one task at a time and intuitive information provision; perceived very low cognitive demand owing to fault resistance of the system and permanent quality checks;
	Problem Solving	perceived low need for problem solving within the task; coordination of different tasks sometimes addressed; coordination could be demanding;	perceived medium to low need for problem solving; need for flexibility addressed; “If something is not as planned, you have to be flexible”;	perceived no need for problem solving; in case of fault events, especially with the AS/RS system, only supervisors able to solve problems; “In case of a failure and you do not have someone who is able to solve it, it is very hard”;
	Skill Variety	skill variety seen as low; especially being able to pay attention over a long period of time, spatial imagination, calculation and equipment-usage skills named;	perceived medium skill variety concerning enlarged and enriched tasks (e.g. IT skills or skills to operate machines that support the worker);	no skill variety seen as necessary; the automation systems and IT systems provide all necessary information and check the correctness; work much more standardised because of automation systems;
	Specialisation	only a slight specialisation seen as an advantage (e.g. knowledge regarding product characteristics);	perceived low skill necessity owing to system support, although knowledge about products, support systems and processes is advantageous;	no specialisation seen as necessary; the automation systems and IT systems provide all necessary information and check the correctness; work much more standardised because of automation systems;

The knowledge characteristics also varied between the workplace types identified. In workplaces with a high maturity and with a widespread use of automation technology, the interviewees were “performers” of standard processes, where every necessary information was provided. In case a process disturbance occurred, the task was not solved by the interviewees but by their supervisors, thus limiting the required knowledge to a minimum. In comparison, workplaces with a high Intralogistics 4.0 maturity but low degree of automation have broader knowledge needs. In most cases, the process was less standardised and had lower rigour compared to workplaces with a high degree of automation and thus, higher knowledge levels were required; however, the interviewees were more adequately supported by the technologies as compared to workplaces with low maturity. Although the knowledge needs changed, they did not decrease because the product and process knowledge had to be replaced by knowledge needed for handling the technological systems. Moreover, the work characteristics exhibited a small positive change but were not negatively affected.

Table III-8: Descriptive results of the interviews on social characteristics.

Characteristics		**Jobs with low Intralogistics 4.0 maturity and no automation** **(Workplace type 1)**	**Jobs with medium or high Intralogistics 4.0 maturity and low degree of automation** **(Workplace type 2)**	**Jobs with medium or high Intralogistics 4.0 maturity and high degree of automation** **(Workplace type 3)**
Social Characteristics	**Social Support**	perceived medium to high social support, e.g. by helping new colleagues or with activities under strict deadlines; team work enabled social interaction during work;	perceived medium social support, for example, with activities under temporal restrictions or helping new colleagues; pick-by-*-systems sometimes hindered social interaction during work; “With the pick-by-voice systems, you cannot talk to your colleagues here”;	perceived low importance of social support; in failure events of the technology supervisor support is required; mainly isolated work without any interaction; “You work on your own and independently”;
	Interdependence	no interdependence with prior processes perceived; interdependence with subsequent process steps perceived as medium to high; importance for performing high-qualitative work;	low interdependence with prior processes perceived; interdependence with subsequent process steps perceived as high; importance for performing high-qualitative work;	no interdependence with prior processes perceived; analog to task significance, interdependence with subsequent process steps perceived as low to medium;
	Interaction outside Organisation	no interaction outside the organisation mentioned, except for truck drivers from service providers;	low interaction outside the organisation mentioned, except for truck drivers from service providers; in enriched and enlarged tasks also further interactions; higher interaction outside organisation in administrative tasks;	no interaction outside the organisation mentioned, except for truck drivers from service providers;

	Feedback from Others	little feedback received from others; most feedback from supervisors only in case an error occurred;	little feedback received from others; most feedback from supervisors only in case an error occurred;	no feedback received from others; most feedback from supervisors only in case an error occurred;

The social characteristics were slightly affected by the technologies applied. Although workplaces with a high Intralogistics 4.0 maturity and a widespread use of automation technologies hindered social interaction in certain ways owing to the workplace design, many social characteristics were not affected by the maturity level. One reason for that could be that these social characteristics were relatively low in all Intralogistics 4.0 maturity levels. In the few cases where social characteristics were impacted, for example in workplaces with a high Intralogistics 4.0 maturity but with low automation technology, a sensory impairment was perceived because of the pick-by-voice-systems. Additionally, social support decreased with higher degrees of automation in the process because the work was performed more isolated.

Table III-9: Descriptive results of the interviews on contextual characteristics.

Character-istics		**Jobs with low Intralogistics 4.0 maturity and no automation** **(Workplace type 1)**	**Jobs with medium or high Intralogistics 4.0 maturity and low degree of automation** **(Workplace type 2)**	**Jobs with medium or high Intralogistics 4.0 maturity and high degree of automation** **(Workplace type 3)**
Contextual Characteristics	**Ergonomics**	perceived as ergonomically not optimal owing to suboptimal product offering (especially long walking distances);	perceived as ergonomically not optimal owing to suboptimal product offering (high-reaching, heavy weights, long distances);	perceived as ergonomically good workplaces; support of the worker;
	Physical Demands	most often perceived as physically high demanding owing to heavy goods and suboptimal product offering;	perceived as physically medium demanding owing to heavy goods; “We always have the right equipment, so we do not have to destroy ourselves”;	perceived as physically low demanding as goods and packages were designed with limited weights; no strenuous movements necessary at the workplace;
	Work Conditions	perceived as improvable, for instance, dusty environment or cold environment in the winter;	perceived as generally good; little need for improvement perceived;	perceived as nearly optimal; no need for improvement perceived;
	Equipment Use	perceived as not very important but helpful, especially for handling heavy material; “The equipment we have is very helpful especially in handling heavy goods”;	perceived as medium important and helpful, as in handling heavy goods; IT equipment helpful for information tasks; necessary knowledge about how to handle the system best perceived as interesting;	perceived as helpful to ease the physical work, especially the automation system, which is supported by the IT systems, but also as a simplifier of work, leading to boring and monotonous workplaces; “Actually I don’t like working with the automated system. […] It is no challenge. And then, it is getting boring”;

Concerning the impact of the Intralogistics 4.0 maturity level on context characteristics, two outcomes can be identified. Workplaces with high maturity and a widespread use of automation technology exhibit great gains for ergonomics and physical demands as well as equipment usage and working conditions. Workplaces with high Intralogistics 4.0 maturity and without automation technology only improve working conditions and equipment usage but have limited effects on physical demands and ergonomics.

Table III-10: Descriptive results of the interviews on individual expectations.

Characteristics		**Jobs with low Intralogistics 4.0 maturity and no automation** **(Workplace type 1)**	**Jobs with medium or high Intralogistics 4.0 maturity and low degree of automation** **(Workplace type 2)**	**Jobs with medium or high Intralogistics 4.0 maturity and high degree of automation** **(Workplace type 3)**
Individual Expectations	**Future Logistics 4.0 Developments**	only minor changes in terms of digital transformation expected in the middle range as tasks are too complex; resistance by older employees expected; hope to ease manual tasks;	no future trend for digital transformation expected owing to already supported processes; hope to ease manual tasks; possibility of support business processes is a current challenge; data security perceived as a future challenge;	no future trend for digital transformation expected owing to already supported processes; fear of complete shutdowns; loss of individuality

The interviewees did not expect any further influence of Intralogistics 4.0 on their own workplaces, either because they were already relatively Intralogistics 4.0 mature or because they were not and the employees did not expect any change to that status. As many differences were found between manually driven and Intralogistics 4.0 mature workplaces, these expectations might seem paradoxical. As experts for their jobs, interviewees considered other jobs (e.g. truck driving) as more likely to be transformed. One possible reason can be the missing knowledge regarding possible IT influences as compared to, for example, robots that were named more often. For instance, order pickers assessed their tasks as too complex for robots; however, they did not address the influences of IT in depth. This underlines the difference between automation and digital technologies for manual workplaces, where automation technology seems to be dominant. On the worker level, most of the hypothesised influences were negatively perceived for their own workplaces and related tasks (e.g. fear of losing their jobs), although positive impacts, such as ergonomic improvements, were also found.

6. Discussion

The results described above hint at the important implications technology application has on work characteristics. The remaining *RQs* 2–4 are answered in the following data interpretation part of this study.

To further answer *RQ* 2—what are the influences of digital technologies as compared to automation technologies on work characteristics and what are the driving and inhibiting mechanisms behind this—the following results can be derived. Our findings show that the impacts of the Intralogistics 4.0 maturity level on work characteristics depend on the technology applied and the importance of the technology for the task that has to be performed. The interviews show that digital technologies and automation technologies have different and diverse effects on work characteristics.

Overall, digitalisation can be seen both as a multiplier and diversifier of work tasks, mainly for manual work tasks in intralogistics as compared to automation technologies. In addition, digitalisation also standardises, speeds up, or replaces work; therefore, work could both be enriched or enlarged. For work characteristics that are only slightly influenced by digitalisation, such as physical demands or ergonomics, the perception of analogue and digitalised workplaces was similar. In contrast to digitalisation, high degrees of automation simplify manual work tasks in intralogistics. Popular systems, such as AS/RSs, reduce the number of work tasks remaining for the intralogistics workers instead of, for example, supporting and cooperating with them. Therefore, tasks were often perceived as highly standardised, redundant and monotonous in such workplaces, and they were not accompanied by job enlargement in most cases. In highly automated environments, the resulting limitation of work tasks led to a deterioration of several work characteristics such as task variety or task identity.

To answer *RQ* 2, also the mechanisms between the implementation of a technology and the impact on work characteristics are relevant. This means that the implementation of a certain technology does not inhibit or improve a work characteristic directly but may do it indirectly due to certain ways of usage, e.g. the implementation of separated pick cells in an AS/RS that inhibit social interaction. To understand these impacts of automation and digital technologies on the work characteristics in more depth, the underlying mechanisms identified in the interviews are presented in Figures III-3a and III-3b. Overall, nine different mechanisms with a negative impact and seven with a positive one were identified. For example, automation technology negatively influences autonomy. The mechanisms behind this are diverse, but the main aspects found are process rigour and a strong division of labour.

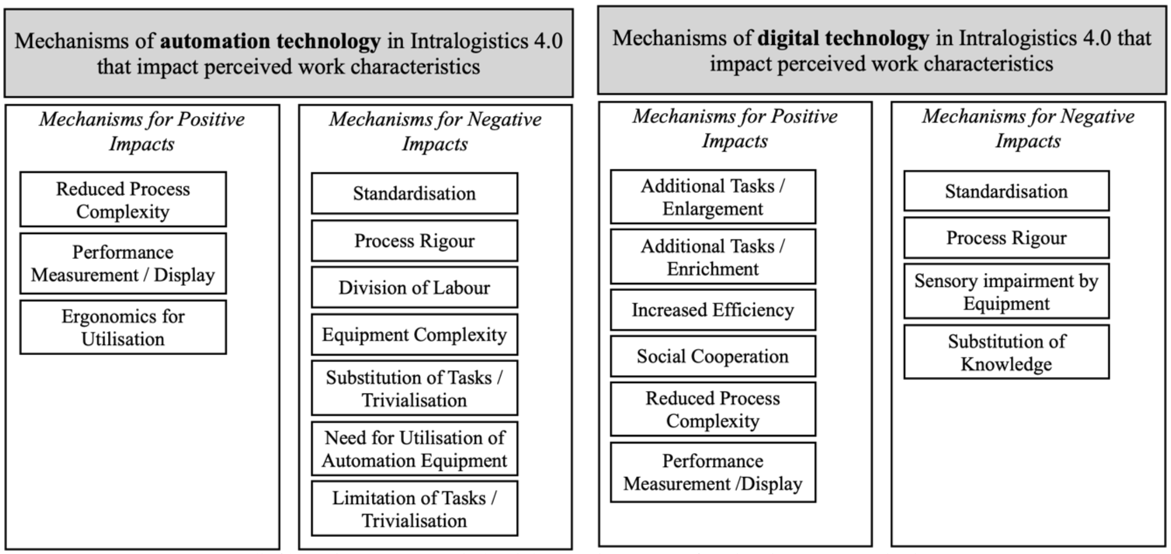


Figure III-3a (left) and Figure III-3b (right): Mechanisms of technology on work characteristics.

The mechanisms identified above can influence the relation between changes in work and work characteristic in complex ways. As exemplarily shown in Figure III-4, a certain change of the process can lead to more standardisation, which could impact the work characteristic autonomy directly and other characteristics indirectly. For example, standardisation could lead to more division of labour, increased efficiency, additional tasks and lastly to a higher task variety. In contrast, the division of labour could also lead to reduced complexity, more process rigour, a limitation of tasks and lastly to reduced task variety. Hence, the identified mechanisms serve as indicators for the actual process design that was comparable within the Intralogistics 4.0 maturity levels.

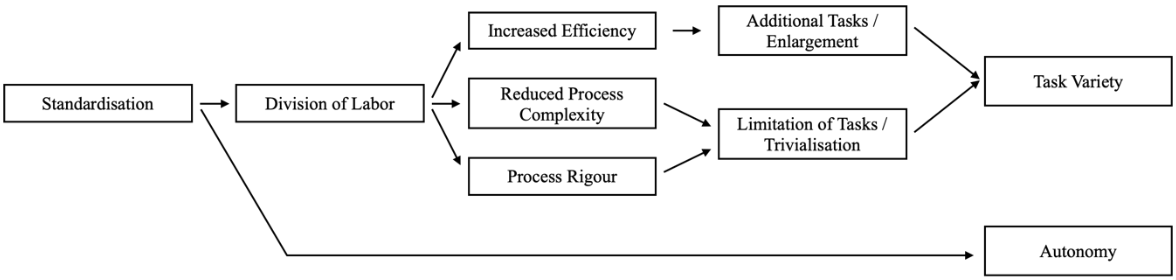


Figure III-4: Process chain of possible mechanisms impacts.

In summary, we found that all four work characteristics categories were influenced by the Intralogistics 4.0 maturity with different mechanisms, although the cases did not achieve the highest Intralogistics 4.0 maturity ratings. Therefore, higher degrees of digitalised or automated processes are expected to have an even more significant impact.

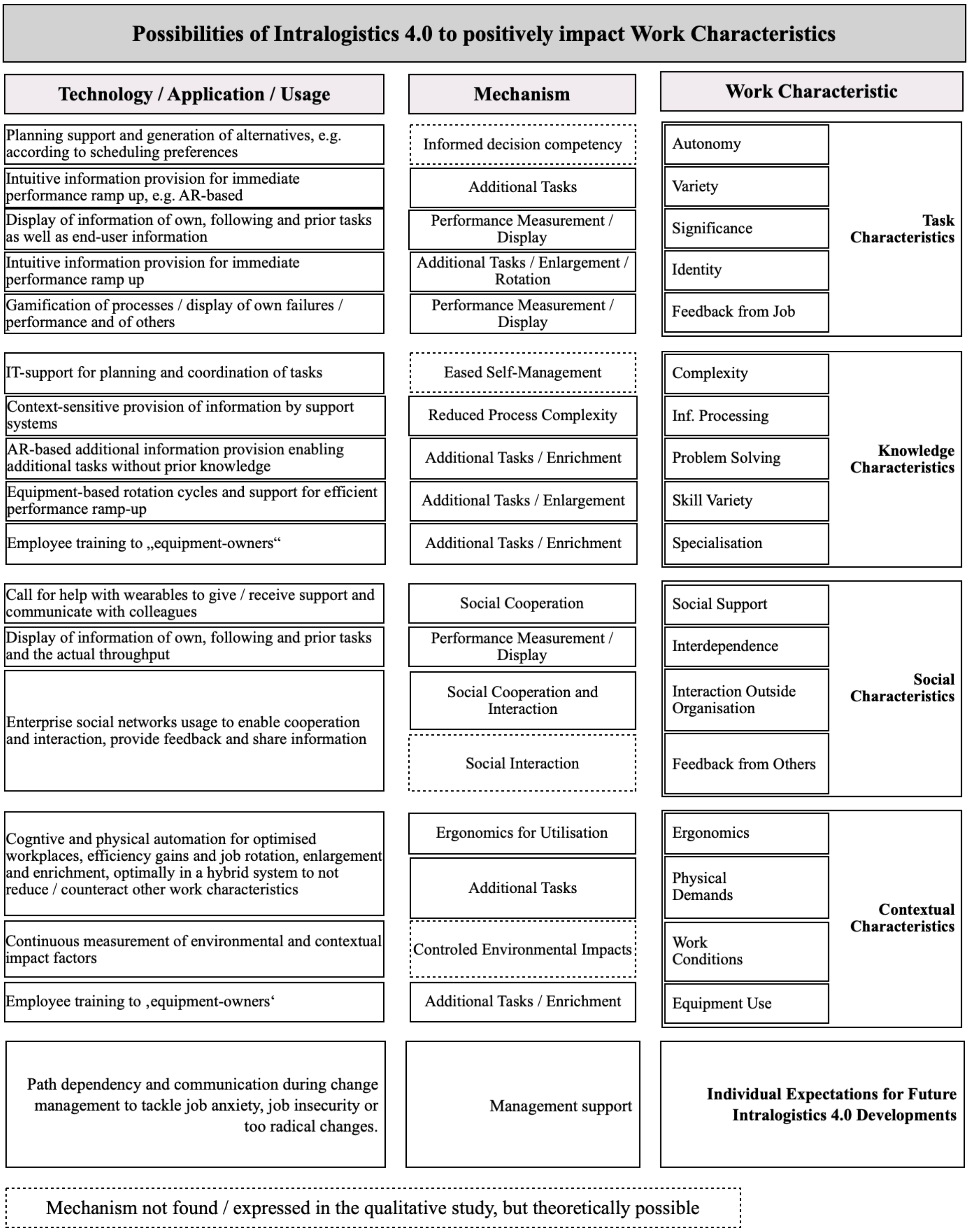
These analyses further enable us to answer *RQ* 3—which role does the Intralogistics 4.0 maturity play in job satisfaction. Considering the impacts of the Intralogistics 4.0 maturity on work characteristics relevant for job satisfaction, the overall effect can be both positive and negative, depending on the exact system design of the workplace and the preferences of the employees. However, for the investigated cases, we found that medium to high levels of Intralogistics 4.0 maturity without or with low degrees of automation improve job satisfaction because the implemented technologies support the workers, leading to enlarged or enriched work, for example, with higher degrees of variety and identity along with lower loads as compared to manual workplaces. This seems plausible because manual work tasks can be impacted/changed, but not fully substituted by digital technologies. In contrast to this, high degrees of automation led to a significant reduction of work characteristics relevant for job satisfaction. Automation technologies can have a strong impact on manual work tasks, which was found to negatively impact work characteristics relevant for job satisfaction in most cases. However, this is not unavoidable as, for instance, adaptive automation technologies in form of robots can also lead to effects comparable to digital technologies, such as job enlargement resulting from more efficient processes. Nevertheless, this observation was not made in this study.

Evaluating our answers to *RQ* 2 and *RQ* 3 in the context of the state of knowledge (see literature summarised in Table III-3), our results confirm earlier findings on how Intralogistics 4.0 may influence job satisfaction, but they also offer new insights: First, we confirmed earlier research that had shown that automation simplifies the work and reduces the requirements, for example in terms of knowledge and capabilities (de Witte and Steijn, 2000). Second, in accordance with the literature, we found that process rigidity increased with technology usage, especially when applying automation technology, and that it negatively impacted the work characteristics; however, increasing process complexity was not found to play a major role in the cases compared to the findings of, e.g. Bala (2013). On the contrary, depending on the Intralogistics 4.0 maturity level, decreasing complexity was identified to have an influence on work characteristics. A reason for this could be the different composition of the interviewees in the earlier studies compared to ours and the scope of work performed that was, for example, not based on complex IT systems in most cases included in the study at hand. In addition, the effects of digital and automation technologies on autonomy, skill variety and feedback were determined; they were diverse depending on the applied technology (Waschull et al., 2020). This clearly indicates that a cross-technological consideration is necessary to determine the impacts of Intralogistics 4.0 on work characteristics to design satisfactory workplaces. Lastly, it was found that digitalisation and automation transform work characteristics, but automation technology was found to have a much stronger impact on work characteristics than digital technologies for the mostly manual tasks in intralogistics. In contrast to the findings on IT systems and the expectations in conceptual studies included in the systematic literature review, processes became less complex or remained comparable complex in high Intralogistics 4.0 maturity levels owing to the standardisation of processes and knowledge provisions at the shop-floor (Waschull et al., 2020). Hence, knowledge needs and skill variety changed (but remained on the same level) or decreased depending on the technological focus of the transformation. In accordance with the literature, we expect this difference to also depend on the skill- and job-level of employees (de Witte and Steijn, 2000).

Improvements of social characteristics were not observed in this study, which is in accordance with the findings in the literature for blue-collar workers (Castellacci and Viñas-Bardolet, 2019). The most important difference between social characteristics for different Intralogistics 4.0 maturity levels can be observed according to social support, which was low for high Intralogistics 4.0 maturity levels with a widespread use of automation technology. In these cases, processes and information provision are standardised to an extent that no social support or interaction is necessary and workplaces do not provide opportunities for this kind of interaction— in short: social was substituted by technological support. As the context characteristics have not been investigated in relation to the digital transformation and job satisfaction until now, we extended earlier findings in this research stream by showing that Intralogistics 4.0 can positively impact these work characteristics, and that workplaces with a high Intralogistics 4.0 maturity and a widespread use of automation technologies have an even higher potential to optimise these characteristics as compared to workplaces with a focus on digitalisation. This might be a consequence of the necessary and predefined structure of the workplaces' automation technology needs and higher demands automation technologies have on the environment the workers benefit from. Additionally, several mechanisms that reach beyond the findings of the literature review were identified and conceptually expected outcomes were empirically verified. For example, process complexity and rigidity were already discussed in the literature, but sensory impairment or performance measurement and display were not addressed in the literature on work characteristics relevant for job satisfaction. Overall, the current study identified several aspects in the literature that need to be discussed and further differentiated to fit the complexity of current developments pertaining to Intralogistics 4.0 systems.

Lastly, RQ 4 was addressed in this context—how practitioners can anticipate the development toward Intralogistics 4.0 in the design of future workplaces in intralogistics. Considering the changes of work characteristics in Intralogistics 4.0, some propositions for practitioners can be derived. These insights can be used by practitioners to derive technology strategies, and they can inspire the organisation of work and the design of workplaces to improve work characteristics. Figure III-5 exemplarily shows how the implementation of technology can positively impact a certain work characteristic: The technology (left column) can trigger the assigned exemplary mechanism in the middle column and finally influence the respective work characteristic in the right column. For example, IT-based planning support for generating alternatives can help employees, such as order pickers, to choose from a number of pick-plans according to personal preferences, e.g. “heavy goods first”, “small orders first”, or similar task scenarios. Although the actual pick sequences may be fixed for these pick-plans, such a decision returns some autonomy to the employees. We termed such mechanisms as “informed decision competency” (see Figure III-5), which was not identified during the interviews. Another example could be the implementation of gamification modules that provide feedback from the job using measures for displaying relevant process information to the employees.

Among all these examples, the inclusion of employees at the beginning of a technology implementation is important for practitioners to avoid an innovation pitfall (Neumann et al., 2021). As outlined above, the overall effect of a certain technology on the work characteristics might not be initially predictable due to overlapping effect chains. Actively designing these effect chains might require deviating from standard solutions, introducing new forms of organisation and thinking out-of-the-box. Therefore, considering the employees’ perspectives provides stronger evidence to the presumed relations. Additionally, a path-dependency was detected in both the development of Intralogistics 4.0 and the subsequent reactions of the employees toward it. As outlined when discussing the future expectations of the interviewees, the employees' perception, anxieties and hopes were diverse and depended on past experiences.



Possibilities of Intralogistics 4.0 to positively impact Work Characteristics

Technology / Application / Usage	Mechanism	Work Characteristic	
Planning support and generation of alternatives, e.g. according to scheduling preferences	Informed decision competency	Autonomy	**Task Characteristics**
Intuitive information provision for immediate performance ramp up, e.g. AR-based	Additional Tasks	Variety	
Display of information of own, following and prior tasks as well as end-user information	Performance Measurement / Display	Significance	
Intuitive information provision for immediate performance ramp up	Additional Tasks / Enlargement / Rotation	Identity	
Gamification of processes / display of own failures / performance and of others	Performance Measurement / Display	Feedback from Job	
IT-support for planning and coordination of tasks	Eased Self-Management	Complexity	**Knowledge Characteristics**
Context-sensitive provision of information by support systems	Reduced Process Complexity	Inf. Processing	
AR-based additional information provision enabling additional tasks without prior knowledge	Additional Tasks / Enrichment	Problem Solving	
Equipment-based rotation cycles and support for efficient performance ramp-up	Additional Tasks / Enlargement	Skill Variety	
Employee training to „equipment-owners"	Additional Tasks / Enrichment	Specialisation	
Call for help with wearables to give / receive support and communicate with colleagues	Social Cooperation	Social Support	**Social Characteristics**
Display of information of own, following and prior tasks and the actual throughput	Performance Measurement / Display	Interdependence	
Enterprise social networks usage to enable cooperation and interaction, provide feedback and share information	Social Cooperation and Interaction	Interaction Outside Organisation	
	Social Interaction	Feedback from Others	
Cogntive and physical automation for optimised workplaces, efficiency gains and job rotation, enlargement and enrichment, optimally in a hybrid system to not reduce / counteract other work characteristics	Ergonomics for Utilisation	Ergonomics	**Contextual Characteristics**
	Additional Tasks	Physical Demands	
Continuous measurement of environmental and contextual impact factors	Controled Environmental Impacts	Work Conditions	
Employee training to ‚equipment-owners'	Additional Tasks / Enrichment	Equipment Use	
Path dependency and communication during change management to tackle job anxiety, job insecurity or too radical changes.	Management support	**Individual Expectations for Future Intralogistics 4.0 Developments**	

Mechanism not found / expressed in the qualitative study, but theoretically possible

Figure III-5: Possibilities of Intralogistics 4.0 to improve work characteristics.

7. Conclusion

This article provides a qualitative approach to deepen our understanding of the impacts of Intralogistics 4.0 on work characteristics and job satisfaction focusing on intralogistics workplaces.

7.1 Contribution to theory

To the best of the authors' knowledge, the current study is the first to investigate the influence of the Intralogistics 4.0 maturity level on work characteristics by intralogistics shop-floor employees, aiming to empirically deduce the impacts of digitalisation and automation on the job satisfaction of employees. We expand the state of research in the field of intralogistics by empirically examining how automation and digital technologies of real work systems affect the work characteristics of manual workplaces, and which mechanisms – that serve as intermediaries between implemented technologies and their effects on work characteristics by means of, e.g. process changes – appear to be essential. Three types of workplaces were found within the cases: workplaces with low Intralogistics 4.0 maturity, workplaces with medium to high Intralogistics 4.0 maturity but without or only a limited degree of automation and workplaces with medium to high Intralogistics 4.0 maturity and a widespread use of automation technology. Evidently, these different technology setups have different influences on the work, mainly in manual workplaces. The different work characteristics evaluated were related to the Intralogistics 4.0 maturity type (*RQ* 1) and technologies applied (*RQ* 2). The results highlighted that a higher Intralogistics 4.0 maturity does not necessarily contribute toward job satisfaction; instead, it depends on the technology applied and mechanisms that are triggered (*RQ* 2). These factors impacted job satisfaction but not in a linear or unidirectional way (*RQ* 3). Although the impacts and mechanisms were diverse, propositions were derived for practitioners that can lead to an improved Intralogistics 4.0 implementation (*RQ* 4).

Taking a wider perspective on these results, this study also contributes to the resource-based view of the firm. As proposed by Neumann and Dul (2010) humans can be considered as a resource in an operation system that, in turn, can have an influence on the sustained competitive advantage of the firm. If the impact of a system change, e.g. through the introduction of Intralogistics 4.0 technologies, on employees is not carefully considered, the risk of systems that fall short of their expectations – so-called phantom profits – increases (Neumann and Dul, 2010; Rose et al., 2013; Sgarbossa et al., 2020). This study shows that technology-induced changes of the work system also impact work characteristics of employees in Intralogistics 4.0. Assuming that the results of prior studies are true also in this development, it is necessary for companies to pay attention to these effects on work characteristics to prevent phantom-profits and develop employees as a key-resource for a successful development of the company.

7.2 Implications for research and practice

For researchers from different disciplines, this study builds an important baseline: first, the researchers are provided with a qualitative analysis that holistically examined the impacts of both automation and digital technologies and their effects on work characteristics. The effects of automation technology evidently outpaced that of digitalisation in terms of importance or radicalness of change. Additionally, the study strongly applied an individual-level investigation across a diverse range of impact factors like workplaces and companies. Thus, this study contributed toward the existing knowledge on effects between technology applications in intralogistics and work characteristics changes and impacts on job satisfaction.

For managers, this study offers initial insights for work design toward the developments of Intralogistics 4.0, especially in cases where new technologies are implemented and the work system is redefined; two main insights were obtained: 1) the study hints at relations between technologies and work characteristic impacts and thus supports the development of workplace designs that are beneficial for the company and the workers, thus enabling an enriched and productive work system and 2) the decision for or against a certain technology could be influenced, because the implemented technologies might determine the work processes and have different influences on work design. In every case, a careful change management should be applied that enables the direct feedback and consideration of necessities, such as training, communication and a more cooperative work design.

Adopting a more general managerial perspective allows to identify additional impacts: The role of human factors is very important in logistics and operations management and several studies highlighted the joint objective of human factors and system performance objectives (Neumann et al., 2021). Hence, paying attention to the effects of the change of the (sociotechnical) operations system on employees also contributes to system performance. As there is a potential impact of introducing Intralogistics 4.0 on employees' work demands and job satisfaction, this study gives first insights into which aspects should be considered carefully during the implementation phase and how the changes can impact employees work characteristics. As outlined by Sgarbossa et al. (2020), "it would be important to consider and predict human effects of adopting a new tool/instrument and subsequently, the impact of HF on system performance and not only on investment cost". In this regard, this study contributes a first step as we evaluated relevant changes of work characteristics in a changing technological environment in intralogistics. However, this study did also not consider the performance impacts, which could be addressed in a follow-up study.

7.3 Limitations

This work has limitations. First, the study was conducted based on the evaluation of work design characteristics. However, there are alternative models that could be assessed as relevant for job satisfaction, which might have led to a different structure of the study. Second, the study only referred to intralogistics workers, which might limit the explanatory power beyond the borders of intralogistics tasks. Having prior different work characteristics might also change the perception of the work characteristics in higher levels of Intralogistics 4.0 maturity and different technologies might have other impacts. Additionally, the number of cases for each workplace type was limited, although saturation occured during the interviews. Nevertheless, a more detailed analysis that could be grounded on the results of this study could further investigate the effects of the digital transformation on work characteristics and the mechanisms between them. Third, although the cases had different characteristics in terms of size, sector and Intralogistics 4.0 maturity, some warehouse systems and organisations are very rare or just emerging. A further study could, for example, investigate new technology implementations such as hybrid order picking systems, where robots share the shop-floor with order pickers. This could lead to promising insights given that recently introduced technologies, such as augmented reality or collaborative robots, were not used in the interviewees' workplaces, and highest levels of Intralogistics 4.0 maturity were not achieved yet. The results obtained in this study could consequently change as new and more adaptive technologies enter intralogistics workplaces. The Intralogistics 4.0 maturity model used in this study could also be revised to exclude the lowest levels of Intralogistics 4.0 maturity from the Intralogistics 4.0 maturity concept altogether. Additionally, there might be further impacts and mechanisms that were not identified within the interviews but that lead to work characteristic changes. Fourth, a statistical analysis of the results was not possible owing to the methodology used and the data interpretation was grounded on subjective representations instead of ratings, as in a questionnaire. In this context, future research could follow up on the insights obtained in this study and try to quantify the impacts of technologies on the identified mechanisms as well as on job satisfaction or examine this in various workplaces such as assembly lines or road transport. Moreover, future research could focus on related topics: For example, future research could additionally incorporate the productivity outcomes of such workplaces in a case study. Does the productivity change with the Intralogistics 4.0 maturity level and job satisfaction level? How can these workplaces be evaluated according to the aim to design economically, ecologically and socially sustainable systems?

Overall, this study showed some major effects of the digital transformation on manual workplaces, particularly in intralogistics. Our results encourage more research on incorporating human factors in the design of Industry 4.0. We argue that both managers and researchers are responsible for establishing workplaces that fit human requirements and needs. The findings of this study could be used for better work design and to improve the job satisfaction of intralogistics workers, which will contribute toward successfully managing the digital transformation of intralogistics in practice.

IV. [Article 3] Industry 4.0 and the human factor – a systems framework and analysis methodology for successful development[4]

Authors: Neumann, Patrick W.; Winkelhaus, Sven; Grosse, Eric H.; Glock, Christoph H.

The Fourth Industrial Revolution we currently witness changes the role of humans in operations systems. Although automation and assistance technologies are becoming more prevalent in production and logistics, there is consensus that humans will remain an essential part of operations systems. Nevertheless, human factors are still under-represented in this research stream resulting in an important research and application gap. This article first exposes this gap by presenting the results of a focused content analysis of earlier research on Industry 4.0. To contribute to closing this gap, it then develops a conceptual framework that integrates several key concepts from the human factors engineering discipline that are important in the context of Industry 4.0 and that should thus be considered in future research in this area. The framework can be used in research and development to systematically consider human factors in Industry 4.0 designs and implementations. This enables the analysis of changing demands for humans in Industry 4.0 environments and contributes towards a successful digital transformation that avoid the pitfalls of innovation performed without attention to human factors. The paper concludes with highlighting future research directions on human factors in Industry 4.0 as well as managerial implications for successful applications in practice.

Keywords:

Human Factors, Ergonomics, Industry 4.0, Digital Transformation, Content Analysis, System Design

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[4] This article has been published as W. Patrick Neumann, Sven Winkelhaus, Eric H. Grosse and Christoph H. Glock (2021): Industry 4.0 and the human factor – A systems framework and analysis methodology for successful development. International Journal of Production Economics 233, 107992. DOI: 10.1016/j.ijpe.2020.107992. This article has been slightly adapted for use in this dissertation, for example to ensure consistent spelling

1. Introduction

The Fourth Industrial Revolution, also termed Industry 4.0 (I4.0), has recently gained considerable attention in the production research domain (Liao et al., 2017; Lu, 2017; Xu et al., 2018). The aspiration behind I4.0 was to propose an industrialisation model suited to Germany's position as both a producer and user of high-technology production systems (Kagermann et al., 2013). Industrial revolutions are often framed in a technological perspective: the 1st Industrial Revolution relating to steam powered systems, the 2nd to the use of electrically powered systems and the 3rd to the adoption of information technology and automation. Speaking broadly, I4.0 refers to the further digitalisation and integration of information technologies including applications such as the Internet of Things (Lu, 2017), cloud-based systems (Lu, 2017), cobots (Bortolini et al., 2017), Big Data analytics (Wang et al., 2016), additive manufacturing (Hofmann and Rüsch, 2017) and cyber-physical systems (Xu et al., 2018). These systems enable a "smart factory" (Frank et al., 2019; Osterrieder et al., 2020), in which humans, machines and products communicate with each other via both physical and virtual means (Kagermann et al., 2013) and can contribute to increased sustainability (Bai et al., 2020). We point out the aspirational nature of I4.0; while previous industrial revolutions were identified and examined mainly after they had occurred, the conceptualisation of I4.0 and associated application of technologies is just beginning and is part of a deliberate industrialisation strategy.

Beside technological push-factors (Frank et al., 2019), I4.0 is also characterised by different pull-factors (Lasi et al., 2014) that contribute to a shift of paradigms. For example, individualised customer demands can be seen as a main driver of I4.0, since the fulfilment of individualised demands without an increase in costs (this is often referred to as "mass customisation" or "product individualisation") is one of the superordinate goals of using the different technologies (Winkelhaus and Grosse, 2020a). However, it is still not fully clear to many in both industry and research what fully realised I4.0 applications might look like or how they might operate. For most practitioners, the digital transformation and its implications on operations processes remain a big black box. The transformation of production due to both technological and paradigmatic drivers leads to fundamental changes of organisations and processes (Matt et al., 2015) and finally also of human work (Kadir et al., 2019; Neumann and Village, 2012). Within this context, attention to HF has been particularly sparse, despite the evident centrality of HF in four of the eight I4.0

developmental priorities (i.e. managing complex systems, safety and security, work organisation and design, and training and professional development) laid out in the seminal I4.0-report by Kagermann et al. (2013). This centrality of human aspects, we will show, is not reflected in the I4.0 research to date.

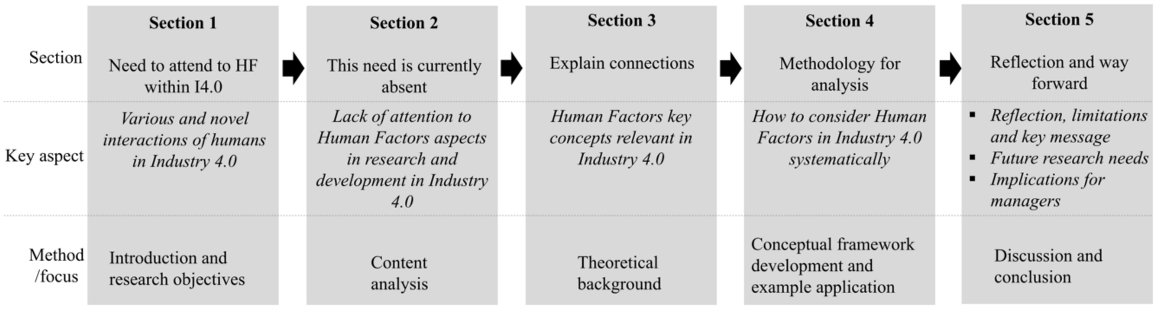
I4.0 and technological change are rapidly transforming virtually all areas of human life, work and interaction. These changes are acutely apparent in the way human work is organised and performed. Prominent examples include the usage of mobile devices for the augmentation of processes and support of workers, e.g. for maintenance or in order picking. Collaborative robots support assembly workers, exoskeletons empower production and logistics workers and cloud-based software solutions for enterprises are emerging at a high pace (see, e.g. Osterrieder et al., 2020). These examples are just a few new forms of interaction between humans and I4.0 technologies within business' transformation that, however, highlight the various and novel interactions humans are confronted with.

First attempts to structure these interactions are made, for example, by Romero et al. (2016b), Ruppert et al. (2018) and Fantini et al. (2020), where the operator is interpreted in different roles, depending on the technologies used. As described by Romero et al. (2016b), augmented reality used by an operator leads to the "augmented operator", who is presumably capable of making more informed decisions when maintaining a machine, for instance. These works, however, still focus on technological possibilities for the worker without analysing their influences on HF demands and operator experience in depth. Moreover, the "Operator 4.0" as proposed by these works is merely analysed in isolation, without consideration of the organisational, processual, psychosocial and technological environment of the humans in the system.

This article discusses how failure to attend to HF in previous industrial system generations has had negative consequences for individual employees, production organisations and for society as a whole. We further show that there has also been a lack of attention to HF aspects in research and development in I4.0 and present and discuss a framework for the systematic consideration of HF in the design and evaluation of I4.0 technologies and technology-assisted workplaces. Addressing these aspects, this paper pursues two research objectives (ROs):

- *RO1: To identify which HF aspects have been considered to what extent in the scientific literature on I4.0.*
- *RO2: To provide a framework that includes foundational theories of HF to support the incorporation of HF aspects into corporate I4.0-system development efforts.*

The remainder of this paper is structured as follows. A content analysis of research dealing with I4.0 is performed in Section 2, which highlights the definite lack of considering HF in this research area. In Section 3, concepts of HF in engineering design are discussed that are relevant for understanding the role of HF for system performance. In Section 4, an analysis framework is derived based on the discussed concepts to highlight how HF can be considered systematically in I4.0 research and development. In addition, an example application of the framework to a typical I4.0 use case is presented. The framework's implications are discussed in light of the insights obtained from the content analysis and theory section, and limitations as well as future perspectives of HF in I4.0 for researchers and managers are outlined in Section 5. Figure IV-1 illustrates the outline of the paper and the research steps.



	Section 1	**Section 2**	**Section 3**	**Section 4**	**Section 5**
Section	Need to attend to HF within I4.0	This need is currently absent	Explain connections	Methodology for analysis	Reflection and way forward
Key aspect	*Various and novel interactions of humans in Industry 4.0*	*Lack of attention to Human Factors aspects in research and development in Industry 4.0*	*Human Factors key concepts relevant in Industry 4.0*	*How to consider Human Factors in Industry 4.0 systematically*	▪ *Reflection, limitations and key message* ▪ *Future research needs* ▪ *Implications for managers*
Method /focus	Introduction and research objectives	Content analysis	Theoretical background	Conceptual framework development and example application	Discussion and conclusion

Figure IV-1: Outline of the paper and interdependencies between sections.

2. Evidence of lack of HF in I4.0 research: a content analysis

We present a content analysis of the literature on I4.0 in the next section to address RO1: examining which HF aspects have been included in the I4.0 literature up to now. We first briefly summarise previous related literature reviews. Subsequently, we outline the methodology and results of a content analysis of the literature on I4.0.

2.1 Insights from literature reviews and related Industry 4.0 works

Two reviews focusing on HF-related issues in I4.0 could be identified. First, Badri et al. (2018) discussed occupational health and safety issues in the emergence of I4.0. In their systematic review, they identified eleven contributions as relevant, seven of these were conference articles. They concluded that "most articles are focused on new technologies driving this revolution and mentioned worker health and safety only briefly" (Badri et al., 2018). Second, Kadir et al. (2019) applied a broader search for contributions that do not only consider health and safety issues, but HF in general. Overall, 40 peer-reviewed articles were identified that use I4.0- and HF-related terms in the title, abstracts or list of keywords in Scopus, but again only 13 of these were journal articles. In a qualitative assessment of the identified articles, the authors pointed at mental, physical and organisational aspects considered, such as human-machine interaction or necessary IT skills as well as the possibility of automation of repetitive manual tasks. They concluded, however, that literature on this topic is still narrow and rare and that more I4.0 research with deeper attention to HF is needed. Since these reviews generated their sample in 2018, we analyse these insights to exploratively update the outcomes. Based on this analysis, we noted that the term "Operator 4.0" has emerged as a research area of note during the last year. We provide a brief overview of this literature here.

Six recent journal articles could be identified dealing with the "Operator 4.0" concept that have not been included in the reviews of Kadir et al. (2019) and Badri et al. (2018) that are generally based on technology-driven approaches. One of these works is the one of Ruppert et al. (2018) that grounds a survey on technologies for the "Operator 4.0" based on the systematisation of Romero et al. (2016b). The focus is on IoT-based infrastructure instead of software-based applications like Big Data. However, since the focus is on technologies, HF are only considered briefly although they are of great relevance for the applications.

Kaasinen et al. (2020) performed user studies in three companies focusing on "Operator 4.0" solutions. Each study used different outcome measures, such as increasing job satisfaction, performance or controllability of production, which are achieved by empowering and engaging the workers using I4.0 technologies, e.g. for knowledge sharing or personalised learning. In the case studies, also challenges were observed, including major doubts about technology usage raised by workers. Zolotová et al. (2020) performed laboratory case studies implementing different technologies. The authors concluded that using various technologies, for example for a “Smart Operator” or an “Analytical Operator”, leads to better results compared to implementing only a single technology. Segura et al. (2020) mainly focused on visual computing technologies, especially augmented reality, but also virtual reality, cobots and social networks. In use cases, the authors showed how these technologies can facilitate decision-making processes of workers.

The last two articles are of a more conceptual character. Dealing specifically with cognitive automation as part of the “Operator 4.0” concept, Mattsson et al. (2020) provided a strategy answering the question of how cognitive automation systems should be designed for an optimal support of assembly workers. The authors developed a framework that could be used to reduce stress and improve complexity handling and transparency in cognitive automation. Lastly, Taylor et al. (2020) provided a different perspective on the “Operator 4.0” asking for chances of such a development for small, capital-constrained enterprises. Taking the economy of New Zealand as an example, they discussed whether there is a transition from an operator-role to a maker-role, since employees are more involved in designing products than in monitoring machines.

Overall, it can be seen that the explicit consideration of HF in I4.0-related research is scarce. The above-mentioned reviews focus on articles that explicitly deal with HF in I4.0 and did not find a large sample to draw their conclusions on. Moreover, even articles that deal with the “Operator 4.0” concept and its impacts on HF are only discussed in a few cases in depth. In most of the studies and also the original contribution of Romero et al. (2016b), HF remain an afterthought and not a design objective, nor a means to achieve good designs. This is consistent with gaps in the industrialisation research identified by reviews in manufacturing (Neumann and Dul, 2010) and in warehouse systems research (Grosse et al., 2015; Grosse et al., 2017). While I4.0 has been reviewed in terms of its impact on sustainability (Bai et al., 2020), the focus was so far on the external environment and not on the internal working environment (Docherty et al., 2002). The work of Bai et al. (2020) deals with the actual interaction of people and the system. These interactions will be crucial to the success or failure of a system design effort to achieve the functionalities proposed in that work. In contrast, the work of Pinzone et al. (2020) addresses social sustainability in cyber-physical production systems directly; it does so, however, from a high-level discussion of functionalities and does not address the specific issue of human-system interactions in the design and application of new technologies. Recognising that there may be relevant discussions inside the body of papers that do not use HF terms in their title, keywords, or abstract, we conducted a content analysis of the body of available I4.0 literature to examine the extent of discussion of HF-related issues compared to purely technical ones.

2.2 Methodology

A content analysis (CA) is an established method to analyse published works systematically and to highlight the core of research as well as to identify research gaps (Cullinane and Toy, 2000; Grosse et al., 2017; Spens and Kovács, 2006). A CA is "a research technique for making replicable and valid inferences from texts or other meaningful matters to the context of their use" (Krippendorff, 2013). According to Neuendorf (2002), a CA enables the recognition of patterns in large data sets. The objective of the CA is to count specific keywords, called recording units (RU), in the sample, assuming that a high number of hits is an indicator for the importance of the keyword (Cullinane and Toy, 2000). We use the CA here as a method to compare the occurrence of use of key terms related to I4.0 and HF. The analysis at hand follows four steps: 1) material collection, 2) descriptive analysis, 3) category selection and 4) material evaluation. We outline these steps in further detail in the following.

The sample consists of all papers containing the keyword "Industry 4.0" in the title, which guarantees a strong focus on I4.0 and a broad sample. The database Scopus was searched for articles, since it is among the largest, transdisciplinary databases for peer-reviewed journal articles, leading to 2650 results in the first step of the development of the sample. We then limited our search to peer-reviewed journal articles written in English, resulting in 646 hits. All sampled works were obtained as or converted into readable PDF documents to allow for the use of the text analysis software MAXQDA. To avoid biases, the reference lists of all papers were removed before starting the count of RU.

As can be seen in Figure IV-2, the sample shows a steady increase of research interest from the first paper on I4.0 published in 2014 until its current climax in 2019. We observed an interdisciplinary character of the sample with regard to journals, which stresses the complexity of research in the emerging digital transformation of work.

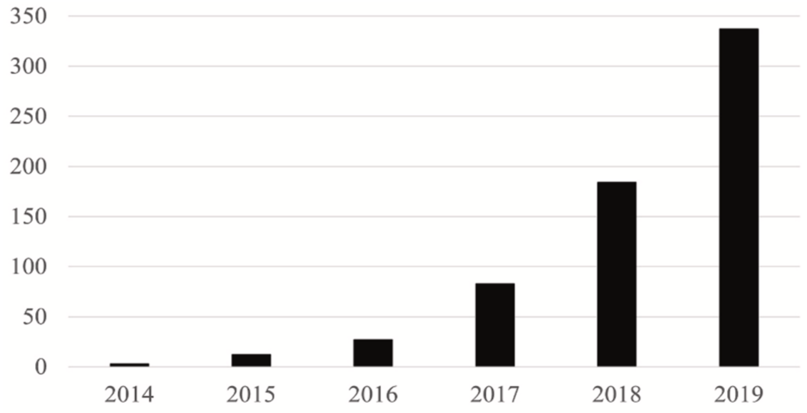


Figure IV-2: Distribution of articles over time.

In the next step, all articles were coded using the method of manifest coding (Babbie, 2013). For the analysis, we chose both a deductive and an inductive approach. In the deductive approach, three categories (I-III) including various subcategories for I4.0 and HF aspects were derived based on the theoretical insights presented in Sections 2.1 and 3.

I. Beginning with I4.0 concepts, there are three subcategories of relevance: First, I4.0 systems are based on the implementation of a wide range of different technologies, like IoT, CPS and Big Data. Second, there is a paradigmatic change, which leads to new targets of the actions performed. Third, a subcategory I4.0 characteristics is added, considering terms like “smart” or “collaborative” which could be seen as a mediator including terms that do not name a certain technology, but instead a certain characteristic of it that is necessary for target achievement.

II. With regard to HF, four subcategories were derived especially based on the perception-cognition-motor action-cycle and the demand-control-model (see Key Concepts 3 and 4 in Section 3.3). The perception of a given situation leads to the cognitive processing and, in accordance with memory interaction, to the decision to perform a motor action. This loops back to the situation, which is perceived again. Besides these, also psychosocial aspects influence the work environment for humans.

III. The third category “General HF terms” includes two sub-categories. The first generally refers to human capabilities or load without referring to a certain system. These keywords are summarised in the subcategory general terms. The second deals with different and changing roles of humans in I4.0, e.g. from an operator role to a machine supervisor role.

Table IV-1 summarises the three categories, related subcategories and RU. Overall, we consider three categories (General HF terms, HF and I4.0) and nine subcategories. For every subcategory, RU were derived deductively based on the theoretical background (Section 3). Different spellings (AE/BE), common abbreviations and different word endings (singular/plural) were considered in finalising the list of RU. This deductive approach was complemented by an inductive refinement, where an entire coding process of all abstracts of sampled papers was performed, counting all words, abbreviations and symbols in the abstracts. The resulting list was then evaluated carefully to inductively refine the category system and RU. This approach ensured that all important RU are contained in the category system.

Table IV-1: Category system and recording units.

Category & Subcategory	Recording Unit (RU)
General HF Terms	
Roles of Humans	customer, maintenance, user, human/s, employee/s, operator/s, worker/s, manager/s, expert/s, partner/s/ partnership, researcher/s, engineer/s, consumer, leader, stakeholder, workforce, staff, practitioner/s, personnel, supervisor/s, technician, employer/s, entrepreneur/s, instructor, programmer, shareholder, politician, co(-) worker, assembler, order picker
General Terms	work, social, risk, decision(-) making, labo(u)r, society, health, human resource/HR, attention, age/ing, effort, workload, human factor/s, assisted/assistive, socio-technical, work organization, ethics, OHS
Human Factors	
Mental	learn, knowledge, training, capabilities, skill/s, experience/s, education, behavio(u)r/al, teach/ing, cognitive/cognition, talent, competencies, hmi, human-machine, mental, qualification, creativity, psychology/psychological, human- centered, confusion/ing/ed, human-robot, e-learning, human-computer, forget/ting, human-technology, memory, reasoning
Physical	physical, safety, manual, ergonomic/s, fatigue/fatiguing, posture, well-being, gesture, musculoskeletal disorder
Psychosocial	involve*, culture/cultural, feedback, motivation, stress/ful/ ing, teamwork, fairness, work design, psychosocial, job satisfaction, job demand, job control, support
Perceptual	read/ing, perception/ual, information processing
Industry 4.0	
Technologies	data, Industry 4.0, technology/technologies, information, machine, network/s, IoT/Internet of Things/Industrial Internet/iiot, sensor, digital/ly, automation/automated/ automatic, CPS/cyber-physical, cloud, robot, virtual/VR, big data, equipment, IT, simulation, digitiz(s)ation/digitaliz(s) ation, mobile, augmented/AR, wireless, autonomous/ autonomy, artificial/AI, rfid, ICT, blockchain, additive, digital twin, 3D printing, wearable, agv, cobot, gamification
Characteristics	smart, environment/al, flexible/flexibility, real-time, intelligent, integrated, predictive/prediction, complexity, lean, embedded, collaborative, robust/ness, data-driven, disruptive, ubiquitous, transparent, cooperative, visible, as a service, self-learning
Paradigm and Targets	performance, sustainability/sustainable, quality, energy, individual, industrial revolution, optimiz(s)ation, productivity, paradigm, customiz(s)ation/customiz(s)ed, privacy, transparency, trust, virtual/virtualiz(s)ed/virtualiz (s)ation, visibility, compliance, resilience, servitization, personaliz(s)ation, cyber security, usability, predictability

To account for possible biases, a sensitivity analysis was carried out, in which both the top ranked RU as well as the top contributing articles were analysed. The results of this analysis show whether only a few RU or a few articles contribute disproportionately to the result of a RU or category. Hence, it is possible to qualitatively account for correction factors (Abedinnia et al., 2017; Grosse et al., 2017).

2.3 Results

Comparing the hits for the two most prominent RU in I4.0 and HF, the results of the CA reveal a strong disparity between both categories, as illustrated in Figure IV-3. In fact, we noticed 29,591 accumulated hits for "Industry 4.0" and "Internet of Things" versus only 254 accumulated hits for "Ergonomics" and "Human Factors".

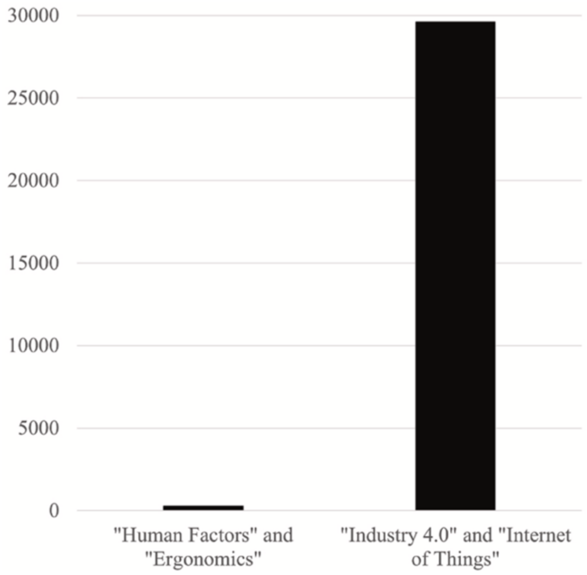


Figure IV-3: Number of recording units for I4.0 and HF.

Table IV-2 summarises the number of accumulated hits for the RU (#) in each subcategory. % indicates the percentage share of each subcategory (in terms of total number of hits of RU), and R shows the corresponding rank. Moreover, considering the different amount of RU per category, the mean # per RU for each category is calculated and the corresponding rank is given to ease comparability.

As can be seen in Table IV-2, 69% of all RU hits are observed in the category I4.0, with the subcategory technologies accounting for 50% alone (although the number of RU presents only 19%), which points to a high relevance this subcategory enjoyed in the sampled papers compared to all HF subcategories together. Also the relative ranks (mean hits per word) are led by all three I4.0-related subcategories. Within the I4.0 category, the RU counting the most hits are general terms like “data” or “Industry 4.0” that are followed by primary technologies like “IoT”. On the characteristics side, “smart”, “flexible” and “real-time” are top ranked, and targets focus on “performance”, “sustainability” and “quality”, but also “individualization” and “customization”. Lastly, there are some terms that were not found at all in the sample like “musculoskeletal disorder”, “job demand”, “job control” or “order picker”, or only a few times as in the case of “job satisfaction” (14 hits), “psychosocial” (3 hits) or “work design” (11 hits).

Table IV-2: Results of the CA category system.

Text only			**Words in Category**				
#	**%**	**R**	**Nr. of RU**	**mean # per RU**	**R**	**Subcategory**	**Category**
30.563	11	2	30	1.019	4	*Roles*	**General HF Terms**
16.457	6	6	18	914	5	*General Terms*	
22.372	8	5	27	829	6	*Mental*	**HF**
7.060	2	8	9	784	7	*Physical*	
9.693	3	7	13	746	8	*Psychosocial*	
978	1	9	3	326	9	*Perceptual*	
145.767	50	1	34	4.287	1	*Technologies*	
29.564	10	3	20	1.478	2	*Characteristics*	**I4.0**
27.385	9	4	22	1.245	3	*Targets*	

The accumulated hits per subcategory are displayed in Figure IV-4. As can be seen, in the four HF subcategories, there are two bars displayed, showing the results for all RU in the subcategory as shown in Table IV-2 in dark grey, whereas the light grey ones belong to the subsequently discussed sensitivity analysis.

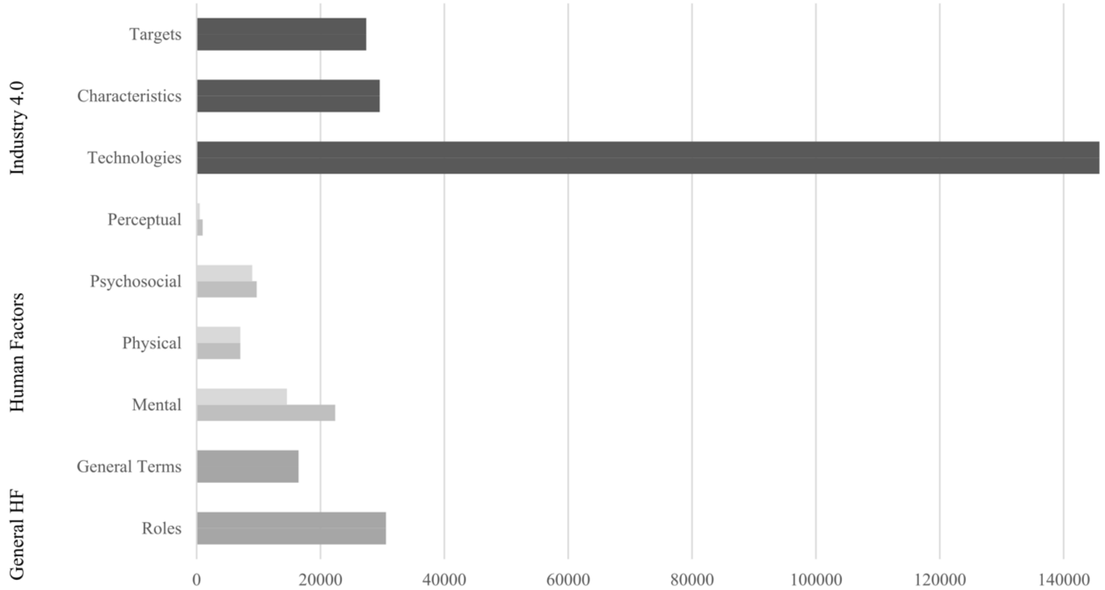


Figure IV-4: Accumulated hits of recording units per subcategory in full texts.

2.4 Sensitivity analysis

Generally, the results of a CA should be reflected in light of possible biases or influential points originating from some RU that can have ambivalent interpretations (Grosse et al., 2017). In our case, a more precise look at the hits in the HF categories is warranted. For example, “learning”, which is a very important HF term (Glock et al., 2019), is increasingly transferred to the I4.0 domain, for example in terms like machine learning, learning algorithms and artificial intelligence. Other critical RU in this regard are “behaviour”, referred to as systems behaviour, “read/ing”, which often refers to tag readings of RFID-based systems, or “feedback”, which is often used in a technical “feedback loop” context. Most of these RU are among the top three in the HF categories; acknowledging their possible relation to I4.0 technologies, the problem stated above becomes even more apparent. We identified six RU as critical in terms of ambiguous interpretations both in I4.0 and HF (shown in Table IV-3) and eliminated these from the analysis. The results change as illustrated in Figure IV-4 (light grey bars in the HF sub-categories). As can be seen, especially the subcategory mental HF as well as perceptual HF decline in their importance. The lack of attention to HF in I4.0 research becomes even more apparent.

Table IV-3: Recording units with possible ambiguous interpretations.

HF Recording Units	Subcategory	Industry 4.0 context
learn/ing	*mental*	e.g. learning algorithms, machine learning
training	*mental*	e.g. training an algorithm/a machine
behavio(u)r/al	*mental*	e.g. system behaviour
feedback	*psychosocial*	e.g. feedback loops
read/ing	*perceptual*	e.g. RFID-/tag-reading
memory	*perceptual*	e.g. computer memory

Besides possible biases caused by RU, articles using a certain RU quite frequently could have biased the results. Therefore, we identified the top ten articles (out of the sample of 646 articles) that contribute most hits for RU in the HF category without considering articles that have been coded incorrectly in the HF category due to the above discussed ambiguous meanings of RU. Having a more precise look on them helps to interpret additional possible biases due to an overestimation of RU. The results are given in Table IV-4.

Table IV-4: Most contributing articles in the HF category.

Paper	Content	Subcategory (Main RU)	Number of hits top RU/ all HF RU
Maisiri et al. (2019)	Performs a systematic literature review about technical and non-technical skill requirements for engineers in I4.0 and how to develop them	*Mental* (skill)	236/380
Shamim et al. (2017)	Conceptualises management practices for I4.0-analogue developments in the hospitality sector including HF influences	Mental (knowledge)	131/351
Longo et al. (2019)	Proposes a solution for training of staff for emergencies in industrial plants using I4.0- technologies	Mental (training)	181/344
Chong et al. (2018)	Investigates the impacts of I4.0-technologies and 3D printing for teaching engineering programs	Mental (teach)	80/337
Hariharasudan and Kot (2018)	Studies I4.0's influences on employee qualification focusing on the effects of Education 4.0 and Digital English	Mental (learn)	105/318
Chi (2019)	Investigates an application for English learning especially for engineering learners within Industry 4.0	Mental (learn)	90/303
Sackey et al. (2017)	Surveys learning factories for I4.0 education in industrial engineering programs	Mental (learn)	161/287
Stachová et al. (2019)	Analyses employee education for I4.0 focusing on external partnerships for personal development processes comparing different countries	Mental (knowledge)	89/279

Hang and Tam (2018)	Surveys influences on training quality and student satisfaction in the context of I4.0 education programs	Mental (training)	148/276
Azmimurad and Osman (2019)	Analyses vocabulary learning strategies among students for the expanded vocabulary needs in engineering within Industry I4.0	Mental (learn)	185/273

All articles focus on how to teach, learn and develop knowledge and capabilities for a future I4.0 environment, but only a few investigate the inherent changes induced by I4.0 for workers and especially for shop floor workers. Following, within the most contributing articles, the focus is not on how to design or interact with an I4.0 system. Based on this analysis, we conclude that there is an even more tremendous neglect of HF in I4.0 as suggested in the accumulated results, because these ten articles are responsible for about 8% of the hits in the HF categories, whereas they only account for about 1.5% of the sample. This is due to an extreme distortion of the mental HF category where only a few articles account for many hits and the different meanings of HF keywords bias the results, too.

We can now conclude on the first research objective, which focused on identifying which HF aspects have been considered to what extent in the I4.0 literature: In the sample of research articles containing the term “Industry 4.0” in the title, we found a clear focus on technologies relevant for paradigmatic changes. The discussion of general HF terms such as roles, as revealed by the results of the CA, seems to indicate an awareness among researchers that their technological developments will influence people. The absence of specific HF terms suggests, however, that this technology focused research rather pays lip service to humans but does not deal in any substantial way with human-system interaction, which causes the concerns that researchers are not paying attention to human aspects in their development work. When considered, then mental HF followed by physical HF have tended to be more common considerations, whereas psychosocial and perceptual aspects have been widely neglected, which manifests a clear lack of HF in I4.0 research. This suggests the I4.0 research is “blind” to the nature of the human system interactions in the systems they are helping to design. This does not bode well for the success of I4.0 approaches, or for the people forced to endure them. To contribute to closing this gap, we develop a framework for the systematic consideration and analysis of HF in the design and evaluation of I4.0 systems in the following sections.

3. HF in engineering design

3.1 HF and worker health

We adopt the definition of HF (synonymous with the term ergonomics) from the International Ergonomics Association as being "concerned with the understanding of interactions among humans and other elements of a system [...] design in order to optimise human well-being and overall system performance" (International Ergonomics Association, 2019). The failure to address HF adequately in the design of work can lead to substantial problems. Current estimates from the International Labour Organisation place the annual work-related mortality at 2.78 Million deaths per year globally (International Labour Organization, 2019). This amounts to about one work-related death every 11.3 s. Musculoskeletal disorders (MSDs), such as repetitive strain injuries, are a global problem caused by the design of work – particularly due to high forces, high duration and repetition of efforts, poor working postures and poor psychosocial work environments (National Research Council and Institute of Medicine Panel on Musculoskeletal Disorders and the Workplace, 2001). Population studies indicate that 20% of the general population suffers from a work-related MSD (Major and Vézina, 2015). In some manufacturing sector studies, MSD rates among system operators approach 100% (National Research Council and Institute of Medicine Panel on Musculoskeletal Disorders and the Workplace, 2001). These disorders are caused by the design of the work system - when the demands on the system operators exceed their tolerance (National Research Council and Institute of Medicine Panel on Musculoskeletal Disorders and the Workplace, 2001; Neumann and Village, 2012). Failures to attend to HF in design have been identified throughout the design and operationalisation process (Kihlberg et al., 2005; Kolus et al., 2018; Neumann et al., 2002; Neumann et al., 2006). In short - these problems are caused by system designers. The costs for workplace injuries are enormous, estimated in the USA to be on par with the costs of all cancers combined (Bhattacharya and Leigh, 2011). While managers frequently look at direct compensation costs as an indicator of the MSD problem, the indirect costs are often much larger and can include hiring costs, training costs, reduced performance, increased errors, increased scrap costs and wasted managerial effort among the many indirect costs aspects related to employees' MSDs in manufacturing (Rose et al., 2013). Efforts to model the costs associated with increased MSD risk factor exposure suggest that 2–8% of product costs may be caused by these risks (Sobhani et al., 2016). The problems caused by poor HF in system design warrants Kagermann et al.'s 4th priority regarding system safety. However, systematic reviews have revealed very little attention to safety issues in the I4.0 context to date (Badri et al., 2018).

3.2 HF and operations performance

While the negative consequences of poor HF in the design and implementation of production innovations are a serious concern, we note also that HF is an essential aspect of organisational profitability and can provide strategic advantages to companies (Dul and Neumann, 2009). Benefits from the application of HF include improvements to productivity, technology implementation, quality and system reliability. Studies examining both human outcomes and system benefits from HF application generally find that the system gains are considerably greater than the financial cost avoidance from reduced compensation costs alone (Rose et al., 2013). System modelling studies revealed that substantial portions of production cost may be due to poor HF in the work system design (Sobhani et al., 2016). While production managers carry considerable tacit knowledge of the strategic advantages available from HF (Village et al., 2016), the quantitative financial benefits are often buried in financial systems and very difficult to isolate – they are "hidden" in the accounting system (Rose et al., 2013). This has inhibited a broader understanding of the importance of HF amongst engineers and managers in operations settings (Broberg, 2007).

Accordingly, in particular the joint objective of performance and well-being are often seen as being in conflict, even though empirical research demonstrates the convergence of well-being and work system performance (Goggins et al., 2008). Besides performance and well-being, there is empirical evidence that considering HF in the design of operations systems also improves quality and reduces errors (Kolus et al., 2018; Zare et al., 2016). Indeed, people-forwards management practices are linked to competitive advantages that are, in the resource-based view of the firm, difficult to copy and that can be leveraged for longer periods than technology-only strategies which are easily replicated (Boudreau et al., 2003). However, despite the evidence that HF contribute to sustained competitive advantage, attention to humans is frequently separated from engineering design and management processes (e.g. Neumann and Village, 2012) and is also under-represented in I4.0 research, as shown in Section 2.

3.3 Key Concepts of HF

We propose five "Key Concepts" from the field of HF that can provide a basis for understanding the interrelation of I4.0 and HF. Key Concept 1 is the fundamental theoretical ground, namely the sociotechnical system theory. Following, a theory of HF in design is given as Key Concept 2, before the human-system-interaction cycle is discussed in Key Concept 3. Key Concept 4 focuses on psychosocial aspects and the demand-control model; an extension of Key Concept 3, and lastly Key Concept 5 gives insights into the theory of organisational drift to unsafe states.

Key Concept 1**:** *Industry 4.0 systems are sociotechnical systems.* In the sociotechnical system (STS) theoretic view, which is an outgrowth of general systems theory (Skyttner, 2001), all work systems are assumed to include social (human) and technical (machine) elements (for a history of STS, see van Eijnatten et al. (1993)). If there is a mismatch between worker capabilities and the demands placed on them by the system, then dysfunctional results, including errors and injuries, can be expected. This leads to a chain of negative consequences for both the worker and ultimately for the system as a whole. There are, we argue, no I4.0 systems that do not engage humans across the lifecycle in designing, installing, maintaining, operating and dismantling (at end of life) these systems (Sgarbossa et al., 2020). Attention to the demands on the people performing these tasks is, therefore, a design requirement (Cherns, 1976; Clegg, 2000).

Key Concept 2: *Attention to HF must occur throughout design.* Figure IV-5 illustrates the design process diagram showing key stages of the design process in which decisions affecting HF are made that have, firstly, (positive or negative) effects on humans in the system which, ultimately, affect system performance. In this view, the design of the product and the process as well as the management of the production system itself will determine the working environment for the employee. This, in turn, will have effects on the worker, which might be good, like gains in experience and motivation, or bad in terms of fatigue, pain and injuries. These worker effects then will have consequences for human performance, which will determine the overall system performance (Neumann and Village, 2012). If HF in system design and management are not appropriately considered, then poor system performance can be expected. This conceptual framework has been validated in case research in a variety of manufacturing contexts (Neumann et al., 2002; Neumann et al., 2006; Sobhani et al., 2015). A recent review of HF-related quality problems in manufacturing identified HF-related quality risk factors in product design, process design and workstation design stages (Kolus et al., 2018). From a design science perspective, we note that making changes to a given design gets more difficult and more expensive throughout the design process, becoming maximal once the system is operating and only retrofitting solutions are possible (Neumann and Village, 2012). Unfortunately, it is typical that HF are only deployed in these late, operational stages (Neumann and Village, 2012; Wells et al., 2013). The lowest cost and maximum opportunity - in essence the best cost-benefit results - come from considering HF from the earliest stages and then throughout the design project.

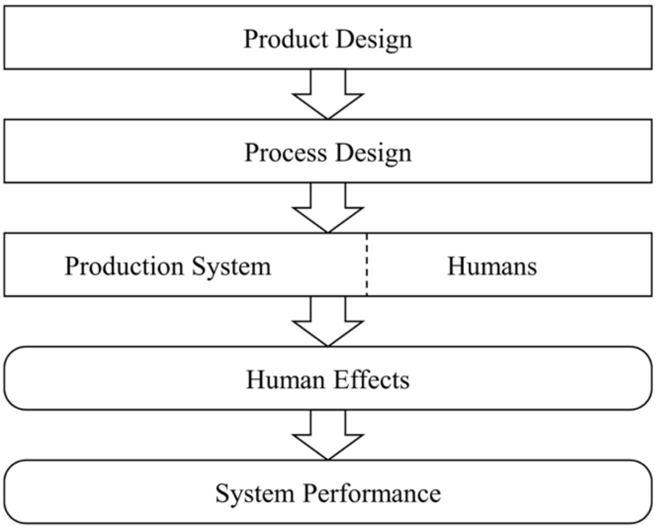


Figure IV-5: Design process diagram (adapted from Neumann and Village, 2012).

***Key Concept 3**: Human-system interaction engages perceptual, cognitive and motor systems.* In the context of human-system interaction, the perception-cognition-motor action cycle is, we argue, always relevant (e.g. Helander, 2006). This model posits a continuous stream of interaction between the person and the system. In the first step, information about the machine is gathered via the sensory system including visual, tactile, olfactory, auditory and vestibular systems – each with their own capacities and limitations that vary by individual. This sensory input is then processed cognitively – also with individual capacities and limits to memory and processing – into an understanding of the situation and planning for any desired action. This plan is then put into action via the musculoskeletal system – also with individual capacities and limitations. If this cycle is successful, the system will respond to the action providing (if it is well designed) new information to the sensory system allowing a new system state to be understood. Humans are continually engaged in this cycle of processing in an ongoing stream. From the design perspective then, it is crucial that sensory, cognitive and musculoskeletal system capacities of individuals are not overloaded (or in some cases under-loaded) and that the user has a robust understanding of the system allowing them to identify the correct actions required to bring the system to its desired state. For this reason, I4.0 system designers must ensure that the demands of their design are matched with human sensory, cognitive and motor capabilities, or they risk negative outcomes for the human or for the sociotechnical system as a whole.

Key Concept 4*: People have psychosocial needs.* Another critical aspect for successful sociotechnical system functioning is the psychosocial working environment – the perception of the social environment in the workplace. Critical dimensions here include job demands, job control, supervisory and co-worker support and job satisfaction (for a more detailed discussion of psychosocial factors and their effect on physical and mental well-being, readers are referred to the review papers of Bongers et al. (1993) and Netterstrøm et al. (2008)). In the foundational model of Karasek (1990), employees experience mental "strain" when under working conditions that involve high work demands with a low sense of control. Under these working conditions, employees will experience significant and substantial increases in a broad range of mental illnesses and physical disorders. The empirical evidence here is substantial (Amiri and Behnezhad, 2020; Kerr et al., 2001; Letellier et al., 2018; Moon and Sauter, 1996; Nieuwenhuijsen et al., 2010; Taouk et al., 2020), and well developed survey tools, such as the Copenhagen psychosocial questionnaire, exist to quantify these factors (Burr et al., 2019). There are few engineering studies examining how system design choices determine psychosocial conditions for employees and how these ultimately affect system performance (e.g. Neumann et al., 2006). If, for example, I4.0 technologies are used to provide automated performance monitoring and enforcement of employees' working to a defined pace, then one might hypothesise that employee's sense of control and job autonomy at work will decline and the overall psychosocial profile will shift towards the "high strain" states associated with negative outcomes.

Key Concept 5*: Organisations tend to "drift to unsafe states"*. Rasmussen (1997) has pointed out that complex organisations engaged in process innovation and improvement will tend to "drift" to unsafe states. The rationale, supported by extensive analysis of organisational accidents, is that the efforts of many different actors working to minimise costs and optimise within their own limited domains will ultimately bring a complex system into an unstable state as they push the boundaries within their various domains in the pursuit of efficiency gains – leading to catastrophic systems failures (Burns and Vicente, 2000; Rasmussen, 1997; Woo and Vicente, 2003). If Rasmussen's assessment of dynamic organisations is correct – then the pursuit of I4.0 innovations is likely to follow this pattern as well: There will be unanticipated and unmanaged consequences emerging from the combined efforts of personnel in different parts of the system (Rasmussen, 2000). Emergent system characteristics can be particularly difficult to manage in design processes (Burns and Vicente, 2000; Neumann et al., 2009; Skyttner, 2001; Steiner et al., 1999). In a case study of the implementation of AGVs, for example, unanticipated interaction between the AGVs and the layout of the workstation resulted in poor working postures and elevated pain levels in assembly operators (Neumann et al., 2006). The "drift to unsafe states" effect of Rasmussen (1997) helps explain why industrial revolutions, or fads like "Lean" (Näslund, 2008), have been seen as contributing to occupational injuries, accidents and deaths. If I4.0 innovations are to try and break this pattern, then a systems approach to applying HF in design is needed (Neumann, 2017; Neumann and Village, 2012) - and researchers must develop better tools and approaches to support such system integration efforts. Isolated developments create unanticipated system risks.

The key HF concepts listed here pose both a challenge and an opportunity for I4.0 innovation. If HF is ignored, or dealt with in isolation, then underperforming systems and the ongoing problem of injured and killed workers can be expected. Deliberate and systematic attention to HF therefore poses an opportunity to break the pattern of previous industrial revolutions (see, e.g. Neumann et al., 2018) examining the effects of a shift from craft to line production and create better, more effective workplaces in the future. This, we will demonstrate next, is not happening yet and therefore the vision of Kagermann et al. (2013) will not be achieved. The key concepts thus point to the need of multidisciplinary research and development that integrates technological and social foci in the design process – a classical problem in design (Kilker, 1999) and science (Snow, 1998). Hence, approaching I4.0 from a technology-driven perspective falls short of the systematic consideration of HF that is needed.

4. How to consider HF in I4.0 systematically

4.1 Framework and method development

Given the apparent inattention to humans in I4.0 research and development work, we propose a systematic framework for considering HF in the conceptualisation, design and implementation of new technologies in operations systems. While we present this in the context of the current I4.0 trend, it is not specific to certain technologies. The framework is applied in five steps: 1) defining the technology; 2) identifying affected humans; 3) identifying task scenarios; 4) task analysis and impacts and 5) outcome analysis. We describe each step briefly and then present an application example in the next section. A blank worksheet is provided in the Appendix (Figure IV-8).

Step 1: Defining the technology. This step is important as the framework operates, initially, as a thought experiment before more detailed testing approaches are chosen. The analysis may require knowledge of the physical form, assembly, use and maintenance tasks as well as possible failure modes for the system in question. Where these are unknown, the analyst would have to investigate alternatives and refine these projections as their development work proceeds. In addition, the characteristics of the technology should be known.

Step 2: Identifying the humans in the system. Following on Key Concept 1 - that all engineered systems are sociotechnical systems -, it is important to list the human roles that will interact with the design. A life-cycle perspective is important here and should include attention to stages of design, assembly, installation, operation, maintenance and disassembly. There may be multiple scenarios for any one stage. For example, operations may include front-line workers in various scenarios and also programmers or engineers engaged in operating the cyber-physical sociotechnical system. This list of stakeholders and human roles should be inclusive and as expansive as possible creating a set of "usage scenarios" (cf. Regnell et al., 1995) for considering the design. Forgetting a stakeholder group, such as maintenance personnel, means that their needs might be missed in system design, with possible negative consequences both for personnel and for long run system performance due, in this example, to increased maintenance costs. The idea of the human in the system can be very diverse. Each person entering the system will bring knowledge and will require new knowledge in order to operate effectively in the new sociotechnical system environment. As Key Concept 2 implies, attention to these stakeholders must be part of I4.0 development in the design stage, not an afterthought. While not every stakeholder of a company will be influenced by every I4.0 implementation, the influences might be more diverse than anticipated when cleaning staff, maintenance and engineering teams etc. are considered.

Step 3: Identifying task scenarios. For each usage scenario, the analyst must consider what tasks are being added to (e.g. more computer monitoring work) or removed from (e.g. paper work, or walking) each human in the system over the technologies life-cycle. How, in other words, will the persons' jobs change when they use this new technology, compared to the current scenario? Due to the design of tasks within these sociotechnical systems, the performance of the system as a whole will be influenced.

Step 4: Assessing the human impacts of the task changes. For each change in task identified in Step 3 - be it elimination of tasks or inclusion of new tasks - the analyst should assess the demands placed on the human in terms of perceptual, cognitive and motor system demands (per Key Concept 3). In particular the implementation of new technologies and the related task changes are suggested to impact on the psychosocial stressors in the job (per Key Concept 4), in particular the effect on psychological job demands, the possibility of job control, role clarity, social support from co-workers and supervisors and job satisfaction. Where these impacts are not understood, further investigation and evaluation may be required. By assessing these impacts, across all stakeholders, it becomes possible to identify more clearly the advantages and potential problems of adopting the proposed technology. In addition, it is important to consider the (new) knowledge needed to operate/use a certain technology.

Step 5: Outcome analysis. In this final step the possible effects of the human impacts, identified in Step 4, on system performance should be considered. In particular, an analyst should consider the possible implications on employee time, on training needs, the probability of errors and hence quality and on the health risks and wellbeing of the worker. If desired, the financial implications of these impacts could also be estimated (e.g. investments costs). An extra consideration in this step is the possibility of "side effects" of the technology. For example, if a "smart scanner" must be strapped to the user's arm, there might be side effects associated with the comfort of straps and mass of the device when worn for 8 h. Another example for side effects of the use of I4.0 technology are headaches, which were reported when using augmented reality glasses (e.g. Wille et al., 2014). Therefore, the two sides of the framework can be considered as a macro-perspective and a micro-perspective. On the one side, especially the company's economic situation could be considered in the outcome analysis according to the work added and removed for every stakeholder. On the other side of the framework, the outcome analysis can especially be used for the micro-perspective, e.g. how to tackle challenges, new demands, secondary effects like negative outcomes of a used technology - although the context specificity of these costs make detailing this beyond the scope of this article and therefor a matter for further research.

As it is not possible to evaluate design and HF elements in isolation and expect safe performance without risking the drift to unsafe states (Key Concept 5), the proposed framework accounts for interaction of system elements. We note, however, that this is highly subjective. If a given user group is missed, if a task scenario is skipped, or if a task analysis is poorly thought out, then the quality of the overall analysis will be compromised. There are many different methods that could be used to evaluate the task loads on users, ranging from qualitative to quantitative, that are compatible with this framework. The flexibility of the framework may be a strength in terms of its ability to be used with a broad range of technological or administrative innovation scenarios. Hence, a comprehensive picture of the influences of an I4.0 element can serve as a basis for the specific design of a work system prior to implementation. Problems identified at this stage can be explored and addressed within the system design to avoid future dysfunctional side effects in the eventual I4.0 operations system. To better illustrate this, we provide an example analysis next.

4.2 Example method application for a cobot

We consider the example of a collaborative picking robot (cobot) introduced as a new I4.0 element in a warehouse (see, e.g. Coelho et al., 2018). The cobot could be used to support operations processes in a smart factory (e.g. in kit preparation or line feeding) or in a smart logistics system. While the framework can result in extensive analyses, an abridged example is summarised in Figure IV-6 as an illustration of an approach to applying this analysis.

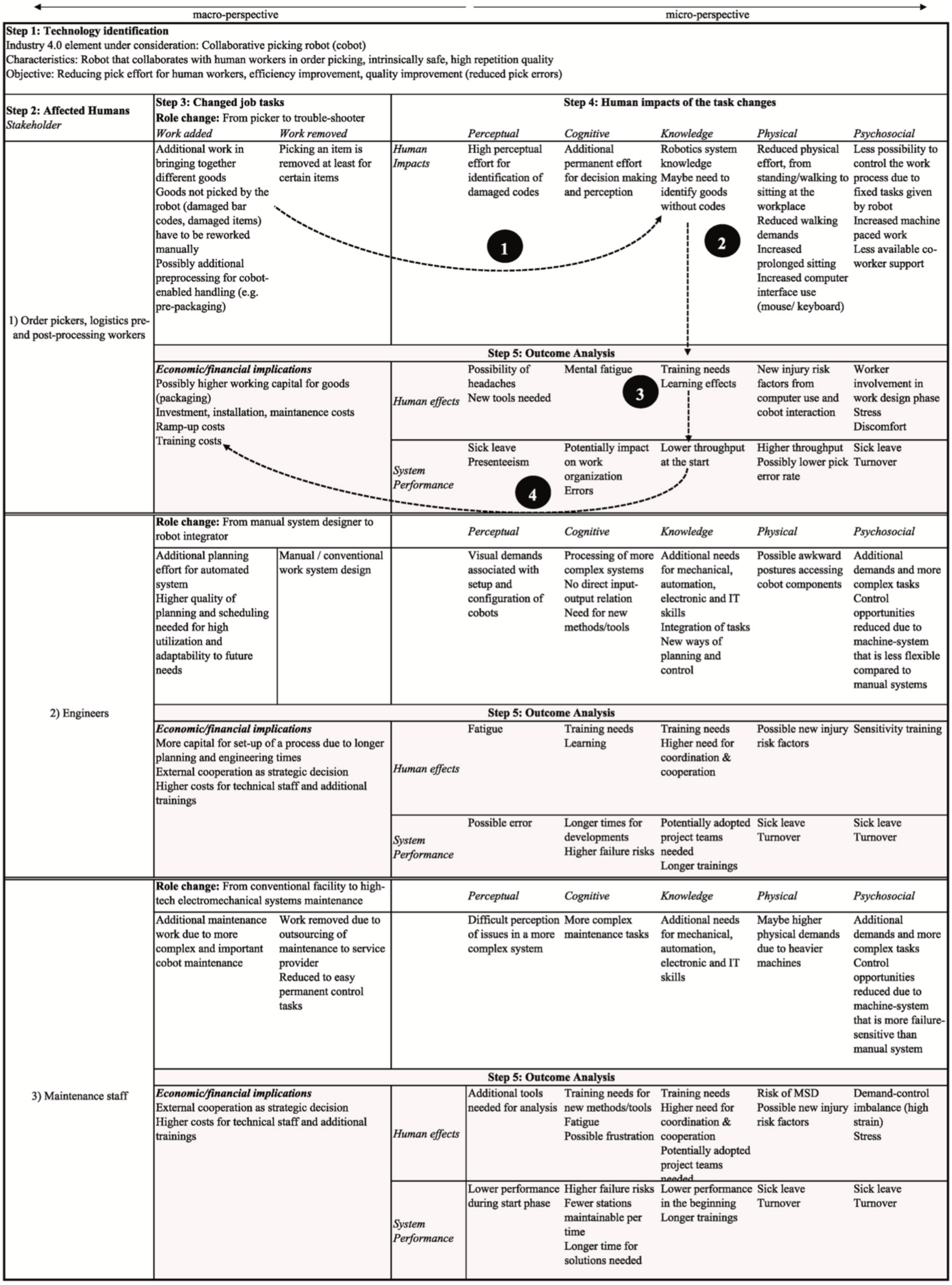
Step 1: Characteristics and objectives of the cobot use are listed. This could be that the robot is intrinsically safe or that it is highly reliable, so failures are reduced. The company's objective in using the cobot is to reduce the physical effort for the workers and to improve efficiency.

Step 2: Stakeholders and human roles are defined. Most affected by the cobot are order pickers working in the same warehouse area, but also workers in pre- and post-operations as the cobot integration might require a different preparation of goods (e.g. special barcodes or RFID tags). This also impacts supply chain partners. Considering the life-cycle perspective, at first, engineering staff is involved in designing and integrating the system and afterwards, maintenance personnel needs to maintain it. Furthermore, administration is also affected and could even be broken down further. The tasks at the end of life disposal of the cobot remains as a final issue to address.

Step 3: In the next step, possible added and removed work is analysed based on task scenarios. Applying the cobot for picking work removes this task from the human worker. On the other side, work is added for the human, such as troubleshooting in cases the cobot was not able to identify goods or malfunctioned in some other way. Maintenance and engineering roles change from a conventional order picking facility to supporting a fleet of high-tech electromechanical systems. The cobot needs to be integrated and maintained which adds new work for both of these groups. Role changes can be derived, e.g. from manual work system designer to robot integrator.

Step 4: In the next step of the analysis, the impacts of technology use on the humans in the system are described. The added and removed work is analysed and the impacts of the technology usage are described on the perceptual, cognitive, knowledge, physical and psychosocial level. By using a cobot, the logistics workplace is changed by transferring picking tasks from the worker to the robot, which reduces the loads to the musculoskeletal system associated with walking and material handling tasks, but increases times working with computer systems using input devices and reading screens (with physical, perceptual and cognitive task loads). The worker then only receives goods with damaged barcodes or even damaged goods that the cobot cannot process, leading to new different loads for the perceptual system and maybe also the cognitive system – e.g. when considering whether a good is still in accordance with the standards or whether it should be rejected. The psychosocial factors might be influenced due to less autonomy and control possibilities or higher pace at work. If for example an employee's performance hinges on the cobot performance, frustration and stress for the operator will ensue whenever the cobot malfunctions. The new robot system can then require technical knowledge and capabilities beyond the usual protocols, which could unintendedly increase the workload not only for front-line workers, but also induce new challenges for engineering and maintenance staff.

Step 5: In the last step of the analysis, the outcome analysis, the objectively described changes are evaluated in terms of possible performance impacts. Using the cobot can increase performance (e.g. throughput by adding a night shift) and can contribute to better service levels due to fewer pick errors. It requires, however, investment and installation costs. The company may be able to lay-off front-line employees but will need more maintenance and engineering staff to manage the cobot fleet. If the cobot needs pre-packaged goods, the working capital might increase as well. Focusing on outcomes of the task and impact on the workers, higher perceptual demands (in co-working with the cobot) could cause headaches or require additional tools to avoid this. Increasing cognitive and knowledge demands might influence work organisation to allow for job rotation or additional training. Changes of the musculoskeletal demands could lead to new ergonomics risks as back injuries due to material handling decrease while shoulder and wrist disorders may increase from the increase in computer workstation tasks. If the robots are poorly designed for maintenance access, then injuries to maintenance personnel may arise as they attempt to keep the cobot fleet operational.



Step 1: Technology identification
Industry 4.0 element under consideration: Collaborative picking robot (cobot)
Characteristics: Robot that collaborates with human workers in order picking, intrinsically safe, high repetition quality
Objective: Reducing pick effort for human workers, efficiency improvement, quality improvement (reduced pick errors)

Step 2: Affected Humans *Stakeholder*	**Step 3: Changed job tasks** **Role change:** From picker to trouble-shooter *Work added*	*Work removed*	**Step 4: Human impacts of the task changes**	*Perceptual*	*Cognitive*	*Knowledge*	*Physical*	*Psychosocial*
1) Order pickers, logistics pre- and post-processing workers	Additional work in bringing together different goods Goods not picked by the robot (damaged bar codes, damaged items) have to be reworked manually Possibly additional preprocessing for cobot-enabled handling (e.g. pre-packaging)	Picking an item is removed at least for certain items	*Human Impacts*	High perceptual effort for identification of damaged codes	Additional permanent effort for decision making and perception	Robotics system knowledge Maybe need to identify goods without codes	Reduced physical effort, from standing/walking to sitting at the workplace Reduced walking demands Increased prolonged sitting Increased computer interface use (mouse/ keyboard)	Less possibility to control the work process due to fixed tasks given by robot Increased machine paced work Less available co-worker support
	Step 5: Outcome Analysis							
	Economic/financial implications Possibly higher working capital for goods (packaging) Investment, installation, maintanence costs Ramp-up costs Training costs		*Human effects*	Possibility of headaches New tools needed	Mental fatigue	Training needs Learning effects	New injury risk factors from computer use and cobot interaction	Worker involvement in work design phase Stress Discomfort
			System Performance	Sick leave Presenteeism	Potentially impact on work organization Errors	Lower throughput at the start	Higher throughput Possibly lower pick error rate	Sick leave Turnover
2) Engineers	**Role change:** From manual system designer to robot integrator			*Perceptual*	*Cognitive*	*Knowledge*	*Physical*	*Psychosocial*
	Additional planning effort for automated system Higher quality of planning and scheduling needed for high utilization and adaptability to future needs	Manual / conventional work system design		Visual demands associated with setup and configuration of cobots	Processing of more complex systems No direct input-output relation Need for new methods/tools	Additional needs for mechanical, automation, electronic and IT skills Integration of tasks New ways of planning and control	Possible awkward postures accessing cobot components	Additional demands and more complex tasks Control opportunities reduced due to machine-system that is less flexible compared to manual systems
	Step 5: Outcome Analysis							
	Economic/financial implications More capital for set-up of a process due to longer planning and engineering times External cooperation as strategic decision Higher costs for technical staff and additional trainings		*Human effects*	Fatigue	Training needs Learning	Training needs Higher need for coordination & cooperation	Possible new injury risk factors	Sensitivity training
			System Performance	Possible error	Longer times for developments Higher failure risks	Potentially adopted project teams needed Longer trainings	Sick leave Turnover	Sick leave Turnover
3) Maintenance staff	**Role change:** From conventional facility to high-tech electromechanical systems maintenance			*Perceptual*	*Cognitive*	*Knowledge*	*Physical*	*Psychosocial*
	Additional maintenance work due to more complex and important cobot maintenance	Work removed due to outsourcing of maintenance to service provider Reduced to easy permanent control tasks		Difficult perception of issues in a more complex system	More complex maintenance tasks	Additional needs for mechanical, automation, electronic and IT skills	Maybe higher physical demands due to heavier machines	Additional demands and more complex tasks Control opportunities reduced due to machine-system that is more failure-sensitive than manual system
	Step 5: Outcome Analysis							
	Economic/financial implications External cooperation as strategic decision Higher costs for technical staff and additional trainings		*Human effects*	Additional tools needed for analysis	Training needs for new methods/tools Fatigue Possible frustration	Training needs Higher need for coordination & cooperation Potentially adopted project teams needed	Risk of MSD Possible new injury risk factors	Demand-control imbalance (high strain) Stress
			System Performance	Lower performance during start phase	Higher failure risks Fewer stations maintainable per time Longer time for solutions needed	Lower performance in the beginning Longer trainings	Sick leave Turnover	Sick leave Turnover

Figure IV-6: Example method application for a picking cobot.

Figure IV-6 summarises the cobot example. Here, we also highlight one possible chain of effects: Implementing a cobot adds work to human order pickers for the identification of goods with damaged barcodes. Therefore, the worker has additional knowledge needs (1). As a result to this human impact, training should be offered to provide the necessary background for process handling (2). Training needs of course relate to initial learning effects that lead to a lower throughput at the beginning of the implementation and thus lower the system performance (3). Lower system performance and additional training needs lastly also have financial impacts for ramp up and training provision resulting from the added or removed piece of work (4). Hence, this chain of effects directly relates to Key Concept 2 and verifies the need to consider HF early in design. To further illustrate the framework, a second application example from manufacturing is presented in the Appendix (Figure IV-7).

These examples are, by necessity incomplete and are meant to illustrate the analysis approach that the framework fosters. Further development of this framework into a user-friendly method is still required.

5. Discussion and conclusion

5.1 Key concepts

The developed framework allows a systematic assessment of the impacts of I4.0 technology implementation on human workers and system performance. It is theoretically grounded on five HF Key Concepts: 1) I4.0 are sociotechnical systems that involve people; 2) the needs of people must be considered via system design; 3) people have perceptual, cognitive and motor capabilities and limitations; 4) people have psychosocial needs; and 5) complex systems often drift to unsafe states. While this list might be criticised as incomplete, it provides a parsimonious basis to explain both the need and the opportunity for considering HF in I4.0 development. The first four concepts are axiomatic in HF engineering. There are no engineered systems without humans. Humans cannot be re-engineered, so designs must be made to suit them. Humans have known characteristics that must be accommodated. These four concepts would require a “black swan” case to refute them - cases we doubt exist in practice.

The last concept, Rasmussen's claim of the tendency to drift to unsafe states, is perhaps more a cautionary observation than a "law". This principle, however, has been well illustrated in a number of disaster scenarios (Rasmussen, 1997; Woo and Vicente, 2003). Rasmussen went on to describe a framework that could help analyse complex systems to isolate the mechanisms that lead to system failures (Rasmussen, 2000). In the case of industrial revolutions, we see similar evidence. The pattern of specific injuries of workers in particular jobs was first observed by Ramazzini (1700) at the start of the First Industrial Revolution as workers began to spend a substantial amount of time performing a limited range of tasks due to the increasingly fine division of labour noted by Adam Smith (1776). This mechanism is still at play in "modern" production systems today (Neumann et al., 2018; Palmerud et al., 2012). Similarly, case studies of automation have shown that, while work tasks (and jobs) were eliminated, some people, especially those working downstream from the robot, had increases in repetitive movements implying increased injury risk (Neumann et al., 2002). While the drift to unsafe states effect is not an inevitable pattern, it seems to occur frequently. Key Concept 5 warns us that I4.0 will also contribute to and extend the global problem of work-related ill health if HF is not included in design stages (Key Concept 2). HF can help I4.0 designers avoid the "innovation pitfall" (Neumann et al., 2018) in which failure to attend to secondary human effects compromises the benefits that designers and managers had counted on for their I4.0 innovation efforts.

The developed framework can assist researchers in finding new topics and systematically addressing these gaps, for example in "human-centred industrial engineering and management" (Sgarbossa et al., 2020). To name only a few examples, the framework could be used to contribute to the diversity agenda, as systematically managing and customising the HF demands can open the door for increased diversity in employee characteristics and hiring (e.g. older workforce or workers with disabilities). There is also a need for more research that can help design teams understand the psychosocial impacts of their design choices (e.g. the implementation of a specific I4.0 technology) on employees and, ultimately, system performance. Psychosocial stressors and their impact on work autonomy, motivation or job satisfaction in the context of I4.0 are still not fully understood and require further research. If new I4.0 systems increase demands on employees, and possibly apply stringent monitoring of task performance (Kaasinen et al., 2020), then the combination of demands and lack of control will increase psychosocial strain in employees which is associated with a wide range of health problems ranging from musculoskeletal disorders to fatal heart diseases (see, e.g. Bongers et al., 1993). The CA suggests that relatively little attention has been paid to these issues in I4.0 research.

5.2 Content analysis

The results of the CA highlighted the lack of attention to HF in current I4.0 research which appears to have a strong focus on technology and only occasional attention of human-system interaction. This failure to attend to HF in I4.0 research has been observed in previous industrial system generations (e.g. Grosse et al., 2017; Neumann and Dul, 2010); and has had negative consequences for individual employees, production organisations and for society as a whole. Although a CA is able to identify such patterns providing quantitative attention to specific keywords within a literature sample, it does not consider the actual content of the paper as might be done in a conventional literature review approach. We note that our analysis highlighted RU that have ambiguous meanings, for example a paper on “machine learning” yielded 260 hits for the HF “learning” category. The sensitivity analysis employed aimed at reducing such biases and increase the reliability of the results. This analysis only used papers with “Industry 4.0” in the title, which might exclude relevant papers. One example for this are the works on “Operator 4.0” (e.g. Romero et al., 2018), which are not included in the sample as I4.0 is not mentioned in the title in these works. However, a more precise look on current writings, as discussed in Section 3.1, highlights that these approaches see the worker rather as the “problem” that I4.0 attempts to “solve” by technological means. These articles, however, do not necessarily address the needs of the people in the system and the broader secondary impacts these technologies may have. We argue that designing a system and considering HF as an afterthought does not lead to an efficient and productive system. Instead of re-designing the human (as proposed by the “Operator 4.0” concept), we propose a “humane” sociotechnical system design approach prior to the I4.0 implementation that will result in systems better suited to people and less likely to be compromised by negative human effects of poor HF in design. Substantial research is still needed to see how the proposed framework and methodology can be applied in practice.

5.3 Application issues and managerial implications

The framework proposed here warrants discussion. We see the framework as a starting point and a "thinking shell" that can be applied as a tool, however without a fixed application approach. While it is comprehensive, the suggested approach (including the length and the way of organising it) is subjective and hinges on the knowledge and imagination of the user. To account for this limitation, a preliminary version of the framework was presented to researchers and managers working in the area of human factors, operations management and Industry 4.0 in an expert workshop where the face validity and utility of the approach was affirmed.

While application studies are needed to identify practical, evidence-based advice for using the methodology, we suggest a top down, staged approach to the framework. Top level management can use the framework on a higher level for a first feasibility and profitability estimation. If the proposed innovation proceeds, the stakeholders involved in the elaboration process, who are closer to the final workplace, can be engaged in cross-functional teams for the more detailed analyses. The identification of specific stakeholders to consider in the analysis will be highly dependent on the organisational context and the innovation under consideration. One of the strengths of the proposed methodology is the use of a life-cycle perspective to help identify relevant roles and personnel to consider and engage. Participation of key stakeholders implicated in the proposed change is a way to both draw on their knowledge and secure their support for the innovation project (de Looze et al., 2003). While this would reduce the chances of the analyst missing a specific issue, it does not overcome problems of "unknown unknowns" in the analysis. Although the framework does not guarantee a holistic picture, it helps structuring the multiple directions and interactions of complex I4.0 elements and channels thoughts on the actual influences on HF in a robust way. Figure IV-6 and Figure IV-7 (in the Appendix) provided, for example, do not include specific action plan elements that would be required in a specific application.

The current framework is intended to help managers avoid HF-related pitfalls in their innovation processes. Further research work is still needed to understand what kind of support, or tools, might be needed to help managers and design teams do this in practice. To the extent that appropriate design-level virtual HF assessment tools exist, it may be possible to conduct quantitative and objective analyses of identified scenarios (Perez and Neumann, 2015). Virtual reality and digital human models (e.g. Case et al., 2016; Chaffin, 2008) can assess postural issues related to the physical layout of the workstation or to access repair points in the system. For other issues, such as identifying psychosocial strain issues, design tools are missing and making prospective assessments can be difficult. More participative and engaging development processes may be required to capture these issues. Further research, including case studies of innovation projects, is needed to develop this analysis approach to increase ease of use and to extend its capabilities. Financial analysis, for example, could be included by building on recent models that predict production costs based on employee risk level exposures (cf. Sobhani et al., 2015; Sobhani et al., 2016).

There are a number of organisational dimensions that are implicit in this framework that managers should consider. For example: who is being held responsible for what in the design of the new system? Will researchers take responsibility to attend to potentially harmful side effects in their research work? Are design teams being given the mandate and resources they need to examine the unanticipated costs associated with the new technologies? Differences in orientation of designers, as being either technically focused or socially focused, has been suggested to be a major source of conflict in design teams (Kilker, 1999). Engineering teams often lack knowledge and mandates to attend to human aspects in their design work (Broberg, 1997). Similarly, social issues have been suggested to have fallen off the agenda in management research (Walsh et al., 2003). Case study research has shown that design teams and managers need unambiguous targets and appreciate quantitative indicators as they develop their capacity to include HF aspects in production system design (Village et al., 2014; Village et al., 2015). The dynamics required to achieve buy-in for HF in engineering design of I4.0 systems remains a research need. Given the range of technologies included in the I4.0 concept and the variety of organisations looking to exploit these innovations, we doubt there will be a “single best way” to adopt and deploy the current framework. Identifying and testing useful approaches for a given context remains a research need.

Finally, the implications of this work are important for corporate strategy (Dul and Neumann, 2009). Managers should be aware that each technology will inevitably affect their people – and that people form a difficult to copy strategic advantage that their origination can leverage for competitive advantage (Barney et al., 2011). Attending to the needs of people in I4.0 system design can support these strategic objectives. Managers can ask themselves, for example: is this being used to make work easier? or to control people tightly?

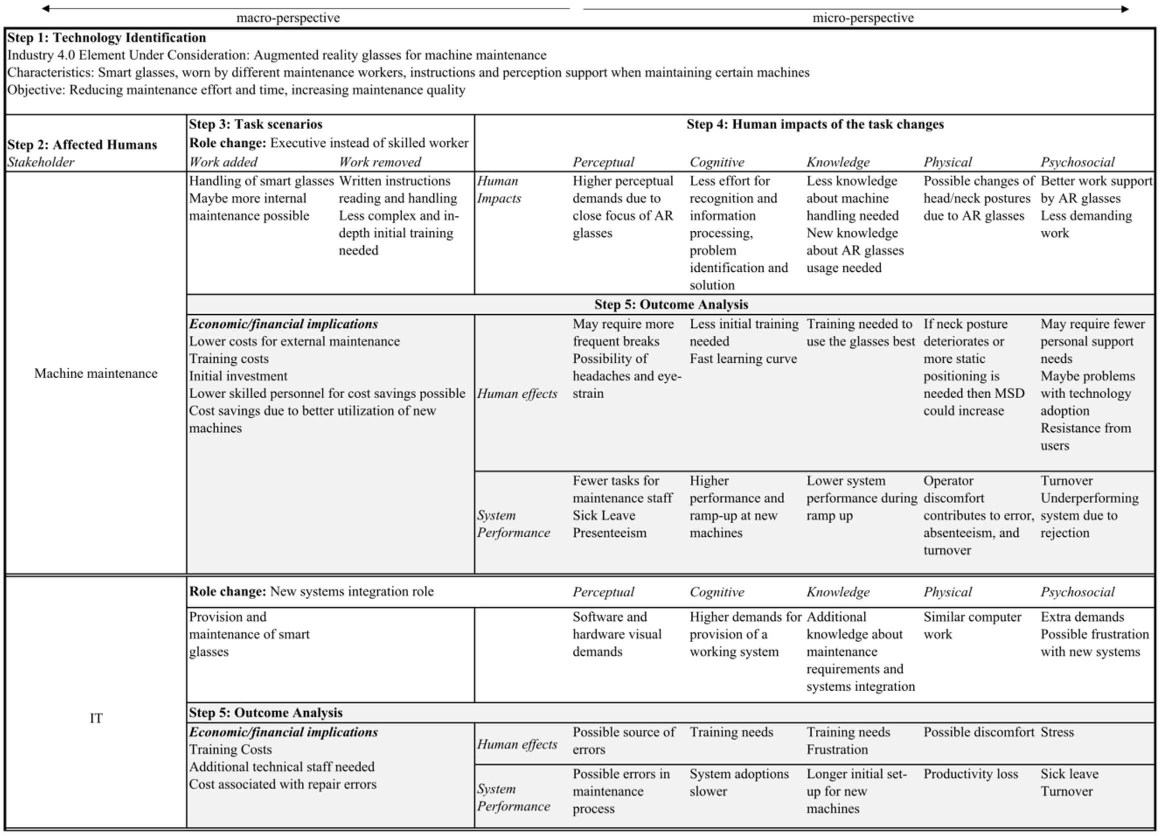
These issues have implications for both physical and psychosocial working conditions in the operations system. Managers and researchers should consider HF as a means, not a goal, to achieve performance and wellbeing. If new technologies are developed or implemented without attention to HF, systems will underperform yielding “phantom profits” (Neumann and Dul, 2010; Rose et al., 2013) and tend to drift into unsafe states. This implies costs to both society and the organisation as secondary effects compromise the technology investment leading managers towards the “innovation pitfall” (Neumann et al., 2018).

5.4 Key message

This article aimed at identifying which HF aspects have been considered to what extent in the scientific literature on I4.0 and at providing a systematic approach that supports corporate I4.0-system development. We show that, to date, current research on I4.0 technologies and implementation have broadly ignored the humans in the I4.0 system. The systematic consideration and attention to HF in the digital transformation of work can avoid negative consequences for individual employees, production organisations and for society as a whole. With this contribution, researchers as well as practitioners have a systematic approach to incorporate HF in the ongoing transformation, ensuring their I4.0 investments do not fall into the “innovation pitfall”. Concluding, we strongly call for the systematic integration of HF in future I4.0 research and development, which can contribute to overcoming the challenges of the digital transformation of work, supporting a satisfied and motivated diverse workforce with expanding capabilities suited to working in the I4.0 environment.

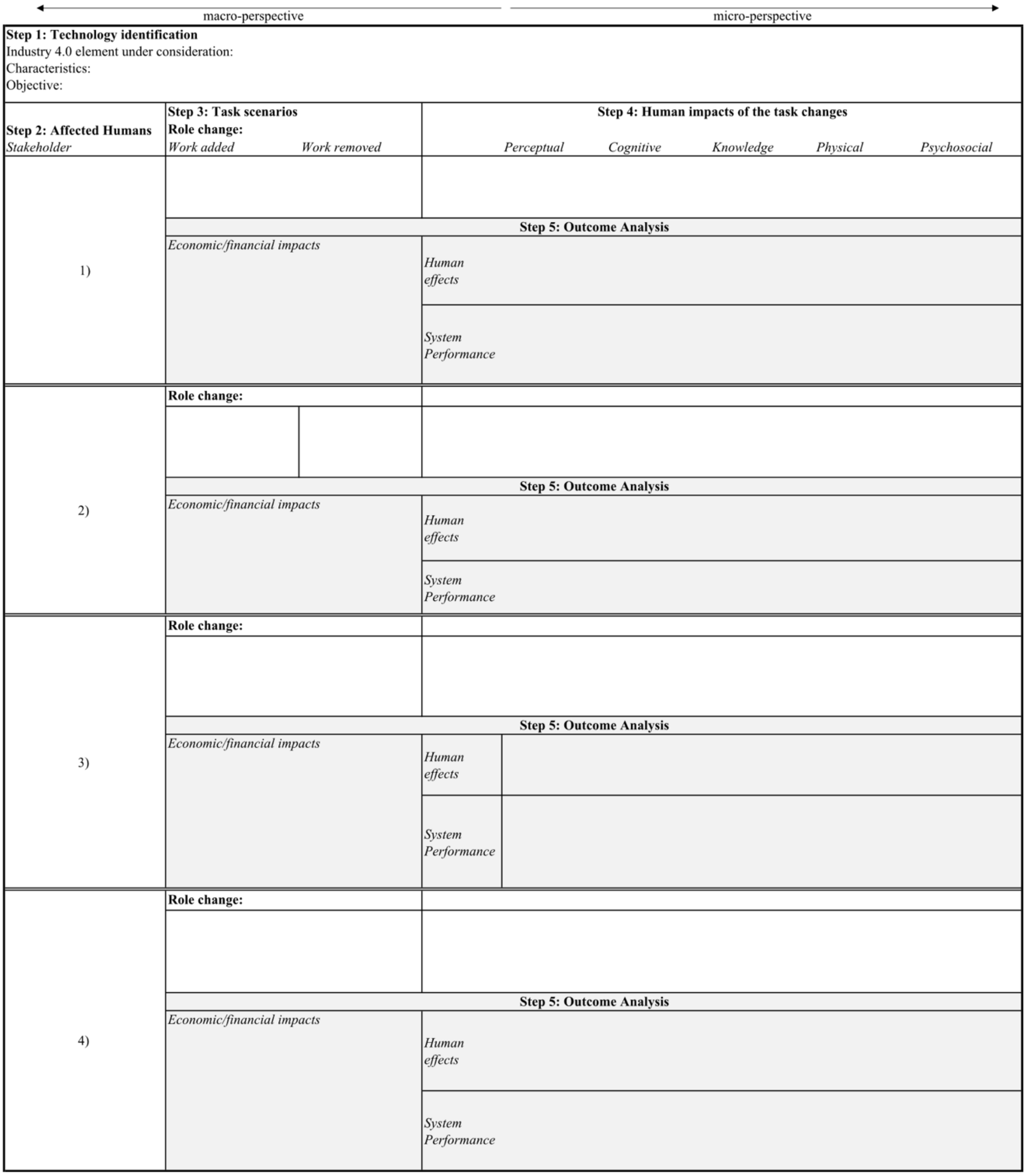
Appendix

The Appendix contains a second application of the framework exemplified at the implementation of augmented reality glasses for machine maintenance (Figure IV-7) and a blank worksheet (Figure IV-8).



Step 1: Technology Identification Industry 4.0 Element Under Consideration: Augmented reality glasses for machine maintenance Characteristics: Smart glasses, worn by different maintenance workers, instructions and perception support when maintaining certain machines Objective: Reducing maintenance effort and time, increasing maintenance quality								
Step 2: Affected Humans	**Step 3: Task scenarios** **Role change:** Executive instead of skilled worker			**Step 4: Human impacts of the task changes**				
Stakeholder	*Work added*	*Work removed*		*Perceptual*	*Cognitive*	*Knowledge*	*Physical*	*Psychosocial*
Machine maintenance	Handling of smart glasses Maybe more internal maintenance possible	Written instructions reading and handling Less complex and in-depth initial training needed	*Human Impacts*	Higher perceptual demands due to close focus of AR glasses	Less effort for recognition and information processing, problem identification and solution	Less knowledge about machine handling needed New knowledge about AR glasses usage needed	Possible changes of head/neck postures due to AR glasses	Better work support by AR glasses Less demanding work
	Step 5: Outcome Analysis							
	Economic/financial implications Lower costs for external maintenance Training costs Initial investment Lower skilled personnel for cost savings possible Cost savings due to better utilization of new machines		*Human effects*	May require more frequent breaks Possibility of headaches and eye-strain	Less initial training needed Fast learning curve	Training needed to use the glasses best	If neck posture deteriorates or more static positioning is needed then MSD could increase	May require fewer personal support needs Maybe problems with technology adoption Resistance from users
			System Performance	Fewer tasks for maintenance staff Sick Leave Presenteeism	Higher performance and ramp-up at new machines	Lower system performance during ramp up	Operator discomfort contributes to error, absenteeism, and turnover	Turnover Underperforming system due to rejection
IT	**Role change:** New systems integration role			*Perceptual*	*Cognitive*	*Knowledge*	*Physical*	*Psychosocial*
	Provision and maintenance of smart glasses			Software and hardware visual demands	Higher demands for provision of a working system	Additional knowledge about maintenance requirements and systems integration	Similar computer work	Extra demands Possible frustration with new systems
	Step 5: Outcome Analysis							
	Economic/financial implications Training Costs Additional technical staff needed Cost associated with repair errors		*Human effects*	Possible source of errors	Training needs	Training needs Frustration	Possible discomfort	Stress
			System Performance	Possible errors in maintenance process	System adoptions slower	Longer initial set-up for new machines	Productivity loss	Sick leave Turnover

Figure IV-7: Example method application for augmented reality glasses for machine maintenance.



macro-perspective
micro-perspective

Step 1: Technology identification
Industry 4.0 element under consideration:
Characteristics:
Objective:

Step 2: Affected Humans
Stakeholder

Step 3: Task scenarios
Role change:
Work added *Work removed*

Step 4: Human impacts of the task changes
Perceptual *Cognitive* *Knowledge* *Physical* *Psychosocial*

1)
Step 5: Outcome Analysis
Economic/financial impacts
Human effects
System Performance

2)
Role change:
Step 5: Outcome Analysis
Economic/financial impacts
Human effects
System Performance

3)
Role change:
Step 5: Outcome Analysis
Economic/financial impacts
Human effects
System Performance

4)
Role change:
Step 5: Outcome Analysis
Economic/financial impacts
Human effects
System Performance

Figure IV-8: Blank worksheet.

PART C - INVESTIGATION OF ORDER PICKING 4.0

V. [Article 4] Towards a conceptualisation of Order Picking 4.0[5]

Authors: Winkelhaus, Sven; Grosse, Eric H.; Morana, Stefan

Order picking is a key task in almost all supply chains and has a significant effect on operational efficiency of warehouses. Although most companies still rely on manual order picking, research on diverse possibilities to automate order picking tasks or support human order pickers with technology is increasing rapidly.

This paper conceptualises Order Picking 4.0 (OP 4.0), considering substitutive and supportive technologies. Based on a conceptual background, a framework for OP 4.0 as a sociotechnical system is developed. A systematic literature review is performed to assess the state of knowledge in this field, and prospective research opportunities in OP 4.0 are highlighted.

Keywords:

Order Picking, Industry 4.0, Sociotechnical systems, Systematic literature review, Framework

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[5] This article has been published as Sven Winkelhaus, Eric H. Grosse and Stefan Morana (2021): Towards a conceptualisation of Order Picking 4.0. Computers and Industrial Engineering 159, 107511. DOI: 10.1016/j.cie.2021.107511. This article has been slightly adapted for use in this dissertation, for example to ensure consistent spelling.

1. Introduction

Industries around the world are currently encountering many challenges because of the digital transformation of economies (Speringer and Schnelzer, 2019). The definition of the term Industry 4.0 for the digital transformation in the industrial sector is not generally consistent (Kagermann et al., 2013). Most definitions focus on the technological side of Industry 4.0 (Culot et al., 2020) stating, for example, that Industry 4.0 relies on the application of CPSs, the IoT, or cloud computing (Xu et al., 2018). However, some authors also indicate the drivers and targets of Industry 4.0 (Hofmann and Rüsch, 2017) which are important for understanding the reasons and objectives in the context of increasing e-commerce and current macro-themes such as globalisation, sustainability and individualisation (Winkelhaus and Grosse, 2020a).

These drivers create new challenges for the logistics domain. In particular, diverse, mass-customised and individualised goods increase the complexity of supply chains (Barreto et al., 2017). This makes the efficient and productive managing of logistics processes more difficult, for example, by decreasing the possibility of bulk handling and shipping. This development is important beyond the boundaries of the logistics sector, since in 2018, logistics costs accounted for approximately 8–10% of GDP in countries with better logistics efficiency and up to 20% in countries with lower efficiency, hinting at the significance of logistics for entire economies (Keller, 2019). Accordingly, a development in the logistics sector, corresponding to Industry 4.0 and denoted as Logistics 4.0, is occurring; it addresses new targets and the implementation of technologies to respond to these challenges. Logistics 4.0 has been defined as “the logistical system that enables the sustainable satisfaction of individualised customer demands without an increase in costs and supports this development in industry and trade using digital technologies” (Winkelhaus and Grosse, 2020a).

Within logistics, order picking, which is the collection of partial quantities of goods to satisfy customer orders (van Gils et al., 2018), often accounts for more than half of a warehouse’s operating costs (Tompkins et al., 2010). Despite the increasing possibility of automating order picking processes, they still rely largely on manual human work, contributing significantly to the relatively high process costs (Grosse et al., 2017; Tompkins et al., 2010). However, increasing technical support for order pickers using digital technologies can be identified in practice (Cimini et al., 2021). Because of the various interactions of humans and technologies, order picking systems (OPSs) can be considered sociotechnical systems (Dregger et al., 2018). Sociotechnical systems are work systems in which social systems, such as employees, and technical systems, such as applied automation technologies and the physical workplace, interact and affect each other (Dregger et al., 2018). By considering OPSs to be sociotechnical systems, a gap remains in research and practice on how digitalisation will transform human work in order picking (Kadir et al., 2019; Winkelhaus and Grosse, 2020a). We refer to these OPSs as Order Picking 4.0 (OP 4.0) in the following and formulate the following ROs:

- *to define the concept of OP 4.0*
- *to systematically review the research in the field of OP 4.0 to identify its various possible concepts*
- *to highlight research opportunities within OP 4.0 at the intersection of social and technical aspects.*

To achieve these objectives, a definition of OP 4.0 is derived in Section 2 based on the sociotechnical systems theory. Section 3 discusses insights from previous relevant literature reviews. Section 4 describes the methodology of the systematic literature search. Section 5 presents the results of the literature review, which are discussed in light of the concept of OP 4.0. Promising research opportunities are outlined in Section 6. Finally, the article is concluded in Section 7.

2. Conceptual background and framework development

2.1 Order picking

In OPSs, technical solutions are increasingly applied that support the manual order picking process. According to the degree to which the order picking process is automated, different OPSs can be differentiated (Custodio and Machado, 2020; Dallari et al., 2009; de Koster et al., 2007). In manual order picking, humans are employed and picker-to-parts OPSs can be categorised as the most manual OPSs (de Koster et al., 2007). Parts-to-picker systems, in turn, incorporate automation technology, e.g. AS/RS, that reduce human tasks such as travelling, but picking (i.e. the retrieval of items) is still performed manually in these systems (de Koster et al., 2007). Hence, these systems are considered manual OPSs. Lastly, machine-based OPSs automate the picking itself by substituting human work; these are called automated picking systems and robot picking systems (Custodio and Machado, 2020; de Koster et al., 2007).

In manual picker-to-parts OPSs, order pickers plan and set up their tasks before they walk or drive through the warehouse to collect the items on a pick list. In addition to walking, the main tasks are searching for the item location, retrieving items in the required quantity and documenting the pick. After completion of the pick list, the order pickers return to the depot, where items are sorted and packed for shipping (Tompkins et al., 2010). Today, technological support is also increasing in manual OPSs, i.e. picker-to-parts as well as parts-to-picker OPSs, which are still most commonly applied (Behnisch et al., 2017; Michel, 2019; Napolitano, 2012). A large 2019 survey indicated that more than 50% of the respondents relied on paper-based order picking in their warehouse, while only 14% used pick-by-voice technology (Michel, 2019). Additionally, AS/RS were only installed by 15% of the respondents (Michel, 2019). Among the technologies applied, IT systems for administration, such as warehouse management systems, were frequently used (85% of the respondents); however, 58% were collecting data manually (Michel, 2019).

Machine-based picking systems, in which order picking is performed e.g. by robots, remain limited in practice because of less flexibility and adaptability to pick heterogenous goods (see, e.g. Correll et al., 2018; Custodio and Machado, 2020) and troubleshooting still relies on human intervention in robotic systems (Kaipa et al., 2014).

Thus, we can validly assume that humans, despite the ongoing trend to automate processes, will remain an inevitable part of order picking in Logistics 4.0, particularly in the trend of rising e-commerce and individualisation with high-mix and low-volume warehouses (Kong et al., 2018). As a consequence of increasing technology use and thus increasing human-technology interaction, the sociotechnical interactions in OPSs are becoming significantly more complex (Dregger et al., 2018).

2.2 OP 4.0 systems are sociotechnical systems

Manual OPSs offer a variety of possibilities for humans to interact with technical systems, which can be both automation or digital technologies (Cimini et al., 2021). Examples include the equipment for pick-to-light systems in manual picker-to-parts OPSs, or AS/RS and robotic mobile fulfilment systems (RMFSs) in parts-to-picker OPSs. In addition to this installed equipment, wearables for information provision like pick-by-voice or pick-by-vision systems are used to support order pickers in manual order picking. Additionally, humans interact with software components to plan, control, or process information, whether on the shop floor or in a control centre. In these scenarios, the human role changes from an executing to a planning and monitoring one. Thus, various and heterogeneous interactions must be managed carefully in order picking; this includes the consideration of HF (Grosse et al., 2015; Grosse et al., 2017).

2.2.1 Integration of human factors

HF (or ergonomics) is defined as „the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimise human well-being and overall system performance“ (International Ergonomics Association, 2019). Hence, the HF discipline can be considered to contribute to the objective of sustainability, e.g. expressed by the triple bottom line (Braccini and Margherita, 2018) and is also part of Logistics 4.0 (Winkelhaus and Grosse, 2020a). Human-oriented work design has four objectives: the work must be feasible, tolerable, reasonable and satisfying (Stern and Becker, 2017).

Three HF aspects were identified as relevant for the interaction of humans and OPSs: perceptual, mental and physical aspects (Grosse et al., 2017), which can be explained using the model of Wickens and Carswell (2006), who proposed a perception, cognition and motor action cycle. Humans perceive the physical environment (in this scenario, the warehouse) and process information. Subsequently, through interaction with prior knowledge stored in the memory, a decision is derived (for example, for a certain routeing or retrieval strategy) that results in a physical motor action of the human. Ultimately, this motor action influences the system again because the environment changes. In considering HF systematically, performance and quality can be increased and injuries, diseases and other harms can be minimised (Grosse et al., 2015). This is particularly important considering the effects of work-related illnesses in logistics. Because of high physical loads in manual OPSs, musculoskeletal disorders are frequently reported, and these injuries result in significant direct costs for enterprises and additional indirect costs (Gajšek et al., 2020; Grosse et al., 2017).

In addition to these steps that primarily focus on the feasibility and tolerability of work, psychosocial aspects are important to achieve satisfying work (Grosse et al., 2017). The increase in people's well-being at work is affected by workplace design, for example, job enrichment, enlargement, or rotation (Morgeson and Humphrey, 2006; Schlick et al., 2010). This is also relevant in order picking, which is often perceived as being highly repetitive. The definition of well-being in the literature has not been generally consistent (Bakker and Oerlemans, 2011), but we can derive that it includes concepts such as engagement and job satisfaction (Bakker and Oerlemans, 2011). For this paper, in particular, job satisfaction is important, since it can be directly affected by workplace and work-task design (e.g. by technology use) (Morgeson and Humphrey, 2006); examples of affected aspects include autonomy, skill variety, task identity, task significance and feedback from the job (Hackman and Oldham, 1975). For OP 4.0 design, work should be feasible, tolerable, reasonable and satisfying considering perceptual, mental, physical and psychosocial work characteristics. Because Industry 4.0-related technologies have been demonstrated to affect job characteristics as well as HF (Cimini et al., 2021) and thus employee outcomes such as motivation or job satisfaction (Waschull et al., 2020), human-technology interaction in future work design must be considered (Neumann et al., 2021).

2.2.2 Technology integration and human–technology interaction

As can be seen, automation enables tasks to be processed without human involvement (Fasth-Berglund and Stahre, 2013). Automation technology is generally related to physical process steps, but digital technologies can enable cognitive automation, which can be defined as "technical solutions helping the operator" (Mattsson et al., 2020) concerning what and how to perform actions. According to the process to be performed, automation and digital technologies play different roles in substituting or supporting the process. In order picking, which is a mainly physical task, digital technologies primarily support the order picker in performing the task because these technologies cannot move the material physically. In contrast, the automation technology mainly substitutes tasks because the physical part of the process step can be performed by either the human or the automation technology. As outlined above, substituting or supporting the process has a significant impact on the operator. While the substitution of tasks might lead to a limitation of tasks for humans, making them more repetitive and reducing their beneficial characteristics, the support of tasks could lead to a more flexible and informed work and thus enlarge or enrich the work (Winkelhaus and Grosse, 2020b).

Hence, the increasing number of different technologies applied in order picking, including supportive and substitutive ones, makes it necessary to develop a classification that considers the different capabilities of these technologies depending on the exact usage and the sociotechnical character of OPSs. Such classification would also allow a reverse usage: the knowledge about the required system characteristics in terms of, for example, throughput and flexibility, can help to identify the most promising OPS (Fasth-Berglund and Stahre, 2013).

A new framework for sociotechnical OPS classification based on the level of automation of supportive and substitutive technologies is presented in Figure V-1. Supportive technologies are indicated on the x-axis, which are especially digital technologies within the order picking context but are not restricted to them. For example, pick-by-technologies facilitate information processing (supporting mental/cognitive tasks), and exoskeletons can reduce the lifting load (supporting physical tasks) but do not replace these tasks. Substitutive technologies are indicated on the y-axis. These technologies directly substitute at least a certain task in the order picking process. For example, applying AS/RS eliminates travelling (a physical task) and searching (a mental task) in most scenarios. Both axes provide different levels of automation including example technologies regarding their capabilities to autonomously support or substitute certain tasks. The levels of automation of supportive and substitutive technologies are based on (Davenport and Kirby, 2016) but adapted to the current state of research in the field of order picking. The different levels of automation are listed in Table V-1.

The resulting sociotechnical OPS framework has thus similarities with the "level of automation matrix" developed by Fasth-Berglund and Stahre (2013) in which the levels of cognitive and physical automation are considered, but it is different in the way that it is process-oriented according to the substitutive and supportive technologies for the explicit order picking process.

Table V-1: Level of support and level of automation for order picking tasks.

	Level of automation for support	**Level of automation for substitution**
No support	Human task performance is not supported by technology in any way	Tasks are not automated by technology in any way
Support for humans	Human task performance is supported by static solutions, e.g. barcode scanners	Tasks are automated by static solutions, e.g. conveyor belts
Repetitive task automation	Human task performance is supported by technical solutions for controlled environments, e.g. highlighting the searched location or lifting	Tasks are automated by repetitive task automation, e.g. storing/retrieving storage bins
Context awareness	Human task performance is supported by a technology that is also context-aware and can adapt to changes, like guiding the order picker to the correct locations	Tasks are automated by a technology that is also context-aware and can adapt to changes, like AGVs following order picker or pick robots
Self-awareness	Human task performance is supported by autonomous and intelligent systems	Tasks are automated by autonomous and intelligent systems

For easier classification of OPSs, the sociotechnical OPS framework is roughly divided into four quadrants related to the level of automation of substitutive and supportive technologies. Manual and traditional OPSs, either picker-to-parts or parts-to-picker, largely rely on simple automation technologies or, most often, solely on human order pickers supported by simple pick lists or barcode scanners. Operator 4.0 OPSs apply mainly higher levels of supportive technologies while physical substitution technologies are not applied, or only at a low level of automation; the Operator 4.0 technologies are adaptive and can thus support the order picker better than the supportive technologies in traditional OPSs (Romero et al., 2016b). Human-reduced OPSs focus on high levels of automation for the physical substitution of process steps and only apply humans where necessary. Finally, hybrid order picking systems (HOPSs) can apply both high levels of automation for substitution of tasks and support of tasks, enabling collaboration between human- and machine-based OPSs for a joint objective within a shared workspace.

Technology examples of the levels of automation for substitutive and supportive technologies are shown in Figure V-1. As can be observed, some technologies, such as pick-by-voice systems, have limited capacities, while others can be used in different ways and levels of automation depending on the exact application, such as AR. These technologies can thus enable, for example, human-reduced OPSs, but also HOPSs. For example, AGVs can be applied as a human-reduced OPS in an RMFS, as the travelling of humans is substituted; in contrast, AGVs can also be applied as a HOPS, transporting goods while travelling with the order picker. In addition, a HOPS can also apply fully autonomous robots together with human order pickers on the same shop floor.

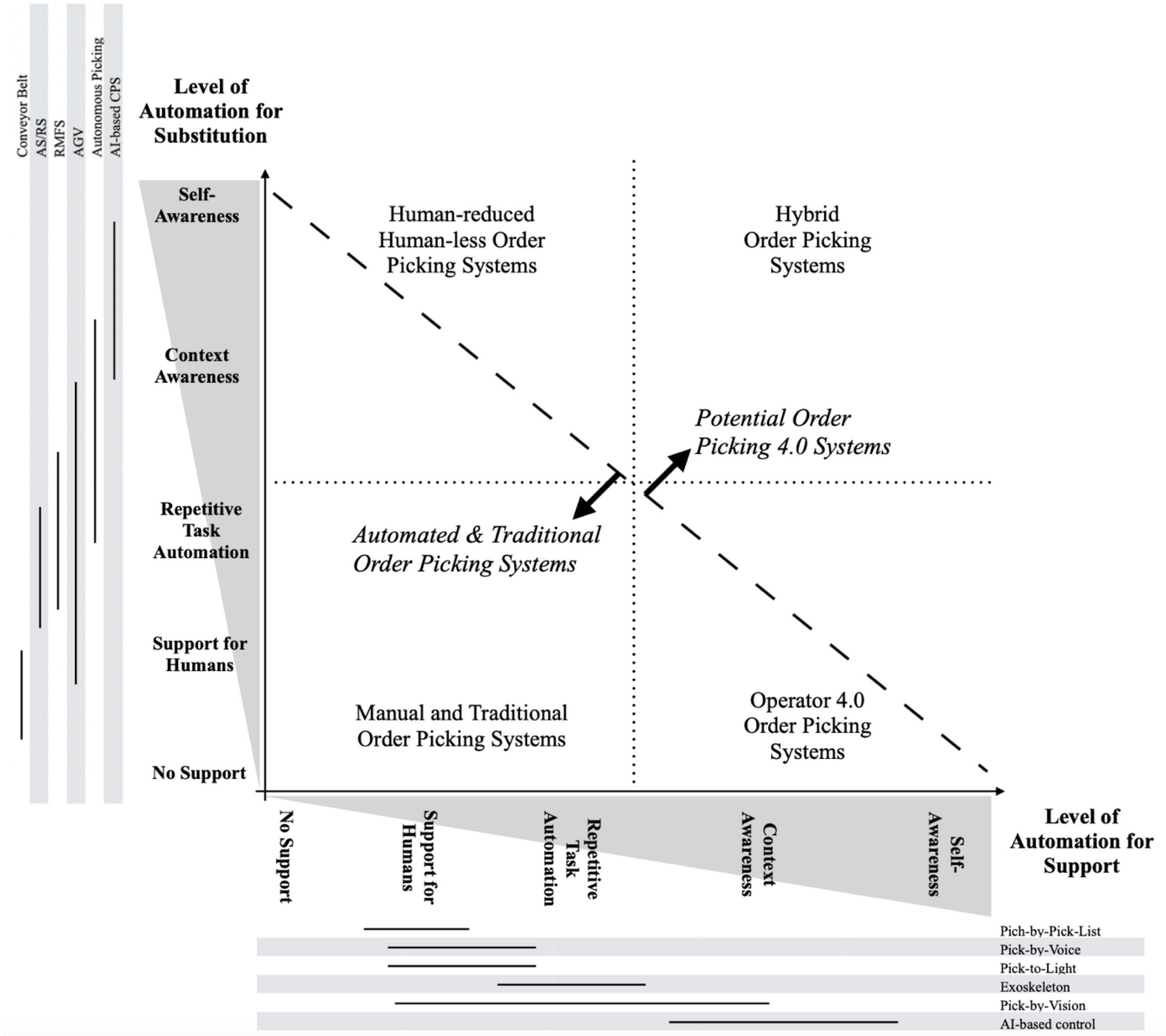

Figure V-1: Sociotechnical OPS framework.

In conclusion, both supportive and substitutive technologies affect the OPS, work environment and tasks of human order pickers. In this sociotechnical OPS framework, the specific OPS type can be located according to the technologies applied and the ways in which they are used.

2.3 Definition of Order Picking 4.0

In OP 4.0, both derived aspects, that is, HF and applicable supportive and substitutive technologies and their interaction, must fit together harmoniously to improve the overall system performance (Neumann and Dul, 2010; Neumann et al., 2021; Zare et al., 2016) and achieve the aims of Logistics 4.0. Correspondingly, HF are satisfied by limiting the loads for humans with respect to perceptual, mental, physical and psychosocial demands. Automation and digital technologies substitute and support tasks during the order picking process, which limits the loads and creates opportunities for diversification and motivation during work. Based on this background, OP 4.0 can be defined as follows (addressing our first research objective):

Order Picking 4.0 is a sociotechnical order picking system in which individual and heterogeneous customer orders are efficiently and sustainably compiled in small batch sizes from a large variety of goods in a warehouse. Thereby, Order Picking 4.0 considers high levels of automation of supportive and substitutive technologies as well as human factors objectives.

Until now, research on OP 4.0 has been limited; however, this research is a necessary step towards fully achieving Logistics 4.0. Hence, this paper reviews and outlines the state of research within the three quadrants in Figure V-1 identified to be relevant for OP 4.0, opens new research directions and derives key aspects from an organisational, HF and economic perspective to avoid an innovation pitfall (see Neumann et al., 2021). To keep the review focused, we did not consider technologies that are solely located within the traditional OPS quadrant. Although these technologies might be applied as complementary technologies in Operator 4.0 or human-reduced OPSs, they are not the focus of the present review but are named in case they are relevant. For a more thorough investigation of the impacts of traditional support and substitution technologies, we refer the reader to the recent works of Glock et al. (2021) and Jaghbeer et al. (2020).

To achieve our second research objective, insights from previous literature reviews are first discussed to outline the state of knowledge before a systematic review of OP 4.0 is performed.

3. Insights from published literature reviews

Order picking is a vital field of research. Figure V-2 shows the number of articles in the Scopus database with the search term "order picking" in the title over the past 30 years. The figure shows a clear trend of a steady increase in research, which hints at the interest in this important topic.

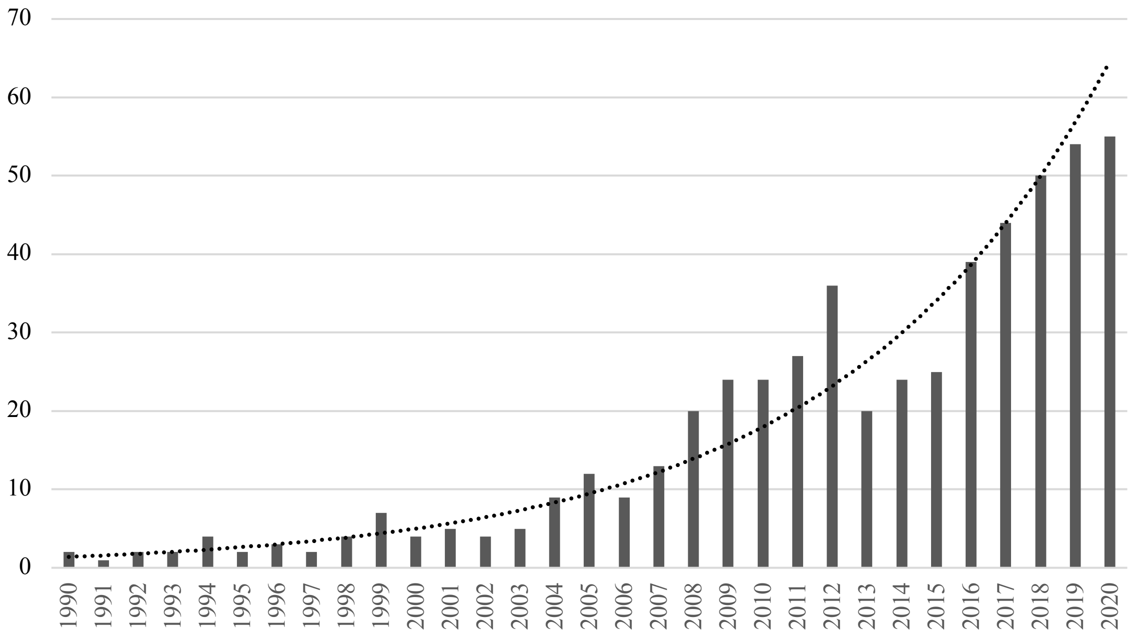

Figure V-2: Number of articles with keyword "order picking" in the title over time.

In particular, four recent reviews can be considered relevant to OP 4.0, since they particularly focus on warehouse operations and the intersection with OPS technologies: the review of Boysen et al. (2019) that addressed OPSs, particularly relevant for the e-commerce era; the review of Azadeh et al. (2019) that focused on robotised and automated warehouses and OPSs; the review of Custodio and Machado (2020) which discussed flexible automated warehousing; and the review of Jaghbeer et al. (2020) which investigated the intersection of system design and performance in automated OPSs. Other reviews that were not in the focus of this research primarily focused on operational planning problems such as order picker routeing (Masae et al., 2020a) or storage location assignments (Reyes et al., 2019). The relevant reviews that focused on the intersection of technology and OPSs are briefly described below, and the discussed OPSs are classified in the sociotechnical OPS framework (Figure V-3).

Boysen et al. (2019) examined nine OPSs. Considering the quadrants in the framework shown in Figure V-3, we can derive that most OPSs (1–9) considered by Boysen et al. (2019) are located in the traditional OPSs quadrant, meaning that less advanced IT systems were applied. Moreover, only simple automation technologies were surveyed, such as conveyor belts or traditional AS/RS. The authors reviewed six of the nine OPSs that were considered relevant for e-commerce by focusing on decision problems. The authors concluded that novel OPSs are available but are not yet part of the scientific discussion (Boysen et al., 2019).

Second, Azadeh et al. (2019) performed a literature review on modern warehouse systems focusing on shuttle-based and AGV-based systems. They reviewed articles on system analysis, design optimisation and operations planning and control. The study has two main findings: 1) Scientific literature on new robotic systems is scarce, although there is increasing use of such systems in practice. 2) All identified fields of planning, e.g. warehouse layout planning, batching, or routeing must be revisited to satisfy the requirements of such new systems.

Third, Custodio and Machado (2020) performed a systematic literature review on flexible automation of warehouses; they defined the flexibility of automation as the possibility to create "any required change in the program of instructions enabling continuous production of different parts or product cycles". The main outcome of the review is the observation that flexible automation in warehouses requires three aspects operating in concert: automation technology, such as AS/RS, robotics, or AGVs; data collection, such as barcode or RFID scanners and pick-by-technologies; and management solutions, such as warehouse management systems, simulations and routeing algorithms. Therefore, the authors considered flexible automation to be a key aspect in solving the challenges of Logistics 4.0, such as mass customisation or shortening product lifecycles.

Finally, Jaghbeer et al. (2020) investigated which design aspects affect the performance of partly or fully automated OPSs. Applying a systematic literature review method, they investigated parts-to-picker, robots-to-part, parts-to-robot and picker-less OPSs. Their findings indicate that most studies in this field focus on throughput, lead time, quality and operational costs for human pickers and picker-less systems, whereas for robot pickers, OPS flexibility is addressed more often.

Analysing these published reviews, we observe a lack of research focusing on novel OPSs holistically and from a sociotechnical perspective. None of the reviews focused on the interactions of human order pickers and OPSs in depth, and only Jaghbeer et al. (2020) referred to HF as affecting system performance, although they could not identify a large sample. Boysen et al. (2019) only referred to ergonomics in their outlook. This brief overview underlines the postulated research gap on OP 4.0. Considering the four quadrants of Figure V-3, prior related reviews focused on the y-axis or the human-reduced-OPS quadrant. Next, we perform a systematic literature review to assess the state of knowledge on OP 4.0 (research objective 2), discussing studies that contribute to HOPSs, human-reduced OPSs and Operator 4.0 OPSs. For review articles on planning and control of traditional OPSs, we refer the reader to recent literature studies such as van Gils et al. (2018) or Masae et al. (2020a).

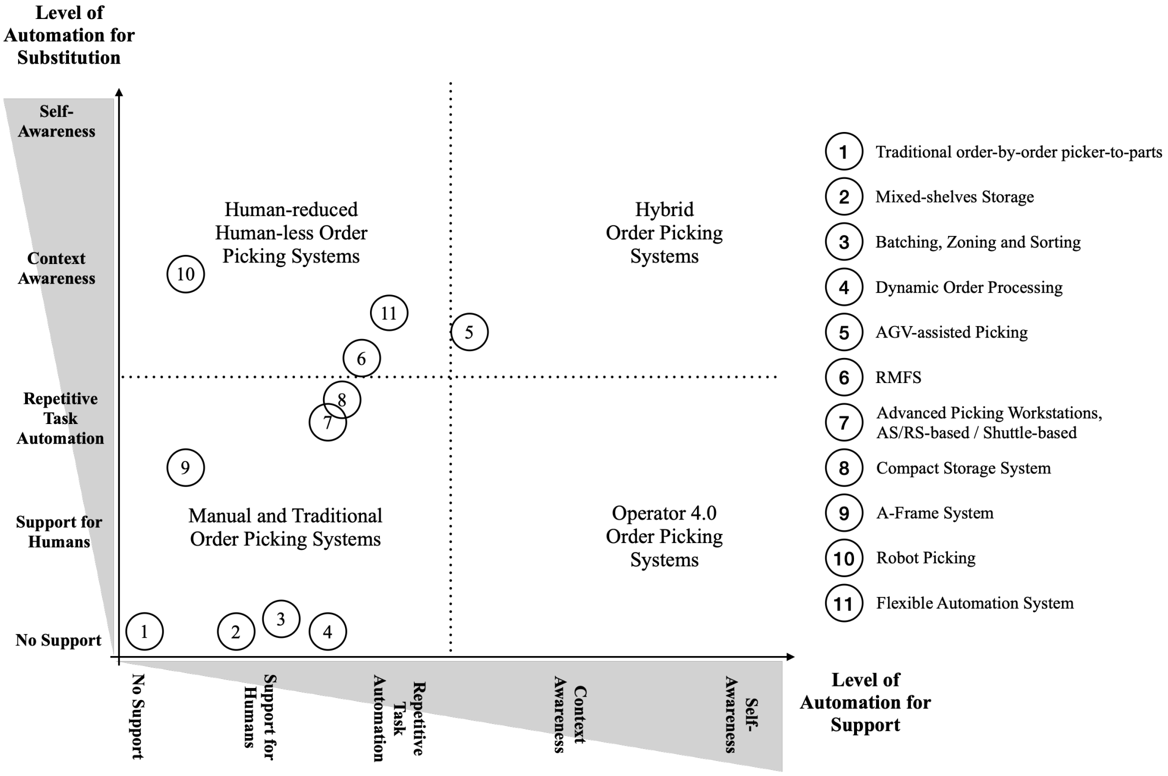

Figure V-3: OPSs reviewed in related review articles classified in the sociotechnical OPS framework.

4. Methodology

4.1 Material collection

To ensure a systematic and reproducible material collection procedure, three steps were performed.

First, the keywords for database searches were defined. In this study, keywords belonging to one of the three groups were identified based on the theoretical background discussed in Section 2. The main categories adopted are a) order picking, b) Industry 4.0/automation technologies and c) the interaction of humans with these technologies (HF). The relevant articles contained keywords in each category. Every possible intersection of the keywords listed in Table V-2, according to these categories, was considered valid.

Table V-2: Keywords used in the database search.

a) Order Picking	b) Technologies	c) HF
Order Picking	Industry 4.0	Human-machine
Order-Picking	Pick-by-Vision	Human-robot
Warehouse Picking	Pick-by-Watch	Human-technology
Order Picker	AR / Augmented Reality	Human-Computer
"Warehouse" and "Picking"	VR / Virtual Reality	HMI
Fulfilment system	Exoskeleton	Technology Interaction
	RFID	Collaboration
	IoT / Internet of Things	Human Factor
	AI / Artificial Intelligence	Psychosocial
	Big Data	Autonomy
	AGV / Automated Guided Vehicle	Job Control
	MRFS / Mobile Robot Fulfillment System	Sociotechnical
	Robot	Ergonomics
	CPS / Cyber-physical system	Perception
	Cobot / Collaborative robot	Cognition
	Smart	Mental
	Digital	Manual
	4.0	Fatigue
	Intelligent	Knowledge
	Digitization	Work organization
	Automation	Workload
	Autonomation	Human-centered
	Gamification	Capabilities
	Blockchain	Safety
	Wearable	Well-being
	Cloud	Job satisfaction
	Grid	Job demand
	Shuttle	Job control
		Musculoskeletal disorder
		Work design
		Support

Second, the keywords were searched (last update in March 2021) in the titles, abstracts and lists of keywords included in the Scopus and Web of Science databases, as these are among the largest scientific databases in the field of research. Because of the novelty of OP 4.0, journal articles and conference articles that contained innovative research before they appeared in journal publications were considered relevant.

Third, duplicate hits from the two databases were excluded. Subsequently, the initial search results were examined to determine whether they were included or excluded from the review. Therefore, five criteria categories that were logically oriented to those of Liao et al. (2017) were derived, but their content was adapted according to the research objectives of this study. The criteria categories are presented in Table V-3. Here, a first refinement step was identified based on "hard facts", for example, because of search engine reasons. In the second refinement step, titles, abstracts and keywords were assessed for their general content fit. Third, articles that could be relevant were read completely to examine their content fit in detail and determine whether the articles belonged to the categories of loose fit, partial fit, or close fit. As can be observed, we only considered articles relevant if they also addressed HF at least in part of the article. Owing to the focus of the review and its sociotechnical foundation, OPSs that do not include human activities within their lifecycle were not taken into account. Hence, these impacts should at least be named within the article to be considered relevant from the applied processual perspective of the present review. Articles that focused solely on the technological development of an OPS were not the focus of this review.

Table V-3: Inclusion and exclusion criteria for the systematic review.

Inclusion/ Exclusion	Criteria	Criteria Explanation (examples)
Exclusion	Search engine reason	The article has the title, abstract, or keywords in English but the text is in a different language
	Non-related	The article is not an academic article, for example, newspaper articles The keywords found relate to another topic because they have a double meaning (e.g. data warehouses)
	Loosely related	The article uses keywords of at least two categories only in a quotation, example, or in the research outlook / future directions
Inclusion	Partially related	The article deals with keywords of the categories of order picking and technology and at least relates to HF in the research outlook / future directions The article deals with the intersection of keywords at least in a part of the article The article deals with the topic, without focusing on the keywords but using similar / equivalent meanings

Closely related	The article deals with keywords of all three categories The article deals with keywords of two categories in depth and mentions the third category

The flow of inclusion and exclusion to the sample is shown in Figure V-4 according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow chart (Moher et al., 2009) which is frequently applied in reviews (e.g. Kadir et al., 2019; Liao et al., 2017). In every step, the results were carefully assessed by the authors for relevance. We note that the literature sample derived in this procedure differs from the published reviews discussed in Section 3 and shows no sample overlap with three of these reviews and less than 5% with the review of Jaghbeer et al. (2020). This highlights the novelty of this study's conceptual approach.

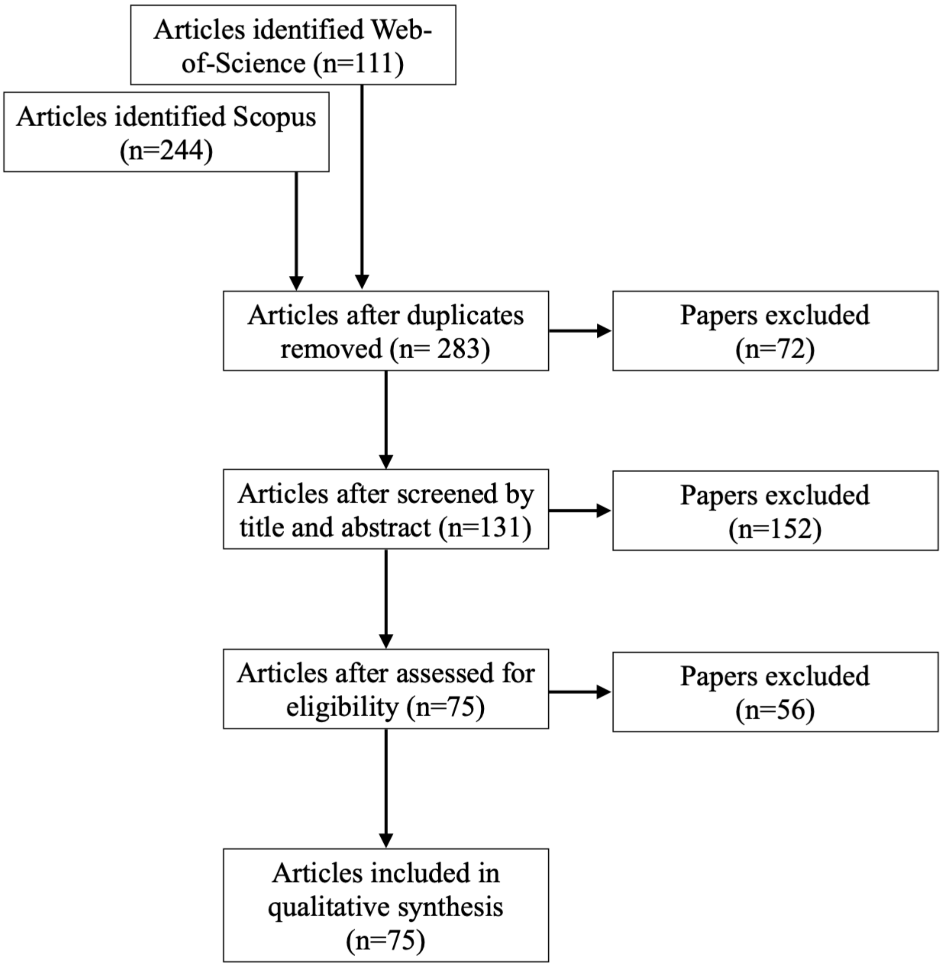

Figure V-4: PRISMA flow chart summarising the literature search process.

4.2 Descriptive analysis

Most of the 75 articles included in the review were published during the past five years. As Figure V-5 shows, the number of contributions per year began to increase in 2015 and peaked in 2019.

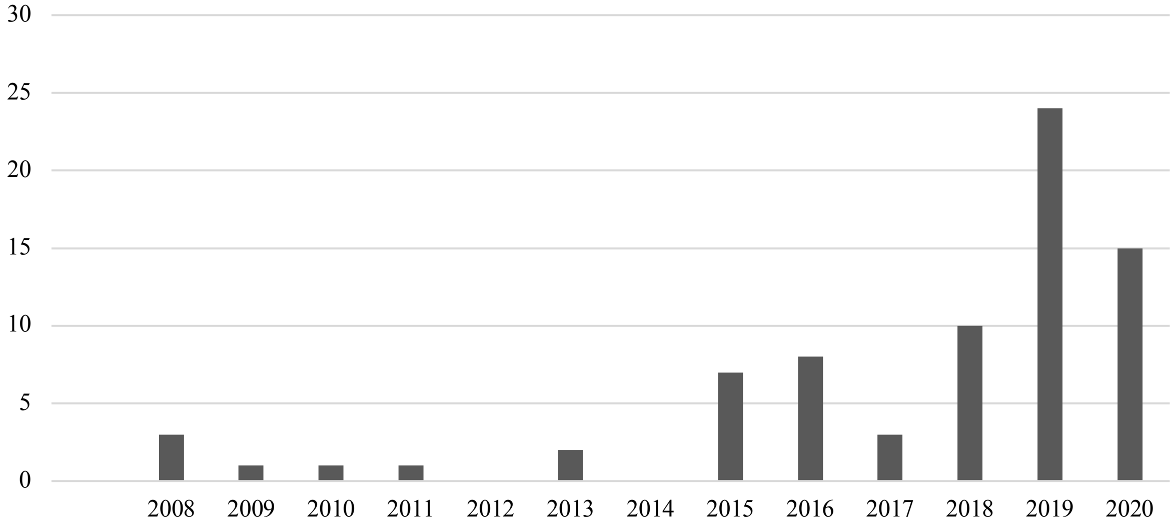

Figure V-5: Number of contributions over time.

Moreover, we noted that most of the contributions were conference articles (Figure V-6). This hints at the novelty of the research in this dynamic field. The trends, i.e. the increasing number of publications and the majority of conference articles, followed the identified trends in prior reviews, for example, on the topic of HF and Industry 4.0 (Kadir et al., 2019; Neumann et al., 2021) as well as on the intersection of Industry 4.0 and logistics (Winkelhaus and Grosse, 2020a).

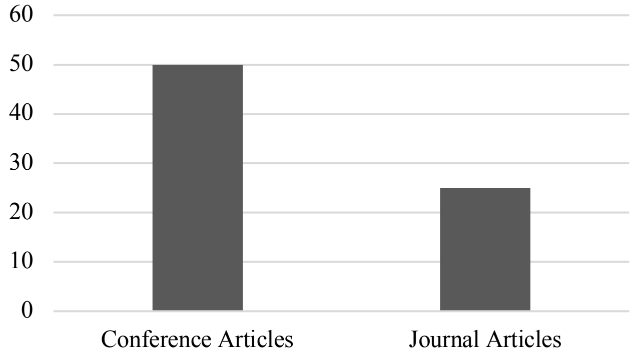

Figure V-6: Contributions by type of publication.

The most contributing journals and conferences are presented in Figure V-7. As can be observed, among the most contributing publication media, only two journals have two or more publications within the sample. The majority of the studies are based on conference publications.

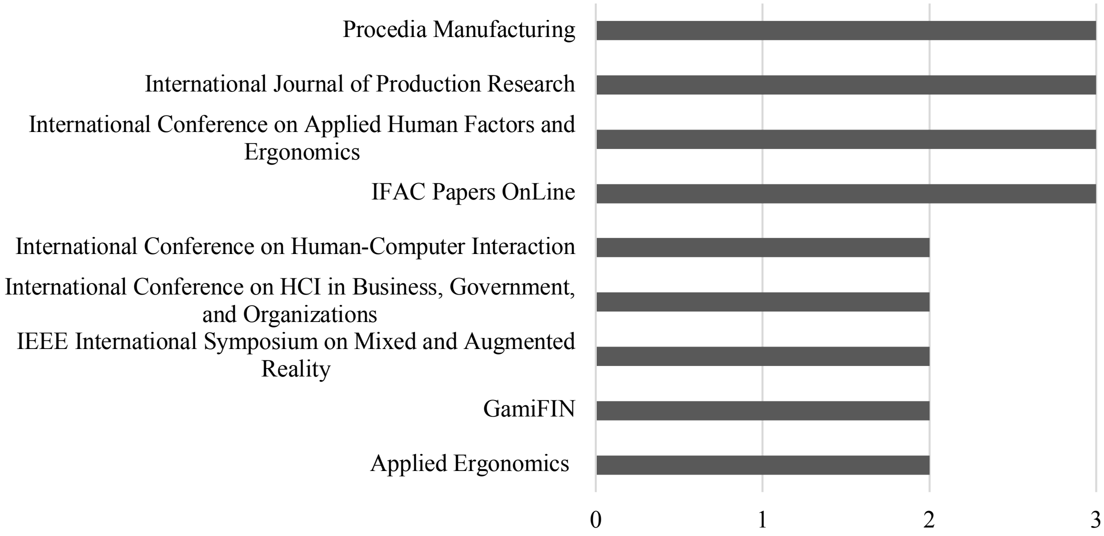

Figure V-7: Number of contributions per journal.

Figure V-8 summarises the methodologies applied to the sampled articles. As can be observed, most articles used empirical data to gain deeper insights into the topics, followed by conceptual studies. Empirical studies are, for example, pilot studies to gain first insights into the usage of technologies from a user perspective. In contrast, purely theoretical studies are rare in this sample. One reason for this finding may be the focus on HF.

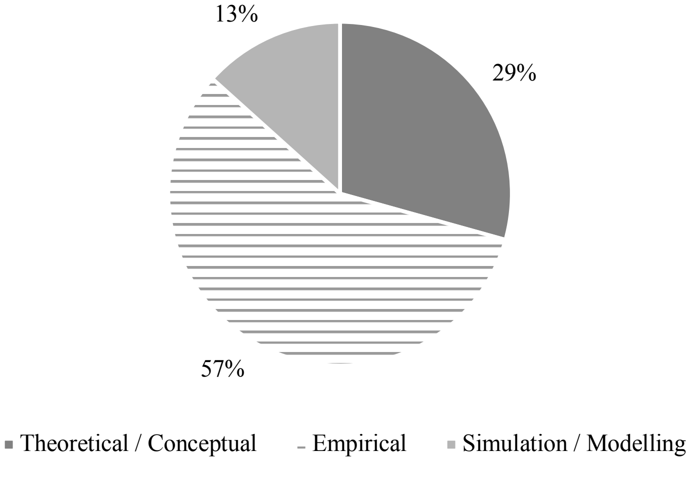

Figure V-8: Number of publications per applied methodology.

The article distribution over the sociotechnical OPS framework is shown in Figure V-9. Because of the inclusion/exclusion criteria, no articles belonging to the quadrant of traditional OPSs were included in the sample. As the figure shows, significant parts of the sampled works focused on the Operator 4.0-OPS quadrant. This might hint at the development stage of OP 4.0, because OPSs still predominantly rely on human work. Accordingly, the most applied technology identified within the sample, as shown in Figure V-10, is AR, followed by RFID applications. AGVs were applied in ten studies, indicating the importance of automation technology for the identified OPSs.

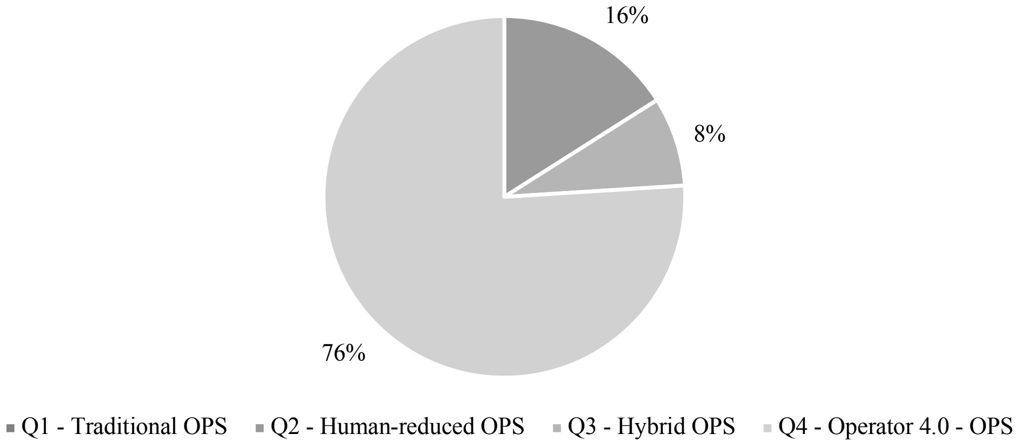

Figure V-9: Distribution of articles over quadrants of the sociotechnical OPS framework.

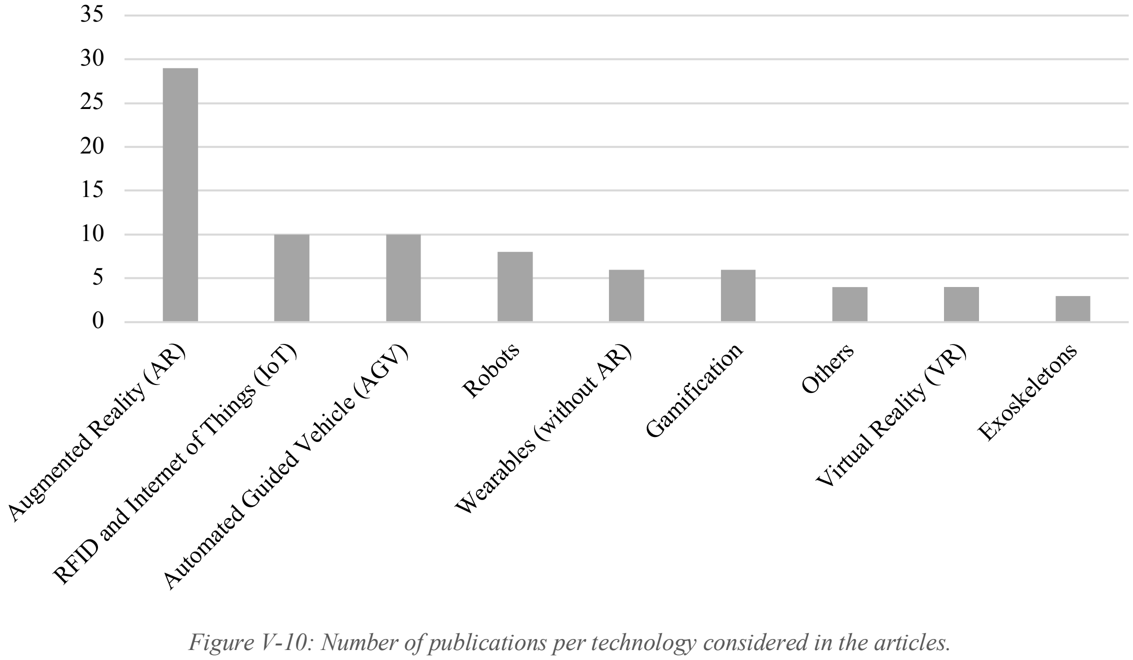

Figure V-10: Number of publications per technology considered in the articles.

This is also emphasised within the keywords most often mentioned within the sample (Figure V-11). As can be found, besides order picking and logistics, augmented reality and smart glasses are the most mentioned keywords, followed by gamification, virtual reality and RFID, among the keywords with a technological focus. Furthermore, the impact on HF and ergonomics is stressed, as these terms are also among the most mentioned keywords in the sample.

Figure V-11: Number of most contributing keywords.

Further examining the contributions per quadrant of the sociotechnical OPS framework over time, we observed that early contributions of Operator 4.0 OPSs were published in 2008, whereas human-reduced OPSs were first considered in 2015 and HOPSs did not appear until 2019. This development is illustrated in Figure V-12. A complete list of all 75 articles and a respective categorisation is provided in the Appendix in Table V-7, including the research topic and related to Figure V-1, the OP 4.0 system, key technologies and affected order picking process step(s).

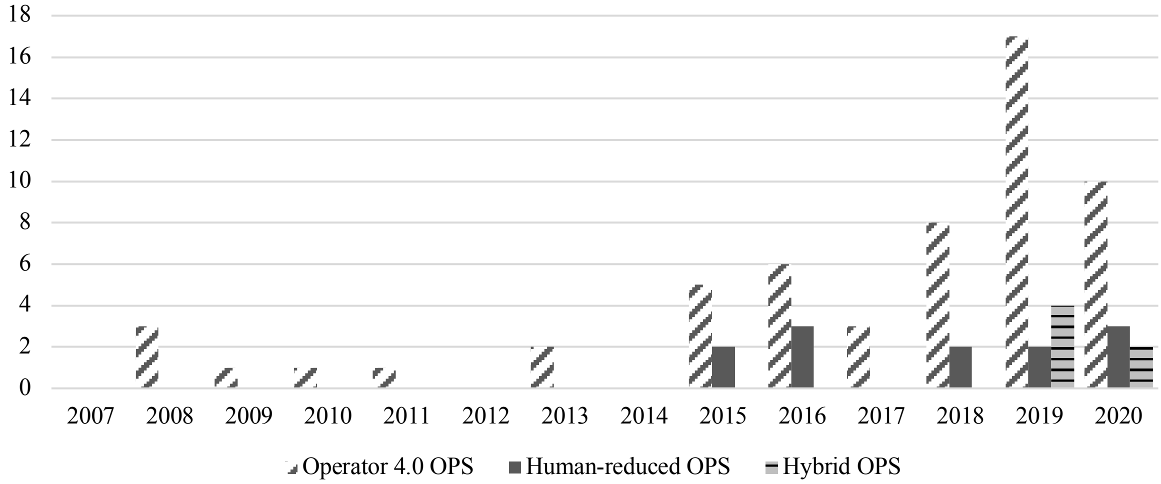

Figure V-12: Distribution of articles over OP 4.0 system and time.

5. State of knowledge on Order Picking 4.0

To structure the analysis of the literature, the sociotechnical OPS framework (Figure V-1) and the insights obtained from published literature reviews (Section 3) were used. Based on this, the structural dimensions of the literature were derived, as presented in Table V-4.

Table V-4: Structural dimensions of the systematic review.

Nr.	(Sub-)Category	Definition
1	OPS	Investigated OPSs according to the quadrants of the sociotechnical OPS framework
2.1	Order picking task	Process step that is supported/substituted
2.1.1	Applied supportive or substitutive technologies	Explicit technologies applied in the OPSs and how they affect the order picking task
2.1.2	HF Interaction	Type of HF implications
2.2	Economic Outcomes	Economic effects of the resulting OPSs

This category system is used to structure the discussion on Operator 4.0-related OPSs, followed by human-reduced OPSs and finally HOPSs. Within each of these OP 4.0 systems, the discussion of the results followed typical order picking tasks. Within each order picking task, the processual aspects and HF effects are discussed. At the end of each section, the most important economic effects achievable by the applied OPSs are summarised. Table V-5 presents the identified articles belonging to the specific OP 4.0 systems according to the sociotechnical OPS framework.

Table V-5: Identified articles according to the sociotechnical OPS framework.

Quadrant	Contributions
Operator 4.0 OPS (Section 5.1)	Andriolo et al. (2013); Andriolo et al. (2016); Avdekins and Savrasovs (2019); Baechler et al. (2016); Baechler et al. (2015); Battini et al. (2015); Bräuer and Mazarakis (2019); Choy et al. (2017); Egbert et al. (2020); Elbert et al. (2019); Elbert et al. (2018); Elbert and Sarnow (2019); Fang and An (2020); Fang et al. (2019); Friemert et al. (2016); Friemert et al. (2019); Friemert et al. (2018); Funk et al. (2016); Funk et al. (2015); Gajšek et al. (2020); Grubert et al. (2010); Guerin et al. (2019); Guo et al. (2015); Herzog et al. (2018); Iben et al. (2009); Kajiwara et al. (2019); Kim et al. (2019); Kinne et al. (2020); Klevers et al. (2016); Kreutzfeldt et al. (2019b); Kreutzfeldt et al. (2019a); Lee et al. (2019); Lind et al. (2020); Mättig et al. (2018); Motmans et al. (2019); Murauer and Gehrlicher (2019); Murauer et al. (2018); Nagda et al. (2019); Pang and Chan (2017); Passalacqua et al. (2020); Plakas et al. (2020a); Plakas et al. (2020b); Ponis et al. (2020); Putz et al. (2019); Renner and Pfeiffer (2020); Schwerdtfeger and Klinker (2008); Schwerdtfeger et al. (2011); Sham et al. (2018); Terhoeven et al. (2018); Thomas et al. (2018); Trab et al. (2017); vom Stein and Günthner (2016); Walch (2008); Wang et al. (2013); Winter et al. (2019); Wu et al. (2015); Yan et al. (2008)
Human Reduced OPS (Section 5.2)	Bogue (2016); Correll et al. (2018); D'Avella and Tripicchio (2020); Fiolka et al. (2020); Huang et al. (2015); Krug et al. (2016); Kudelska and Niedbał (2020); Lager et al. (2019); Lee et al. (2018); Liang et al. (2015); Su et al. (2019); Yuan and Gong (2016)
HOPS (Section 5.3)	Fager et al. (2020b); Masae et al. (2020b); Papcun et al. (2019); Rey et al. (2019); Wang et al. (2019); Zou et al. (2019)

5.1 Operator 4.0 OPS

Operator 4.0 OPSs generally focus on manual picker-to-parts systems and sometimes on workplaces that are additionally equipped with traditional automation technologies such as simple AS/RS. Technologically, the contributions range from direct support of the order picker, such as with AR systems, to indirect effects such as the use of gamification.

5.1.1 Planning and preparing the pick tasks

Before the order picker can begin the picking task, the actual task sequence must be determined and the order picker must prepare the picking tour. Although physical preparation of the pick tour was not identified within the review as a supported process step, information-related preparation attracted interest. Thus, planning and adapting pick routes are particularly relevant.

To include human order pickers in this step, adaptive systems must loop back information into the software. This information can be of two types: environmental data (including process and location data) and data from human order pickers. With the aid of IoT and Big Data technologies, location and process data are obtained and processed (Trab et al., 2017;

Wang et al., 2013). Therefore, the order picker workload can be balanced (Wang et al., 2013) and warehouse efficiency improves (Trab et al., 2017). In contrast, sensor-based data of order pickers (for example, gained through wearables) are used to predict human emotion and improve the task management (Kajiwara et al., 2019) or definition of breaks (Mättig et al., 2018). This permanent measurement differs in the possibility of adapting the planning by constant tracking and adaption of the tasks, in contrast to other systems that, for example, apply motion capture systems that measure order pickers sporadically for training reasons (Calzavara et al., 2016).

Applying planning systems that loop back data affects physical HF. For example, balancing the workload for order pickers was an objective in some studies (Wang et al., 2013), thus affecting the fatigue of order pickers. Additionally, mental and psychosocial HF are also affected, suggesting improvements in emotion and reduction of tiredness (Wang et al., 2013) or supporting decisions to improve safety concerns (Trab et al., 2017). In addition, psychosocial HF are directly affected by deriving the emotional state of an order picker to design the task management. Hence, stress, motivation and job satisfaction can be influenced (Kajiwara et al., 2019). Overall, three positive effects of Operator 4.0 OPS can be derived: physical health, reduced mental load and psychosocial well-being (Mättig et al., 2018).

5.1.2 Travelling and transporting

Travelling and transportation tasks can be affected by different systems and organisational aspects. However, no studies on the support of travelling and transportation tasks were identified in the sample that was assigned to Operator 4.0 OPSs. Closely related research is discussed in Section 5.1.3.

5.1.3 Searching the pick location

Before an order picker can select an item on the pick list, the location of the correct items must be found. This search process can be demanding in warehouses with a high variety. AR has attracted significant attention as a support for the searching task during order picking. AR-supported OPSs frequently use head-worn displays, most often wearable glasses, to show visual information to the order picker (see, e.g. Fang et al., 2019; Murauer et al., 2018; Terhoeven et al., 2018). This information can be of different adaptability and context sensitivity from less adaptive systems that primarily display information up to more advanced systems that guide the order pickers through the warehouse (Fang and An, 2020), provide additional aid such as highlighting the storage location (Fang et al., 2019), or adapt the information provision to the order pickers' requirements (Kreutzfeldt et al., 2019b). This supports the order picker while he or she searches for the correct location and makes his or her way through the warehouse, which can reduce the search time. Different techniques to guide the order picker in an augmented reality to an item location are developed for easier routeing, showing either one location after the other or multiple locations at the same time. The different guidance techniques have varying preferabilities in warehouse environments, indicating a preference for showing multiple locations at the same time (Renner and Pfeiffer, 2020).

In addition, AR systems are combined with scans of the locations of goods picked for quality reasons. Therefore, a combination of RFID and IoT was selected in different studies, similar to an RFID pick-to-light system (see, e.g. Battini et al., 2015; Thomas et al., 2018). Hence, these systems are applied in picker-to-parts environments and low-level automation environments (Friemert et al., 2016; Friemert et al., 2019).

In summary, there is a great diversity of applications and different AR hardware that can be applied, with or without the additional application of RFID. Hence, a methodological support was developed for enterprises that need to decide on the right hardware and information provision to be applied in the OPS to support the order pickers throughout the process (Egbert et al., 2020).

VR can be used to train the order picker even before the first real-world contact with the warehouse. VR is used to train order pickers and for ergonomic assessments (Friemert et al., 2018). Although order picking is often perceived as repetitive or monotonous (Azadeh et al., 2019; Lee et al., 2018), unlearned order pickers perform tasks slower and gain learning effects over time (Grosse and Glock, 2013). To counteract these observations, VR was applied to train order pickers prior to actual warehouse work. In manual picker-to-parts OPSs, VR training has been observed to have training effects on real-world processes (Elbert et al., 2019; Elbert et al., 2018).

Although searching itself is not a physically demanding task, the process step can be improved using AR and VR systems. A well-designed AR-supported OPS has been observed to have positive effects on the physical workload indicated by incorrect postures (Friemert et al., 2019). Although differences exist, a VR-based mock-up warehouse can be generally used for ergonomic analysis in order picking (Friemert et al., 2018).

Mental aspects and perceptual effects are within the focus of the search process. For example, AR systems have been investigated in laboratory experiments to determine the best content-displaying type, investigate the usability of the glasses and compare them with other order picking technologies such as pick-by-voice or paper-based picklists (Iben et al., 2009; Kim et al., 2019; Murauer et al., 2018). The results indicate that AR-based pick-by-vision systems adequately support order pickers, particularly for shorter periods (Friemert et al., 2019), but the design of the AR system is crucial (Elbert and Sarnow, 2019; Kim et al., 2019). The results indicate that mental and perceptual workloads differ at the individual level (Friemert et al., 2019; Thomas et al., 2018). Additionally, mental workloads can be reduced by applying comfortable guiding techniques (Fang and An, 2020), which aim to decrease the time that new employees require for the learning process (Plakas et al., 2020b). In addition, VR can be considered capable of reducing mental loads (Elbert et al., 2019) because the learning effects are transferable to real-world scenarios (Elbert et al., 2018). Concerning the psychosocial impacts, it was found that a certain amount of autonomy should be left to the order pickers in the process of choosing their paths through the warehouse (Renner and Pfeiffer, 2020).

5.1.4 Picking the items

After the right pick location is reached, the actual pick is performed. Two different methods can be applied in this process step: 1) exoskeletons can be used to directly support the order picker in this step and 2) smart workwear can support the order picker indirectly by providing immediate feedback on bad postures.

Exoskeletons are adaptable and do not inhibit the order picker from the frequent work process but provide physical assistance to the order picker. Thus, the order picker can perform tasks more frequently without the risk of injury. In contrast, augmented vibrotactile feedback on postures can be applied that does not support the order picker directly. Instead, when performing tasks in bad postures, this feedback, generated by a smart workwear, supports the correction of posture and thus reduces the load during order picking (Lind et al., 2020).

Exoskeletons are used to reduce the physical load of order pickers, but experiments have also shown that back muscle activity is reduced only moderately (approximately 10%) (Motmans et al., 2019). Instead, using an exoskeleton was suggested as the last action to reduce the physical workload because of limited support (Motmans et al., 2019). This was also because of the difficulty in user acceptance of exoskeletons that was identified (Motmans et al., 2019) and the limited time in which the exoskeleton actually supports the order picker but has to be worn during an entire shift (Winter et al., 2019). On the contrary, smart workwear providing posture feedback showed a reduction in worktime in different postures (high trunk inclination, high arm elevation) and generated learning effects on the humans who used it (Lind et al., 2020).

5.1.5 Confirming the pick

In all OPSs, it must be ensured that the correct item is selected. Therefore, the pick can be confirmed for quality reasons and the order pickers can be trained to pick the right items. Confirming the pick reduces the possibility of selecting wrong items and is the signal to obtain information on the next pick location in some pick-by-systems. Two possibilities are available to support the order pickers in this process step: 1) support the order picker by equipping them with a technology that takes over this task and provides a hint if errors occur – RFID and the IoT are primarily used for this purpose, or 2) sensitise and motivate the order picker to perform this process better – gamification is particularly relevant here.

For the first possibility, RFID pick-to-light systems have become popular; the order picker wears an RFID-glove that reads the pick location and prevents the picker from selecting the wrong item in manual picker-to-parts systems (Andriolo et al., 2013, 2016). Other systems that rely on RFID or IoT use applications for mobile devices that support the order picker in real time, for example, in updating the pick lists automatically (Sham et al., 2018).

For the second possibility of confirming a pick, gamification is considered relevant. Gamification operates within the entire order picking process and aims to generate higher motivation and job satisfaction (Plakas et al., 2020a; Ponis et al., 2020). Gamification uses real-time information from the shop floor to display different pieces of information, either on screens or individually, to the order picker (Bräuer and Mazarakis, 2019; Klevers et al., 2016; Putz et al., 2019). In particular, badges and leaderboards are investigated to improve the pickers' performance in manual picker-to-parts OPSs using gamified competition and achievement incentives (Bräuer and Mazarakis, 2019). Additionally, different goal-setting models are discussed, applying either competitive goals, achieving standardised goals (Ponis et al., 2020), or self-set goals (Passalacqua et al., 2020). Hence, order pickers' attention can also be improved for pick confirmation as part of the gamified task (Klevers et al., 2016).

Gamification is also discussed to be applied within AR systems that combine the benefits of both gamification and AR in searching the item location and ensuring the correct location.

The application of these systems affects the mental workload of order pickers. By supporting quality checks using, for example, an RFID-glove, the mental load of order pickers is reduced and errors are prevented (Andriolo et al., 2016). In addition, gamification can generally improve HF in the workplace (Putz et al., 2019), particularly concerning psychosocial factors that are rarely addressed in most other scenarios. For example, gamification has been reported to increase employee engagement and is promising to also impact the long-term intrinsic motivation of order pickers and decreasing fatigue (Passalacqua et al., 2020; Plakas et al., 2020a; Ponis et al., 2020). Nevertheless, careful system implementation is mandatory to increase motivation because negative side effects (such as technology rejection) are possible (Bräuer and Mazarakis, 2019).

5.1.6 Economic effects

The most basic economic target is the order picking efficiency. Most of the supportive technologies result in more efficient processes by reducing unproductive times for searching or confirming the pick, or they result in fewer errors during order picking. For example, AR-supported OPSs focus on reducing search and quality control times. Hence, process quality increases and errors are reduced (see, e.g. Iben et al., 2009), which also depends on the exact system design, for example, information provision method (Renner and Pfeiffer, 2020). However, even before applying the AR support system, costs can be reduced by applying methodological decision processes for hardware selection that are grounded on a human-centred design approach (Egbert et al., 2020). This is necessary as there are restrictions according to, for example, challenging software programming, user acceptance and investment costs (Egbert et al., 2020). Gamification promises to increase order pickers' motivation and decrease fatigue, thus increasing the productivity and efficiency of order picking (Plakas et al., 2020a; Ponis et al., 2020). VR systems can be applied to train order pickers outside the real-world environment, resulting in improved efficiency during ramp-up processes (Elbert et al., 2018). Similarly, IoT and RFID-based systems are particularly valuable in terms of picking quality because preventing picking errors increases the order picking efficiency and effectiveness (Andriolo et al., 2013).

In addition to these direct economic effects, indirect effects due to HF improvements are expected. For example, adaptive planning systems aim to reduce throughput times by balancing the workload (Trab et al., 2017; Wang et al., 2013) and increasing safety in the warehouse. Additionally, head-worn displays in AR-supported OPSs enable both hands to handle goods and receive information simultaneously. This reduces bad postures during material handling in the warehouse and reduces the injuries and illnesses of employees (Friemert et al., 2016). Additional ideas were also examined for exoskeletons, although other actions should be preferred before using them (Motmans et al., 2019). However, some authors mentioned difficulties and limitations in the application of AR, such as eye strain symptoms (Grubert et al., 2010) or increased mental demands, which can have a potential negative impact on performance and safety (Kreutzfeldt et al., 2019b).

In addition to the economic effects of physical ergonomics, gamification methods support motivation to increase the efficiency and accuracy of picking (Putz et al., 2019). Using adaptable organisation systems that directly rely on the physiological parameters of order pickers, stress can be reduced and motivation increased; thus, efficiency can be improved (Kajiwara et al., 2019). Furthermore, health problems and the resulting absence of order pickers, which are costly, can be reduced (Mättig et al., 2018).

In contrast to these, mostly positive economic effects, only a few studies have addressed investment costs for these systems, which might hinder a cost-efficient implementation in practice. For example, AR-based systems require investments that might not be profitable in small warehouses, particularly when combined with RFID technology (Nagda et al., 2019). Therefore, more affordable and scalable AR-supported OPSs are under development with the aim of providing the above-described benefits for all warehouse sizes using the Raspberry Pi platform (Fang and An, 2020; Nagda et al., 2019).

5.2 Human-reduced order picking systems

Human-reduced OP 4.0 relies on highly automated and autonomous technical systems, resulting in parts-to-picker or fully automated OPSs. Partly automated OP 4.0 systems combine the approaches of automation technology for higher efficiency, but also consider the effects on HF to maintain a balance between them. Within these OPSs, interactions with order pickers occur at every transition between the substituted and unsubstituted tasks. In contrast, OPSs can rely on automation technology for execution and significant parts of control tasks. Furthermore, in substituted tasks, new tasks occur for human order pickers, for example, for monitoring or troubleshooting.

5.2.1 Preparing the pick tasks

Preparing and planning the pick task are also relevant in these OPSs. Highly automated systems that substitute the actual task execution affect the pre-processing or post-processing workplaces. Hence, they substitute human work, trivialise it, or require manual human intervention if an error occurs (Huang et al., 2015). Although several articles for highly automated systems were found in the database search, most articles in this field did not address the effects on order pickers. Hence, for human-reduced OPSs, no contribution was identified that investigated the role of human operators in the process of preparing automated picks or supervising the necessary planning tasks.

5.2.2 Travelling and transporting

Travelling and transporting items are important for human-reduced OPSs. AGV-based RMFSs have been identified as a dynamic field of research in which racks with goods are moved to order pickers. Therefore, human tasks are substituted by automation technology and travelling and transportation tasks are no longer performed. In RMFSs, the racks are brought to the picking station, and the order picker searches for the pick location and grasps the items. The order picker waits at a pick station for the next rack to be processed. RMFSs are frequently addressed in the literature and can be considered to be a more adaptive, scalable and flexible type of automation compared with traditional stacker-crane systems (Huang et al., 2015). However, the consideration of the interaction of order pickers with the system is remarkably absent in most scenarios.

In contrast, there is initial research that addresses the interaction of humans and AGVs in an advanced human-reduced OPS comprising the transportation of goods via AGVs and the control of the AGV via a brain-computer interface (Fiolka et al., 2020). This allows the order picker to work with both hands free and control the AGVs at the same time.

Ergonomic considerations are scarce and most studies have focused on physical HF. For example, the possibility of injuries being reduced because of fewer physical tasks to be performed in human-reduced OPSs has been indicated (Bogue, 2016; Yuan and Gong, 2016). Additionally, physical HF are addressed by focusing on safety issues for order pickers, for example, addressing the substitution of safety fences (Krug et al., 2016; Lager et al., 2019). The mental workload is also promised to be reduced with such systems owing to reduced searching effort and reduced task variety (Kudelska and Niedbał, 2020). Perceptual or psychosocial consequences were not investigated in the sample for RMFSs. However, mental and psychosocial HF have been addressed with regard to the brain–computer interface control of AGVs. This type of control requires concentration over longer periods which could lead to fatigue on the one hand, but learning effects are expected on the other hand; in addition, the hedonic qualities of the new control system impacts psychosocial HF (Fiolka et al., 2020).

5.2.3 Searching the pick location

Depending on the extent of automation, searching tasks can be impacted as well. Two different approaches can be identified: 1) humans pick the items that are highlighted by the automated OPS and 2) robots pick the items that are searched by the human operator.

Concerning the first approach, partly automated OPSs (particularly RMFSs) were observed to be expanded. An intelligent pick-to-light system was identified, which can be considered a substitution of searching tasks for order pickers (Su et al., 2019). Within this application, the human performs the picking task within a shelf that carries different items. By highlighting the correct item location, searching is substituted, and the human picks the item out of the highlighted location.

In the second approach, human operators are applied to perform the mental task of searching the correct item in a cluttered environment, and by defining the right item over a graphical interface, a robot executes the actual picking operation (D’Avella and Tripicchio, 2020). The application can be used to include impaired operators in industrial work environments despite their disabilities, thus having positive impacts on HF (D’Avella and Tripicchio, 2020).

5.2.4 Picking the items

Picking an item is a process step that is most often still left to order pickers in human-reduced OPSs. The task performed is reduced to only a few movements, and the order picker performs the picking tasks at higher frequencies. The actual pick-execution differs according to the applied system. In most scenarios, the actual pick is comparable to the pick in manual picker-to-parts OPSs because RMFSs offer a wider range of storage locations presented to the picker compared with traditional stacker-crane-based systems in which single boxes are provided at a fixed picking workstation. Although an RMFS can be considered to be a more adaptive type of AS/RS, and is thus considered relevant, a study comparing AS/RS with an AGV-based RMFS observed that the last system had worse ergonomics in terms of risks of upper limb disorders compared with the first one because of very high and very low picking slots (Lee et al., 2018). Hence, this type of OP 4.0 system might also have partly negative effects on ergonomics in contrast to other AS/RS, although the repetition cycles vary more. In contrast, perceptual HF are affected by environmental factors that differ in partly automated OPSs, such as reduced noise and workstations that are better equipped than it would be possible in picker-to-part order picking, for example, with improved lighting (Huang et al., 2015).

In addition to the impacts a partly automated OPS has on order pickers, articles that address the effects of high levels of automation on humans during automated picking are scarce. Contributions in this field often focus on various topics that must be addressed for efficient fully automated order picking, such as motion planning and grasping of different, oddly shaped goods, particularly in unstructured environments (Correll et al., 2018). The resulting effects on side processes, such as pre-packaging or similar processes, remain unaddressed.

5.2.5 Confirming the pick

Finally, in human-reduced OPSs, picks must be confirmed and checked for quality reasons. Therefore, the easier provision of quality checks of the tasks (for example, because of complete substitution of the pick by the automation technology, or because of the substitution of the quality check procedure) is relevant and reduces the mental load. For example, the identified combined intelligent pick-to-light OPS considers the physical and mental workloads as direct consequences of an intelligent system that, in addition to the substitution of physical work tasks, substitutes mental tasks such as item identification and searching.

5.2.6 Economic effects

The partial automation of OPSs identified within the sample in this category aims to reduce the order pickers travelling time, which increases the system efficiency. The use of mobile robots promises to be more efficient than manual OPSs in terms of throughput (Huang et al., 2015); thus, operating costs can be reduced (Bogue, 2016). Additional economic parameters, such as space utilisation (Huang et al., 2015), are considered to be improved by such systems. On the contrary to efficiency improvements, investment costs are still high and thus implementing such systems can be risky for enterprises (Huang et al., 2015).

Until now, for fully automated OPSs that can be highly efficient and can thus optimise the warehouse output, several challenges have been encountered that prevent a broad, profitable application. Low volume/high mix environments, such as those in e-commerce, are challenging (Huang et al., 2015), especially referring to still limited grasping capacities for tightly packed goods that are needed for high storage densities (Correll et al., 2018). In addition to that, reliability needs to be assessed critically (Correll et al., 2018). The resulting limitations, such as the use of standard boxes, reduce space utilisation and result in necessary pre- and post-processing. These issues might also explain why investment costs and potential ROI have been scarcely considered within the identified studies.

Additionally, the changing roles of human order pickers, which are particularly relevant with higher levels of automation, remain unaddressed in most scenarios. Although certain planning and physical tasks can be substituted by automation technology, many tasks remain for human operators, such as quality control, pre- or post-processing, supervising and trouble-shooting and the highest levels of automation have not yet been achieved. Hence, order pickers are crucial for such systems, affecting the economic profitability. However, very few articles in the sample addressed this discussion.

5.3 Hybrid order picking systems

A HOPS exists if autonomous systems and human order pickers work together on one shopfloor (Kauke et al., 2020) for a joint target. These systems can be of various types, for example, parts-to-picker, picker-to-parts and even fully autonomous in combination with manual OPSs. Although fully autonomous order picking robots that share an order picking task with a human order picker were not identified within the study, different applications have been found to be relevant.

5.3.1 Preparing the pick tasks

Planning and preparing a pick task are still important topics in HOPSs. Because of the various interaction modes possible in HOPSs, planning problems become even more complex (for example, because of a joint robot–OPS and human–OPS workload scheduling or order batching). This may also affect human intervention and system interactions. However, because there is a strong relationship between planning and task performance in a HOPS, relevant contributions are discussed jointly in the subsequent sections, where necessary.

5.3.2 Travelling and transporting

Travelling and transportation are two tasks in HOPSs that can differ in many aspects. People and goods can be transported in different relationships; automation systems can guide the order picker or vice versa, and different technologies can be used.

AGV-based systems are particularly relevant here. Different applications of AGV-based HOPSs have been identified, all of them as picker-to-parts systems, which is in contrast to human-reduced OPSs. In these systems, AGVs travel to the pick location, wait for the order picker to pick the item and transport the picked goods either to the next location or back to the depot. This task can be assigned to one or several order pickers (Rey et al., 2019; Wang et al., 2019). Additionally, AGVs can be routed independently from order pickers or follow them (Masae et al., 2020b). Another type of transportation of goods considers zones where the AGV can facilitate the transportation of picked goods between different pick zones that are operated manually (Zou et al., 2019).

In this shared workspace of AGVs and order pickers, human–robot interaction is important and sensors and AR are used for safety reasons. For example, the planned paths of AGVs can be visualised for human order pickers, and virtual safety walls can be created (Papcun et al., 2019). Hence, HF improvements are aimed at increasing safety with the use of AR as well as reducing the physical workload as a result of fewer transportation tasks (Papcun et al., 2019). Although psychosocial aspects are mentioned, describing the performance of order picking tasks as a waste of human talent (Papcun et al., 2019), these concerns are not addressed by the resulting OPSs.

5.3.3 Searching the pick location

As mentioned earlier, applying a HOPS results in various systems, which in turn affect the searching tasks. Although many methods are possible, only one simple method has been identified in the literature. Because AGVs can be used to travel to pick locations autonomously, the order picker is not required to search the pick location spending a long time as the AGV is already waiting right in front of it (Rey et al., 2019). The search process is then limited to the location of the AGV.

5.3.4 Picking the items

The actual pick was not addressed in depth within the relevant contributions of this sample. In most scenarios, the investigated system could be considered either an Operator 4.0-related or a human-reduced OPS. However, one contribution was identified that considered a hybrid pick-and-sort approach in which a human order pickers picks an item and a cobot on the picking cart performs the corresponding sorting task (Fager et al., 2020b). Using this solution, the order picker is relieved of this additional task and can further concentrate on picking the correct items.

5.3.5 Confirming the pick

In contrast to the actual picking task, a HOPS was observed to affect pick confirmations and quality control tasks. Because of the interaction with AGVs, sensors that identify items can be applied. This can be done, for example, by weighing sensors that compare the weight of the item and the expected one (Rey et al., 2019). Both tasks, searching the pick location and confirming the pick, can be impacted in a HOPS and thus also related HF.

5.3.6 Economic effects

The application of a HOPS has different targets. The main economic objective is better utilisation of human and robot capabilities, thus increasing the system efficiency while reducing errors and ergonomic risks (Papcun et al., 2019; Wang et al., 2019). Additionally, splitting tasks in combined picking and sorting systems can reduce the human workload and lead to economic benefits, especially when extensive sorting is required (Fager et al., 2020b). This, in turn, also means that economic preferability is limited in case only a few sorting tasks need to be performed. HF objectives can be achieved because of the reduced physical load, which increases safety and thus improves the economic results (Papcun et al., 2019;

Rey et al., 2019). However, the human physical load is considered to be a trade-off between system throughput and investment in robots (Wang et al., 2019). Additionally, further research was pointed out as necessary that also impacts economic figures, such as the impact of uncertainties and human-robot safety issues (Wang et al., 2019).

Furthermore, HOPSs can affect the system flexibility because the system configuration has significant effects on the OPS, for example, by benefiting from the human flexibility and maximising robot efficiency (Zou et al., 2019). However, robot utilisation can be in a trade-off with the human travel distance depending on the OPS. Practical and experimental applications are rare and most systems are simulated or mathematically modelled under limiting assumptions and constraints.

6. Discussion

6.1 Implications of this review

The results obtained can be reflected in terms of the sociotechnical OPS framework (see Figure V-1). This review highlights a variety of key tasks and systems in OP 4.0. Along the three dimensions identified, the main insights into technologies, HF and economic effects can be summarised as follows:

Technologically, OP 4.0 is grounded in different supportive and substitutive technologies. Supportive systems mainly focus on AR systems and IoT-based planning, control and monitoring systems. The technical system design has an impact on the level of automation; for example, AR systems range from simple text-visualising devices to highly adaptive and context-sensitive ones and are thus applicable to different tasks and needs of human order pickers. The identified supportive systems focus on the performance of human order pickers, for example, by reducing unproductive times and workload (Friemert et al., 2019; Iben et al., 2009). These systems can extend the human capabilities and enable them to work faster and be more productive. Most supportive systems are digital ones; physical ones, such as exoskeletons, received less attention and did not show great potential within the studies included in the sample. This could be due to the fact that these studies are mostly pilot studies and the industrial usage of, e.g. exoskeletons is still in its infancy. For instance, early exoskeletons were perceived as uncomfortable (Winter et al., 2019). Interestingly, the physical aspects are also targeted using supportive and digital systems by providing training, avoiding incorrect postures, measuring the load and adapting the work accordingly to reduce costly work-related injuries (see, e.g. Elbert et al., 2018; Lind et al., 2020). Thus, a crossover exists between digital systems developed for cognitive automation and physical work processes.

Substitutive systems, in contrast, have received less attention in this review, as few contributions consider the impacts of technology on human order pickers. AGVs are predominantly discussed because fully autonomous pick-robots are still not common for many pick tasks. Nevertheless, in certain environments and for certain tasks, these robots are already applied in practice with the aim of cooperating and collaborating with humans (see, e.g. Zalando SE, 2019) and further robot-based warehouse automation systems are developed for different tasks (see, e.g. Boston Dynamics, 2021). The identified contributions within the sample focus on safety and ergonomic risks; however, psychosocial impacts, such as order pickers' motivation or job satisfaction, are mostly neglected, and long-term studies on how order pickers perceive their work in these systems are still rare. This occurs despite the fact that HOPSs and human-reduced OPSs may find their way into an increasing number of warehouses in the future and will have an enormous impact not only on directly affected employees, but on the warehouse as a whole. The practice has already taken the first steps here, but they were only accompanied to a limited extent in this study's identified sample.

Summarising the impact of technologies on HF, the three reviewed OP 4.0 systems are presented in Table V-6 with representative/significant technologies used. These are clustered with HF aspects that are affected and the relevant tasks are indicated in brackets. As already indicated, the physical and mental workloads are frequently addressed, but the corresponding effects on psychosocial aspects such as motivation, job satisfaction and job autonomy remain mostly unaddressed within all the relevant OPSs reviewed. In addition, technology acceptance considerations focus on Operator 4.0 OPSs, where order pickers are directly equipped in most cases (Motmans et al., 2019). Organisationally, the identified OPSs do not fundamentally differ from picker-to-parts or parts-to-picker OPSs in most scenarios although they can enable new forms of human–technology interaction. Additionally, HOPSs outstand in this regard, because this type of OPSs potentially goes beyond traditional picker-to-parts or parts-to-picker systems.

Table V-6: Applied technologies per OP 4.0 system and task.

	Operator 4.0 OPS	Human-reduced OPS	Hybrid OPS
Physical OP Tasks (setting-up, walking, grasping, Transporting)	Exoskeletons, Wearables	AGVs, Robots, Sensors	AGVs, Robots
Mental OP Tasks (planning, checking)	AR, VR, IoT, Big Data	Sensors, AGVs	Sensors, AR
Perceptual OP tasks (identifying)	AR, Pick-to-Light, RFID	Sensors	Sensors, AR
Psychosocial OP Tasks (interacting)	Gamification, Apps	Sensors	Apps

Finally, the economic effects of the applied systems are not the focus of research in most cases. Investments in technology require a holistic economic analysis, which is absent in most studies, and the economic applicability of technologies is rarely discussed. The exemptions critically reflect on the use of AR systems in small- and medium-sized warehouses (Nagda et al., 2019).

6.2 Future research directions

Overall, it appears that a holistic view of possible OP 4.0 systems has not yet been performed in parts of the topic; instead, individual aspects of the process with single technologies and few organisational forms are focused on, not considering the overall possible benefit of the resulting sociotechnical OPS. Although it must be recognised that this is vital research in this field and new applications are proposed, also considering the impacts on HF and economic results at least conceptually, there are probably multiple technologies that have not yet attracted attention. The literature addressing particular technologies is very valuable for identifying system characteristics but can also result in an innovation pitfall when the impacts on organisations and humans are left aside (Neumann et al., 2021). Because of the increasing complexity of OP 4.0, a drift to unsafe states (Rasmussen, 1997) must be avoided by extending the management capabilities in order picking and systematically monitoring and understanding the systems' behaviour, including the human order pickers. To fulfil our third research objective, we outline future research opportunities. As we characterised OPSs as sociotechnical systems, all components of a sociotechnical system must be considered for a holistic view on OP 4.0 and all technology-induced changes that we identified within the sociotechnical OPS framework (Figure V-1) need to be addressed carefully. Hence, to structure these future research opportunities in accordance with the theoretical foundation outlined in Section 2 and Figure V-1, we follow the systematics of the well-established framework of sociotechnical systems of Bostrom and Heinen (1977) (Figure V-13) to discuss future research opportunities accordingly for the three identified OP 4.0 OPSs as these can have different impacts on the sociotechnical OPS.

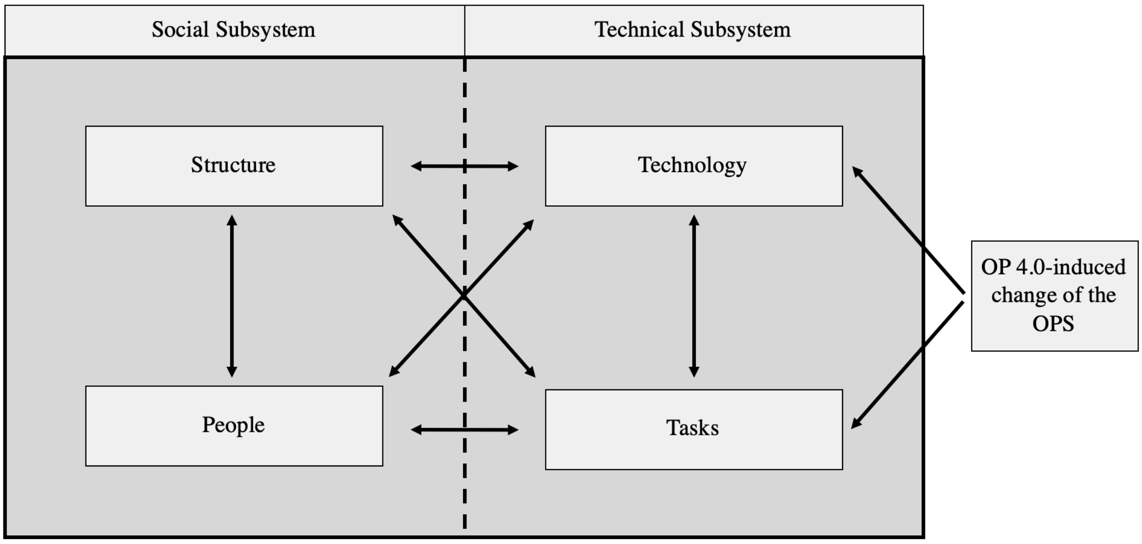

Figure V-13: Categories of possible research opportunities in OP 4.0.

The interacting social and technical subsystems are impacted directly or indirectly by the change towards an OP 4.0 OPS, which has an impact on the system performance and thus on the economic profitability. The review provided detailed insights into the three identified OPS types, but aspects that have not yet been considered are addressed subsequently.

6.2.1 Research opportunities in Operator 4.0 OPS

Technical Subsystem: Within the review, most of the identified contributions relate to Operator 4.0 OPSs. Although a large variety of technologies have already been investigated for multiple tasks, some aspects have received less attention or have not yet been considered. On the one hand, research over longer periods of usage is recommended to study the long-term impacts on the social subsystem and to investigate how performance impacts behave over time. On the other hand, Operator 4.0 OPSs might apply several technologies at the same time that might support or counteract one another; for example, gamification was found to be applied together with AR systems, as these might support one another, while on the other hand, applying gamification together with simple automation technologies, such as

AS/RS, could counteract one another as the performance of the operator is limited by the AS/RS, which could be demotivating. In addition to that, the application of, e.g. exoskeletons, gamification and AR systems together could lead to higher resistance of the operators, which should be investigated further to support practitioners in selecting profitable combinations of technologies without the risk of a “technology overload” of the human order pickers. Some tasks could be further supported, especially regarding the physical activities of transportation and picking. In addition, other technologies like smart lighting systems have not been studied in detail in the literature although there are several opportunities to support humans in Operator 4.0 OPS with this technology (see Füchtenhans et al., 2021).

Social Subsystem: According to these findings, the social subsystem is impacted in diverse ways. This is especially related to the structural/organisational aspects as well as the complex interactions of technologies with humans. According to the task support and allocation of supportive technologies, a change in the role of order pickers is possible and should be further investigated, so enterprises can anticipate the expected changes. This also impacts psychosocial HF, which could be further investigated according to their effects on, e.g. job satisfaction, learning and skill requirements and motivation to use the technologies. For example, we found that the introduction of gamification can lead to technology rejection by the order pickers (Bräuer and Mazarakis, 2019).

Economic impacts: The economic impacts are already in the focus of Operator 4.0 OPSs (see, e.g. Nagda et al., 2019), but can still be investigated further. This, for example, concerns the investment costs of systems and their potential benefits in different tasks and environments. This is especially important when focusing on the indirect effects that result from adaptions of the social subsystem to changes in the technical subsystem. Research on the interactions of multiple technologies and HF should receive further attention in research owing to the possibility of simultaneously applying diverse technologies to support order pickers. In addition, research on the direct and especially indirect economic effects over a long period of time is recommended, taking investment costs into consideration.

Outlining specific research directions, the following questions seem important:

- *How does the interaction of multiple technologies affect HF? Are there possible positive or negative effects of simultaneously applying diverse technologies to support or substitute certain tasks of order pickers?*

- *How do indirect effects of the application of certain technologies affect the return on investment and the total cost of ownership in the long run? Owing to the large amount of research on AR applications, especially AR seems to be important to be investigated also from an economic point of view.*

6.2.2 Research opportunities in Human-reduced OPS

Technical Subsystem: In human-reduced OPSs, RMFSs are the dominant application within the identified literature, possibly owing to their prominent distribution in practice, for example, in Amazon warehouses (Bogue, 2016). However, these systems focus on reducing travelling and transportation tasks, and further tasks may require additional technologies to automate them. Contributions focusing on, for example, autonomous picking robots are considered less often, but are highly recommended as they gain importance in practice and become increasingly common in the market (see, e.g. Boston Dynamics, 2021).

In this regard, the different tasks are considered to a different extent, and there is a lack of studies on preparing pick tasks, picking and confirming the pick. When considering the task substitution in the identified human-reduced OPSs, the impact on the social subsystem is comparable to that of traditional stacker-crane-based OPSs. This occurs although other, more advanced systems, might be possible, such as those concerning the picking itself and processing the picked items, with new impacts and design requirements for the social subsystem.

Social Subsystem: In this regard, the focus is on physical and mental HF while perceptual and psychosocial HF are addressed less frequently. One example that also addresses psychosocial HF are an advanced human–technology interface (Fiolka et al., 2020), but examples are scarce and should be investigated further.

In addition, the impacts on the task structure and organisation and the respective outcomes on, e.g. task autonomy, task significance and task variety, should be further examined to provide examples of workplaces and new roles for order pickers in human-reduced OPSs. In addition to the sole substitution of humans in this process, there might be a shift of tasks, possibly to more supervisory ones, which should be further examined.

Economic impacts: The economic impacts of human-reduced OPS investments in automation systems are not the focus of most studies compared to system characteristics such as higher space utilisation. In this regard, more holistic indicators such as ROI and total cost of ownership are interesting aspects that are currently rarely considered in the literature with only a few exceptions. In particular, a holistic view of the system performance and efficiency, together with its impact on the social subsystem, is relevant. Although high performance is possible, for example, in RMFSs, higher-skilled jobs might be necessary, which are costlier and affect the cost–benefit ratio. In addition, applications that automate most or all the tasks of the order picking process should be considered in more depth taking into account the economic aspect. In this view, scalability, adaptability and investment costs should be taken into consideration in the identified dynamic business environments of warehouses.

Outlining specific research directions, the following questions seem important:

- *How can the physical preparation of the picking tour, e.g. loading and unloading a picking cart, be automated also considering HF impacts?*
- *How can human-reduced OP processes (in different levels of automation) be organised under real-world conditions and which shift of tasks and skills should be expected by the enterprises that needs to be anticipated prior to an implementation?*
- *How can practitioners be supported to find the right human-reduced OPS in respect of the scalability, adaptability, investment and running costs of the diverse possible systems?*

6.2.3 Research opportunities in Hybrid OPS

Technical Subsystem: The review identified interesting HOPSs, but it became obvious that major aspects have not yet been addressed in the technological subsystem. First, fully autonomous pick robots that cooperate or collaborate with order pickers need to be investigated considering their impacts on the human factor. Some initial systems are available on the market but have not yet been investigated considering these aspects (see, e.g. Zalando SE, 2019).

Additionally, there is a strong focus on transportation tasks within HOPS, as identified in the review. Only a few applications consider further applications, such as sorting (Fager et al., 2020b) or pick confirmation (Rey et al., 2019) and only to a limited extent. Therefore, we recommend research that systematically addresses different task allocations between robots and pickers in order picking with different robot characteristics and a subsequent analysis of impacts on HF. In addition to that, the support of order pickers in a HOPS did not find attention yet but might be necessary for an optimal system performance, for example, owing to increased human-technology interaction. Therefore, besides physical HF and mental demands, perceptual and psychosocial aspects should also be taken into consideration.

Social Subsystem: HOPSs have strong impacts on the social subsystem as they involve a deep human–technology interaction. Until now, most contributions have focused on physical HF considering, for example, reduced transportation tasks for order pickers. However, the perceptual, mental and psychosocial aspects are also influenced in HOPSs: task variety and autonomy for humans can, for example, be reduced, but also extended in a HOPS with different effects on motivation and job satisfaction depending on the chosen organisation. Impacts on skills and learning effects are expected and it would be interesting to investigate this aspect in future research. In addition, studies of technology acceptance are recommended to investigate how to implement a HOPS avoiding that order pickers reject the system or worry about the change.

Economic impacts: As economic impacts have still only been identified on a conceptual basis and the indirect effects on HF have not yet been considered, case studies are relevant to evaluate the profitability under real-world conditions. In such studies, the direct outcomes are relevant, which could be limited by interruptions of the work process due to technology breakdowns. In addition, the effects on, for example, the number of sick days, job satisfaction and the development of the performance of human employees should be considered and how this performance could possibly be limited by the respective technical system.

Outlining specific research directions, the following questions seem important:

- *Which are the most efficient task allocations between humans and robots and which market-ready HOPS solutions enable this?*
- *How can HF be considered and improved in human-robot collaboration in order picking?*
- *How is the acceptance of the technology to be assessed, also considering changing skill requirements for operators?*

7. Conclusion

This article contributes to the scientific and managerial knowledge of OP 4.0 by extending the current insights into various aspects. In this study, order picking is investigated as a sociotechnical system that is exposed to the extensive effects of Industry 4.0, on the logistics sector. A holistic study and a precise definition of OP 4.0 are provided. A systematic review of OP 4.0 systems was performed, and the main effects on the order picking process are discussed herein. This paper is particularly valuable as it, based on the literature review, systematically analyses order picking from a processual perspective, considers the possible technological effects within the sociotechnical OPS framework and subsequently investigates specific OPSs. Hence, a transition from an unstructured and only loosely defined field of possible developments to a systematic and targeted development path is enabled. In outlining open research opportunities, detailed insights into possible future research fields are provided, which must be addressed to avoid an innovation pitfall. Therefore, researchers and practitioners are provided with a holistic framework, which requires consideration in OP 4.0 system development. Order pickers often have only limited possibilities to influence their workplace, which is why one might argue for the responsibility of engineers and managers to design as good workplaces as possible for the order pickers without counteracting the work safety or economic targets. The derived sociotechnical OPS framework can therefore guide practitioners and researchers toward designing new OPSs, supporting research paths and application guidelines. The level of automation and the tasks supported or substituted for humans are relevant parameters for the further development of OPSs.

Although the study revealed new and important insights into future OPSs, it also had limitations. First, the sample generation process aimed at explicitly considering HF in OPSs to address the research gap of technology interaction with HF in order picking. This condition for the sample derivation resulted in the exclusion of articles that might subordinate HF. Hence, smaller blind spots may be present. Second, the focus was on technologically advanced systems and not on traditional manual OPSs. In a future study, this limitation can be addressed to determine whether some of the results achieved in these systems are transferable. Third, as a final consequence, the research methodology relies on subjective decisions. Although the research process of a systematic literature review is applied to provide a reproducible method and guarantee scientific rigour, it is not a quantitative measurement (for example, when applied to a content analysis-based approach).

Nevertheless, we believe that a qualitative content-sensitive approach is necessary to extract the interactions of parameters instead of extracting the discussed topics solely. Finally, the analysis is based on a conceptual definition of OP 4.0 based on sociotechnical systems theory, which can be critically discussed.

Appendix

Table V-7: List of sampled articles and categorisation according to OP 4.0 system.

Article	Research topic and key technology	Focused process step	OP 4.0 system*
Andriolo et al. (2013)	Feasibility of **RFID** pick-to-light system	Searching	OPe4.0
Andriolo et al. (2016)	Comparison of **RFID** pick-to-light system with other picking support systems like pick-by-voice	Searching	OPe4.0
Avdekins and Savrasovs (2019)	Developing a **smart, IT-based** storage assignment strategy to optimise order picking performance	Set-up	OPe4.0
Baechler et al. (2015)	Developing a **projection**-based order picking support for impaired employees	Searching	OPe4.0
Baechler et al. (2016)	Evaluation and possibilities of a **projection**-based order picker support for impaired employees	Searching	OPe4.0
Battini et al. (2015)	Comparison of different pick-by-technologies including **RFID** pick-to-light in order picking	Searching	OPe4.0
Bogue (2016)	Overview of storage **robot** applications recently introduced to the market	All	HR OPS
Bräuer and Mazarakis (2019)	Comparison of the effects of two **gamification** elements in order picking	All	OPe4.0
Choy et al. (2017)	Developing an **RFID**-based storage assignment decision support system	Various	OPe4.0
Correll et al. (2018)	Results and lessons learned from a competition for the development of **robot** order picking	All	HR OPS
D’Avella and Tripicchio (2020)	Testing a supervised stowing system in which the operator chooses the item to be picked and the **robot** performs the physical pick	Picking	HR-OPS
Egbert et al. (2020)	Decision support model for **AR** hardware selection in order picking	Searching	OPe4.0
Elbert et al. (2019)	User evaluation of **VR** for training in order picking	All	OPe4.0
Elbert et al. (2018)	Transferability of **VR** training to real-world order picking	All	OPe4.0
Elbert and Sarnow (2019)	Cognitive ergonomics for using **AR** in order picking considering information availability	Searching	OPe4.0
Fager et al. (2020b)	Modelling **cobot** sorting in manual order picking and impacts on costs	Picking	HOPS
Fang and An (2020)	Development of a scalable wearable **AR**-based order picking navigation system	Searching	OPe4.0
Fang et al. (2019)	Development of a scalable, low-cost pick-by-**AR** system	Searching	OPe4.0
Fiolka et al. (2020)	Study of an **AGV**-supported OPS with a brain–computer-interface control	Travelling	HR-OPS
Friemert et al. (2016)	Evaluation of **AR** impact on physical workloads in order picking	Picking	OPe4.0
Friemert et al. (2019)	Acceptance of **AR** usage in order picking and impacts on physical and mental workloads	Searching/ Picking	OPe4.0
Friemert et al. (2018)	Comparison of postures during order picking in **VR** and in real-world environments	Searching/ Picking	OPe4.0
Funk et al. (2016)	Usability of head-worn in-situ **projection** for augmented order picking	Searching	OPe4.0

Funk et al. (2015)	Usability of mobile **projector augmentation** for order picking	Searching/ Confirming	OPe4.0
Gajšek et al. (2020)	Impacts of diverse technologies, like **RFID** in picker-to-parts order picking, on human factors	Various	OPe4.0
Grubert et al. (2010)	Long-duration impacts of **AR** usage on order pickers	Searching	OPe4.0
Guerin et al. (2019)	Cognitive work analysis-based modelling approach of **human–machine cooperation** in Industry 4.0 exemplified by order picking processes	All	OPe4.0
Guo et al. (2015)	Experimental investigation of **AR**-supported order picking	Searching	OPe4.0
Herzog et al. (2018)	Optometric issues in **AR**-supported order picking	Searching	OPe4.0
Huang et al. (2015)	Role and possibilities of diverse **robot** applications in e-commerce logistics	All	HR-OPS
Iben et al. (2009)	Comparison of paper-supported and **HMD**-supported order picking efficiency	Searching	OPe4.0
Kajiwara et al. (2019)	Predicting emotion and engagement during order picking related to their impact on efficiency and human errors using **wearables**	All	OPe4.0
Kim et al. (2019)	Impact of display type and user interface in **AR** on order picking outcomes	Searching	OPe4.0
Kinne et al. (2020)	Questionnaire-based investigation of **passive exoskeletons** effects on human workload in an order picking context	Picking	OPe4.0
Klevers et al. (2016)	Development of a model to implement **gamification** applications	Various	OPe4.0
Kreutzfeldt et al. (2019b)	Impacts of gait and the pick support technology, between headsets and **smart glasses,** on the attention of participants in an order picking context	Various	OPe4.0
Kreutzfeldt et al. (2019a)	Evaluation of device-specific performance in order picking using **smart glasses** and headsets	Searching	OPe4.0
Krug et al. (2016)	Development of a **robot**-system for autonomous and human-friendly execution of simple robot picking tasks	All	HR-OPS
Kudelska and Niedbał (2020)	Simulation of warehouse performance with **AGV**-supported order picking task	Travelling	HR-OPS
Lager et al. (2019)	Architecture and research needs for reactive **robot** applications with a warehouse order picking use case	All	HR-OPS
Lee et al. (2019)	Developing a **smart picking monitoring system** with a focus on small and medium sized warehouses	Various	OPe4.0
Lee et al. (2018)	Comparison of HF impacts of different AS/RS, e.g. using **AGV**s	Travelling	HR-OPS
Liang et al. (2015)	Developing an automated pick **robot**	All	HR-OPS
Lind et al. (2020)	Evaluation of a **smart workwear** system to reduce physical loads during material handling	Picking	OPe4.0
Masae et al. (2020b)	Developing an optimal order picker routeing strategy for an **AGV**-supported order picking	Set-up / Travelling	HOPS
Mättig et al. (2018)	Evaluation of stress detection by measuring physiological data with **wearables** in order picking	Various	OPe4.0
Motmans et al. (2019)	**Exoskeleton** impact on posture and load during order picking	Picking	OPe4.0
Murauer and Gehrlicher (2019)	Method to evaluate the suitability of processes for **AR**-support in the order picking context	Searching	OPe4.0
Murauer et al. (2018)	Evaluation of confirmation methods in **AR**-supported order picking	Confirming	OPe4.0
Nagda et al. (2019)	Development of a cost-efficient **AR**-based order picking support	Searching	OPe4.0

Pang and Chan (2017)	**Smart, IT**-based storage location assignment strategy for travel distance reduction	Set-up	OPe4.0
Papcun et al. (2019)	**AR**-support tool for workers in **AGV**-served warehouses	Various	HOPS
Passalacqua et al. (2020)	Evaluation of **gamification** settings in order picking	Various	OPe4.0
Plakas et al. (2020a)	Proposition of an **AR**-based OPS in combination with gamification elements	Various	OPe4.0
Plakas et al. (2020b)	Case study of **AR** implementation	Searching	OPe4.0
Ponis et al. (2020)	Survey on the acceptance of **AR** and **gamification** in order picking	Various	OPe4.0
Putz et al. (2019)	Acceptance of **gamification** in order picking	Various	OPe4.0
Renner and Pfeiffer (2020)	Comparison of attention guiding methods in **AR**-supported OP	Searching	OPe4.0
Rey et al. (2019)	**AGV**- and app-based assistance for transportation of goods in manual order picking	Travelling	HOPS
Schwerdtfeger and Klinker (2008)	User studies to evaluate the usability of **AR** for order picking	Searching	OPe4.0
Schwerdtfeger et al. (2011)	User studies to evaluate the usability of **AR** for order picking	Searching	OPe4.0
Sham et al. (2018)	Development of a smart trolley application and use of **RFID** to reduce errors in order picking	Various	OPe4.0
Su et al. (2019)	Human-centred pick-to-light system in **RMFS** order picking environment	Various	HR-OPS
Terhoeven et al. (2018)	Acceptance and expectations of users concerning **AR**-supported order picking	Searching	OPe4.0
Thomas et al. (2018)	Comparison of a combined **RFID**- and **AR**-supported order picking method with traditional pick methods	Searching / Confirming	OPe4.0
Trab et al. (2017)	Control and monitoring of safety risks using **IoT**-applications in a warehouse	Various	OPe4.0
vom Stein and Günthner (2016)	**AR**-supported order picking for hearing impaired employees	Searching	OPe4.0
Walch (2008)	Order picker training in **augmented** and **virtual environments**	Searching	OPe4.0
Wang et al. (2019)	Developing a routeing strategy for a **robot**-and-picker-to-parts OPS	Set-up / Travelling	HOPS
Wang et al. (2013)	Developing a real-time synchronised **RFID**-based information system to balance the workload in zone order picking	Set-up	OPe4.0
Winter et al. (2019)	Investigating the impacts of **passive exoskeletons** on physical HF in an order picking context	Picking	OPe4.0
Wu et al. (2015)	Comparison of pick-by-light order picking with pick confirmation and an **AR**-supported order picking	Searching	OPe4.0
Yan et al. (2008)	Warehouse management system based on **RFID**-data to improve accuracy	Various	OPe4.0
Yuan and Gong (2016)	Investigation of **RMFS** concerning improvements in speed and throughput	All	HR-OPS
Zou et al. (2019)	Optimisation of a manual OPS with different zones connected by **AGV**s	Travelling	HOPS

**OPe4.0: Operator 4.0 OPS; HR-OPS: Human reduced OPS; HOPS: Hybrid OPS.*

VI. [Article 5] Hybrid order picking: conceptualisation and simulation of a joint manual and autonomous order picking system[6]

Authors: Winkelhaus, Sven; Zhang, Minqi; Grosse, Eric H.; Glock, Christoph H.

Order picking is a key process in supply chains and a determinant of business success in many industries. Order picking is still performed manually by human operators in most companies; however, there are also increasingly more technologies available to automate order picking processes or to support human order pickers.

One concept that has not attracted much research attention so far is hybrid order picking in which autonomous picking robots and human order pickers work together in warehouses within a shared workspace. This study aims to present a conceptualisation of such systems. In addition, a simulation model that considers various system characteristics and parameters, such as picker blocking, was developed to evaluate the performance of hybrid order picking systems. Our results show that these systems are generally capable of improving manual order picking operations in terms of throughput and cost. Based on the simulation results, promising future research potentials are discussed.

Keywords:

Warehousing, Collaborative order picking, Autonomous picking robot, Picker blocking, Agent-based simulation

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[6] This article has been submitted as Sven Winkelhaus, Minqi Zhang, Eric H. Grosse and Christoph H. Glock (2021): Hybrid Order Picking: Conceptualization and Simulation of a Joint Manual and Autonomous Order Picking System. Computers and Industrial Engineering. It is currently under review. This article has been slightly adapted for use in this dissertation, for example to ensure consistent spelling.

1. Introduction

During recent decades, warehouses have undergone significant changes with respect to the operating policies and technologies used. Warehousing systems are challenged by rising demands in terms of the variety and volume of products to be stored, for example, because of a continuing trend toward e-commerce and customer requests for short delivery times and high service quality (Boysen et al., 2019; Winkelhaus and Grosse, 2020a). These developments have pushed managers to ensure high process efficiency and space utilisation in warehouses. Order picking is a warehousing process in which products are retrieved from storage facilities to satisfy customer orders (van Gils et al., 2018), and it has frequently been the subject of research as it is considered a key determinant of warehouse performance. Traditionally, order picking has been performed manually with operators travelling along the aisles of the warehouse, which is still the most prevalent method in practice (these systems are usually referred to as person-to-goods systems; see de Koster et al. (2007); Grosse et al. (2017)). Order picking is therefore characterised by considerable manual labour, making it a very cost-intensive process step in warehousing (Grosse et al., 2017).

To ensure efficient order picking operations, different decision problems have to be solved, with zoning, batching, routeing and storage assignment among the most important ones (cf. Silva et al., 2020). These decision problems are most commonly solved with the objective of reducing unproductive times, for example, the time spent on travelling, which usually accounts for approximately 50% of the total order picking time (Tompkins et al., 2010). In addition to the development of mathematical models that support managers in solving the above-mentioned decision problems in person-to-goods systems (see, e.g. Masae et al., 2020a; van Gils et al., 2019), several technical solutions have recently been developed to support order pickers, reduce their manual tasks and limit their cognitive and physical workload (Glock et al., 2021). In particular, unproductive travelling and searching tasks were reduced or substituted by IT and automation technologies to increase the pick performance of order pickers. Some of these technical solutions transform person-to-goods systems into goods-to-person systems, such as RMFSs or AS/RSs (Gharehgozli and Zaerpour, 2020; Li et al., 2020). In goods-to-person systems, a certain quantity of the requested product is brought to the order picker’s location using a technical system (Boysen et al., 2019). The operator then only physically retrieves the correct quantity and confirms the pick.

In addition to traditional stacker-crane-based AS/RSs, several types of goods-to-person systems have recently gained attention, such as shuttle-based, AGV-based and grid-based AS/RSs (Azadeh et al., 2019). From a technological perspective, these systems have different features in terms of scalability, fail-safety, redundancy, performance and flexibility (Boysen et al., 2019; Huang et al., 2015). Most of these systems still rely on standardised load carriers for storing and retrieving goods and do not directly handle the goods themselves (Huang et al., 2015). By establishing separated workspaces with fixed pick stations and by reducing both system interactions and the scope of work for human operators to a necessary minimum, goods-to-person systems again try to reduce search times and walking distances to increase the pick frequency of order pickers. The economic impact of different goods-to-person systems, e.g. in terms of space requirements or warehouse extension costs, are discussed in the literature as well (Huang et al., 2015).

Current developments in order picking technologies aim to overcome some of the limitations of goods-to-person systems. For example, pick-and-fetch robots are discussed to support warehouse operators in optimising picking efficiency (Fragapane et al., 2021). In light of the high investment costs associated with establishing a completely automated warehouse and the restrictions that still exist, such joint manual and collaborative autonomous robot OPSs could be an interesting option for companies to start the transformation of manual operations. Despite continuous technological improvements, most studies forecast the reliance on human operators in logistics to continue in the foreseeable future (Correll et al., 2018). This study combines both perspectives – the anticipation of the further penetration of automation technologies in warehousing and the continuing reliance on human operators – and investigates joint manual and autonomous systems, which we refer to as hybrid order picking systems. In HOPSs, autonomous robots such as pick robots collaborate with human operators. Both actors (robots and humans) share the same goals and sub-goals while working on the same warehouse shopfloor allowing shared processes (Onnasch et al., 2016) (see Figure VI-1 for an example).

Figure VI-1: Example of a HOPS at Zalando employing TORU robots by Magazino GmbH.

With this approach, the boundaries of current AS/RSs are dissolved, enabling an OPS that can handle a large range of diverse products and that can easily be adapted to changing warehousing requirements. In HOPSs, AGVs could, for example, be applied for transporting goods and people, and fully autonomous pick robots could support human operators and share work (Fragapane et al., 2021). Technical systems that work in a hybrid order picking application and that are also able to perform the actual picking of goods have already been introduced in practice, such as the TORU of Magazino (see Figure VI-1). These systems have been mentioned in the literature (Azadeh et al., 2019; Fragapane et al., 2021); however, in-depth investigations of such warehouse technologies, particularly in a hybrid approach, are lacking.

An advanced robot-picking system that can holistically support human operators, instead of replacing them, could offer advantages in different practical applications. As human operators and automation systems have different advantages and disadvantages, as conceptually shown in Figure VI-2, a system that can flexibly adapt to the environment the company faces and that leverages the individual strengths of both OPSs could increase the performance of the warehouse. HOPSs thus have the potential to maintain human flexibility and ensure an improvement in productivity through robot efficiency.

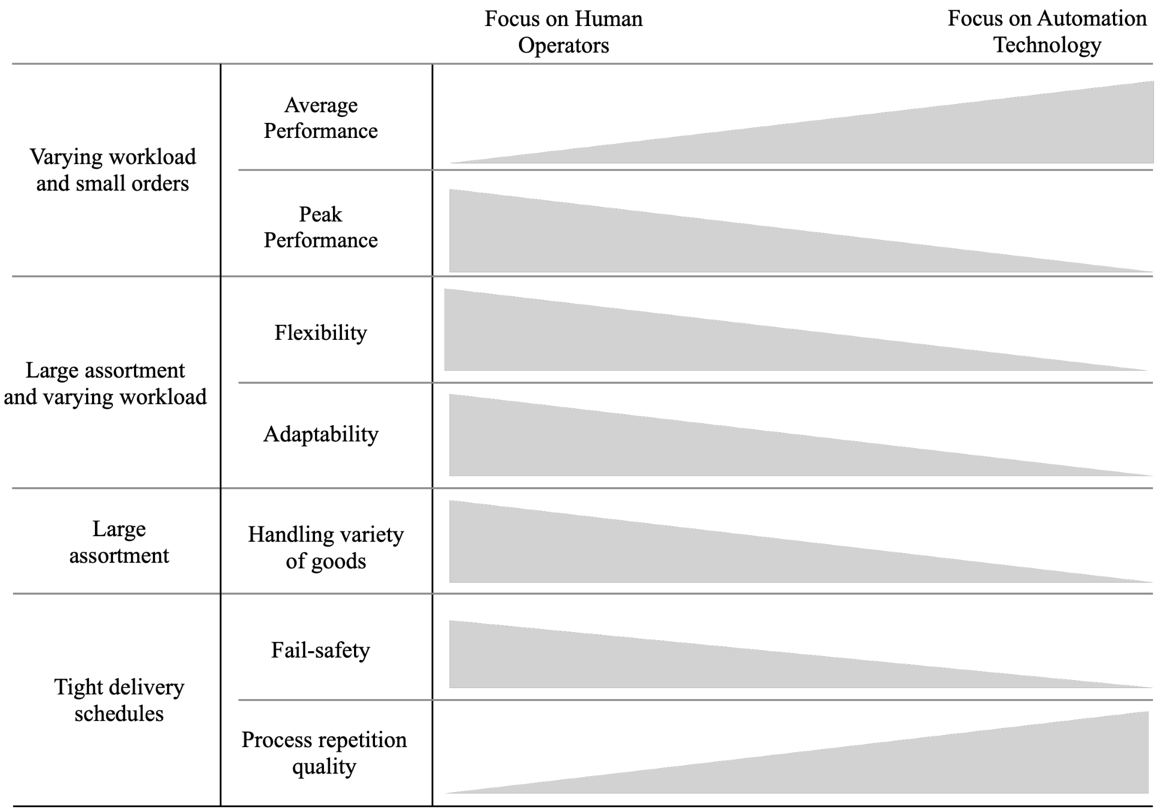

Figure VI-2: Simplified capabilities of human operators and ordinary automation technology (Huang et al., 2015; Boysen et al., 2019) to meet the operationalised requirements of the e-commerce warehouse, as formulated by Boysen et al. (2019).

As HOPSs have not yet been investigated in detail (this is discussed in more detail in Section 2), we address this research gap by studying a HOPS in which human operators and autonomous pick robots share the tasks. This work aims to contribute to the development of HOPSs by addressing the following ROs:

- *Develop the concept of hybrid order picking systems;*
- *Investigate the potential of hybrid order picking systems to improve order picking performance for different warehouse operating policies and market characteristics.*

Our analysis shows that HOPSs are generally capable of improving manual order picking operations in terms of system throughput and costs. The major determinants of HOPS performance are the total workload handled and the assigned item classes (and their demand frequency) as well as the occurrence of blocking. Our results show that HOPSs are promising for a wide range of real-world warehouse applications. We discuss these insights in detail in Section 4.

The remainder of this article is organised as follows: In Section 2, HOPSs are conceptually defined to address RO 1. Based on this conceptualisation, the HOPS-related literature is reviewed to highlight the research gaps addressed in this paper. Section 3 describes the simulation methodology and outlines the simulated HOPS in detail. To achieve RO 2, the simulation results are presented in Section 4 and comprehensively discussed in Section 5. In addition, future research possibilities are derived. Finally, Section 6 concludes the paper.

2. Conceptualisation and literature review

2.1 Conceptualisation of HOPSs

To the best of the authors' knowledge, HOPSs have not yet been defined in the literature. In a first attempt to characterise HOPSs, Figure VI-3 illustrates how a HOPS may support one or more steps of the order picking process in a *cooperative* or *collaborative* manner. The possibility of switching between the support modes, as well as pure manual steps, was also included.

To differentiate HOPSs from current automated OPSs, the type and extent of cooperation and collaboration are relevant: 1) the extent of temporal and 2) spatial interactions, 3) the extent of adaption and interaction and 4) the congruency of task goals and sub-goals (Onnasch et al., 2016). In a *cooperative system*, operators and robots share the workspace at the same time but have separate tasks, and they only share the overall goal. In this case, operators and robots usually have a strict task division, e.g., operators pick the items while robots transport them to the depot. This cooperative activity usually requires mutual responsiveness, commitment to the joint activity and to the mutual support (Bratman, 1992). If, e.g., the robots are defect, the responsibility of transporting items will be, again, taken by the operators, so that a cooperation no longer exists. In a *collaborative system*, in contrast, such a strict task division is usually not applied, as both operators and robots are able to fulfill all the tasks, so that more flexibility in planning a collaborative system can be foreseen. In the context of order picking, owing to the capabilities of robots, operators and robots can work on the same tasks together to achieve a sub-goal, such as picking different items of a single order so as to pursue lower system costs.

Each individual process step and consequently the order picking process as a whole, can be performed manually, cooperatively or collaboratively, leading to a large variety of possible HOPS setups. Depending on the warehouse, the two coworking types have different effects on the performance objectives, time, costs and quality. In addition to the potential economic benefits of certain types of HOPSs, they may also improve working conditions ergonomically and foster well-being at work. Although this is not the focus of the current study, HOPSs could contribute to human-centred work design. However, human factors as well as possible negative side effects of human-robot interaction need to be analysed in detail in this regard (Neumann et al., 2021).

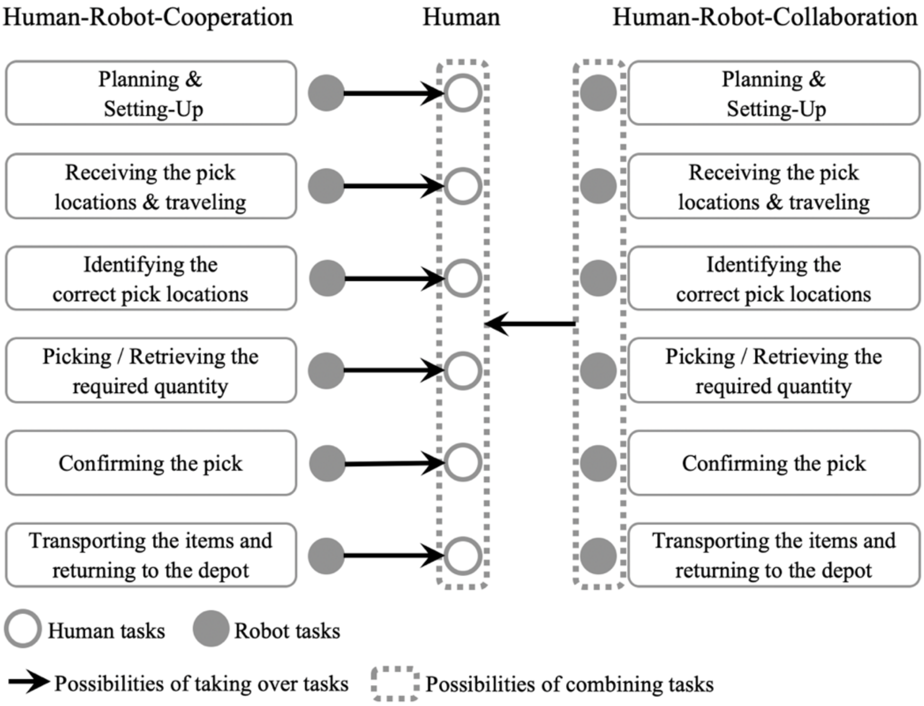

Figure VI-3: Possible configurations of cooperative, manual and collaborative order picking operations.

Based on this discussion, we define a HOPS as follows:

A hybrid order picking system applies one or multiple automation technologies, such as robots, to cooperate or collaborate with human order pickers in one or multiple process steps to jointly optimise system performance in a shared workspace.

The next section reviews HOPS-related literature based on this definition.

2.2 Related literature

HOPSs offer diverse design opportunities because a large variety of tasks must be performed for which automation technologies can support human operators. We focus on a processual and organisational perspective, acknowledging that the resulting OPS relies on technologies in the work environment that are not investigated in depth in this article. These enabling technologies are, for example, identification and wireless sensor systems, the Internet of Things, or advanced data processing tools based on artificial intelligence. For an overview of the technologies, we refer to recent literature (see, e.g. Glock et al., 2021; Winkelhaus and Grosse, 2020a).

The order picking process in person-to-goods warehouses consists of the following steps: 1) planning and setting up the pick process, 2) receiving the pick locations, 3) travelling through the aisles to the location, 4) identifying the correct location, 5) retrieving the required quantity of the item, 6) confirming the pick, 7) transporting the selected item(s) to the next location, 8) repeating this procedure until the picker's loading capacity is reached or the order is fulfilled; and 9) returning to the depot. In this process, steps 3, 5 and 7 are the main physical tasks.

The literature that is relevant to our overview deals with human-robot interactions in the main physical order picking process steps in a shared workspace. Hence, two topics related to our HOPS concept need to be investigated: collaboration in travelling and the transportation of goods and collaboration in retrieving goods. The collaborative systems are, in general, at least partly autonomous in contrast to, for example, conveyor belts, industrial trucks, or forklift trucks. Although applied in the same workspace, these technologies are operated by employees instead of automatically adopting to the work environment.

2.2.1 Support of travelling and transportation

The first research stream discussed investigates OP systems in which order pickers interact and collaborate with an AGV to reduce the travel distance. AGVs have recently been investigated in an order picking context as RMFSs. RMFSs, such as the so-called KIVA systems (Li et al., 2020), use AGVs as a new form of goods-to-person OPS, in which racks are lifted and brought to the human order picker by AGVs (Boysen et al., 2019). Although these systems might be considered as a step towards HOPSs, the actual human-robot interaction does not differ from a traditional AS/RS, because tasks are performed in separated workspaces and without a direct interaction between humans and the RMFS. Thus, these systems are not considered relevant here, as HOPSs in the context of our study aim for a deeper interrelation between technology and human operators, be it spatially, timely, or interactively.

An alternative, more adaptive type of co-working is based on a concept in which the operator follows an AGV to the pick location, picks the item and places it on the AGV. Once the capacity of the AGV has been reached, it autonomously travels to the depot and a new AGV replaces it (Boysen et al., 2019; Löffler et al., 2018). Hence, there is an adaptive form of direct human-robot interaction within an order picking (OP) process step. Even though picks are still performed manually, the unproductive time of a human order picker is reduced because of a higher pick density and fewer returns to the depot. To ensure that AGV-supported order picking works as efficiently as possible, some authors, such as Masae et al. (2020b) and Wang et al. (2019), developed routeing algorithms that minimise the order picker's travel distance by sequencing picks and defining locations where order pickers and new AGVs meet. In addition, Ono and Ishigami (2019) developed a routeing algorithm for collaborative picking in warehouses between human order pickers and AGVs considering different parameters, such as the travel speeds of human operators and AGVs. The robots carry items picked by order pickers and deliver them to a dispatch area. Related to this approach, Yokota (2019) developed a scheduling algorithm in which items are picked and placed on an AGV that collects the items assigned to a certain batch.

In addition to these studies, Rey et al. (2019) provided an experimental study of an AGV-supported OPS, in which the AGV also weighs the selected items for verification. Finally, Zou et al. (2019) developed a heuristic for an AGV-supported OPS by considering a zone-picking approach aimed at minimising the total time for picking the items of the assigned orders. The investigated system utilises AGVs to transport items between different zones in which human operators perform picking tasks to complete a customer order.

As can be seen, most of these studies are first attempts to investigate such systems and leave many interactions and scenarios unaddressed, leading to the need for further research.

2.2.2 Support of retrieving and handling items

The second research stream includes technologies that support the actual retrieval of items; of these systems, cobots are among the most discussed. We found a few works that addressed the automatic picking of items in related applications and briefly discuss these works in the following paragraphs.

Kaipa et al. (2014) developed a framework for bin-picking tasks prior to assembly, in which humans and robots collaborate. In the investigated system, items are retrieved by robots and humans assist them in solving problems that are detected during this task, such as grasping failures, or humans perform tasks that are too difficult for the robots. Fager et al. (2019) and Fager et al. (2020a) investigated cobot-supported picking and kitting tasks. In such systems, the human retrieves the items and the cobot sorts them. Laboratory experiments indicated that this system setup may lead to a lower cycle time variability. The authors also found that mounting the cobot on an AGV to sort items while the human retrieves items leads to a significant cost reduction when extensive sorting is performed. Boudella et al. (2018) also considered kit preparation and investigated a hybrid human-robot system. The authors studied a kitting system combining both robotic and human picking sections that work in series but that are decoupled from each other. The objective of the authors was to reduce the cycle time by assigning items to the robot and operator. Additionally, Coelho et al. (2018) provided a simulation tool for a hybrid kit preparation in a manufacturing supermarket. An arriving order is assigned to either a human or a cobot in a shared workspace. The results suggest that humans perform faster but cobots are more flexible, leading to lower variations in the number of kits prepared per minute under uncertainty.

In their simulation study, Kauke et al. (2020) investigated a HOPS in a small warehouse with only four aisles and concluded that spatial interactions between humans and robots while performing their tasks increase with increasing numbers of applied human and robot pickers, which has a negative impact on the number of orders picked per applied order picking agent. Relying even more on robot picking, Verbeet et al. (2019) investigated a cooperative HOPS in which robots perform all order picking tasks but can call for humans in case of picking failures. Based on the resulting human intervention, information in a database used by the robots to learn how to grasp different items and to improve process stability was expanded. Lastly, Fragapane et al. (2021) surveyed the opportunities of autonomous mobile robots as decentralised robotic applications for material handling, collaboration and full-service provision in intralogistics. Focusing on decision problems such as zoning and scheduling, as well as the number and type of vehicles, the authors identified several warehousing applications in which autonomous mobile robots can support and optimise work systems and, in cooperation and collaboration with human operators, these robots can also help in terms of productivity, flexibility and cost efficiency. However, the authors concluded that further studies are needed to explore autonomous mobile robots and that agent-based simulations are promising for gaining knowledge in this area.

2.2.3 Summary

Our review of research on the physical order picking process showed that studies explicitly addressing the intersection of supported manual tasks and adaptive automation technology in a shared workspace are scarce. Robotic OPSs such as TORU of Magazino (Magazino GmbH, 2020) were mentioned, for example, in the review by Azadeh et al. (2019); however, no research explicitly dealing with such systems has been identified. Most HOPS variants resulting from Figure VI-3 that may lead to benefits for certain warehouse applications have not yet been discussed. Examples include the automated or supported loading and unloading of manual transportation carts or the support of the operator in travelling through the aisles. The studies we identified discuss only a selection of the performance indicators that are relevant in a warehousing context, such as the reduction of human errors (Fager et al., 2020a), reduction of cycle time (Boudella et al., 2018) and system throughput (Fager et al., 2020a; Wang et al., 2019). Other important parameters, especially cost efficiency, were not addressed in most cases.

Three research gaps emerge from our review of the literature. First, the identified systems only provide limited insights into the various applications that may be considered as HOPSs. With regard to AGVs, different modes of co-working have been identified; however, further ones may be possible. Although AGVs play a major role in RMFSs, they are, in most cases, not a hybrid order picking application and are not in the focus of this article. The operation of autonomous order picking robots together with human operators was less frequently studied than the use of AGVs. Second, most of the research on this topic adopts a techno-centric perspective and does not study the operator in depth. Hence, the possible impacts of human factors, such as picking outside the optimal range of the operator, remain unaddressed. Third, the organisational and procedural aspects of the proposed systems are rarely considered, leading to a research gap concerning the circumstances and actual use cases in which the hybrid system has advantages over completely manual or completely automated systems. For example, the application of such systems in night shifts or for picking preparation to make order peaks easier to handle is not discussed, leading to an underestimation of possible system benefits.

In the following, we address these research gaps and investigate a collaborative HOPS for which we assume that human operators and robots work together in a B2C e-commerce warehouse.

3. Simulation model

3.1 Description of the investigated scenario

The investigated warehouse has to handle a large product assortment with small orders and tight delivery schedules (Boysen et al., 2019). The investigated HOPS combines a traditional human OPS with an OPS in which an autonomous robot picks the requested items. The functionality of the robots is comparable to that of TORU of Magazino (see Figure VI-1), which is a market-ready autonomous robot for order fulfilment in a manual warehouse. Our earlier literature review indicated a research gap with respect to such systems. In the HOPS considered in this study, robots and human order pickers travel through the aisles of the warehouse and pick items from the shelves. The two teams (human and robotic order pickers) have the following characteristics:

Human team: The work of human operators in the collaborative HOPS is comparable to the traditional manual processes described above. The performance of the human operators is not restricted by the externally given performance of the automated system, as would be the case if an AS/RS was used. Therefore, the HOPS can benefit from human flexibility and adaptability and can also manage peak loads through the flexible deployment of employees.

Autonomous robot team: Autonomous picking robots work as co-pickers and can be assigned to tasks that are not performed by humans. The systems are intrinsically safe and thus can perform their tasks together with human operators without security fences or similar equipment. The robots receive pick locations, travel to the right location, identify it, pick the items, confirm the pick, transport the items and deliver the completed batches to the depot, where the items are merged by human operators with those picked by other robots or human operators. Although the variety of goods that can be picked by market-ready robots is still limited, a certain level of standardisation of goods can be assumed because of pre-packaged or similarly shaped goods such as books or shoeboxes (Magazino GmbH, 2019b). Today, autonomous picking robots are slower in retrieving goods from shelves than humans are; however, they are able to work continuously without the need for rest breaks, except for charging. Nevertheless, they require an initial investment and running costs (Magazino GmbH, 2019a).

The described HOPS generally meets the requirements formulated in Section 1 for a flexible and efficient warehouse. In addition, it also supports maintaining the operators' job satisfaction as it does not replace individual human tasks, which is the case for other automation technologies; instead, it maintains the complete process for the human operators and even adds tasks, such as the support of robots in the case of failures. Within the investigated scenarios, we also show opportunities for reducing the physical workload of the operators. In summary, the applied HOPS can be viewed as an opportunity for job enlargement within the order picking process and thus supports humane work design. The HOPS is fail-safe owing to the combination of human operators and decentral-autonomous picking robots.

As real implementations of HOPSs are still scarce, a simulation study enables an investigation of the system's behaviour for different system configurations and OP environments. In the following, we first describe the applied simulation methodology and then introduce the proposed simulation model. Subsequently, we outline the assumptions made and the parameters used in the simulation experiment. Finally, we describe the validation of the simulation model and present the results obtained in the simulation study.

3.2 Agent-based simulation

In the remainder of this article, we analyse the performance of the HOPS under different operating policies and market characteristics. Analytical methods usually lose accuracy and efficiency when dealing with highly dynamic and complex systems (Borshchev and Filippov, 2004). Therefore, a simulation is considered to be a more suitable approach for this study, and an agent-based simulation (ABS) model was developed using Tecnomatix Plant Simulation 15. An ABS usually consists of three components (Borshchev and Filippov, 2004): 1) agents with individual behaviour rules, 2) direct or indirect interactions and 3) environmental models. This unique feature makes ABS well-suited for this study. The three components are briefly addressed as follows:

1) Agents and individual behaviour rules: The HOPS consists of two types of teams, human operators and autonomous picking robots, which have different characteristics. This leads to insufficient knowledge about the behaviour of the system. By modelling human operators and robots as agents, a natural representation of both can be provided, which generates the system behaviour from a "bottom-up" perspective.

2) Interactions: With several agents working in the same area, interactions between them are inevitable. For example, one agent may block another in a picking aisle. The occurrence of such interactions is difficult to predict. ABS, as a decentralised approach, is a suitable tool for measuring the impact of interactions between agents on the system's performance.

3) Environmental models: To create a working environment for the agents, certain process flows need to be represented as a discrete-event simulation (DES). In our case, for example, creating orders is actually an external process and thus simulated in a top-down approach that cannot be affected by the behaviour rules of each agent. ABS can easily incorporate DES mechanisms and provide a realistic simulation model.

ABS, a fairly novel approach, has recently been introduced in studies of warehouse operations. In an order picking context, ABS has mainly been used to study goods-to-person systems, such as AGV-based (Ribino et al., 2018), multi-shuttle (Güller and Hegmanns, 2014) and cellular transport systems (Güller et al., 2018). Analogously, ABS has also been applied to investigate more traditional person-to-goods systems (e.g. Shqair et al., 2014), in which efforts have been made to also consider human factors. Incorporating human route deviations (Elbert et al., 2017), picker blocking (Franzke et al., 2017; Heath et al., 2013) and carrying capacities of pickers (Elbert and Müller, 2017) led to more realistic simulation model results.

3.3 Conceptual model

The simulation model is organised in three functional blocks (A, B and C), as summarised in Figure VI-4.

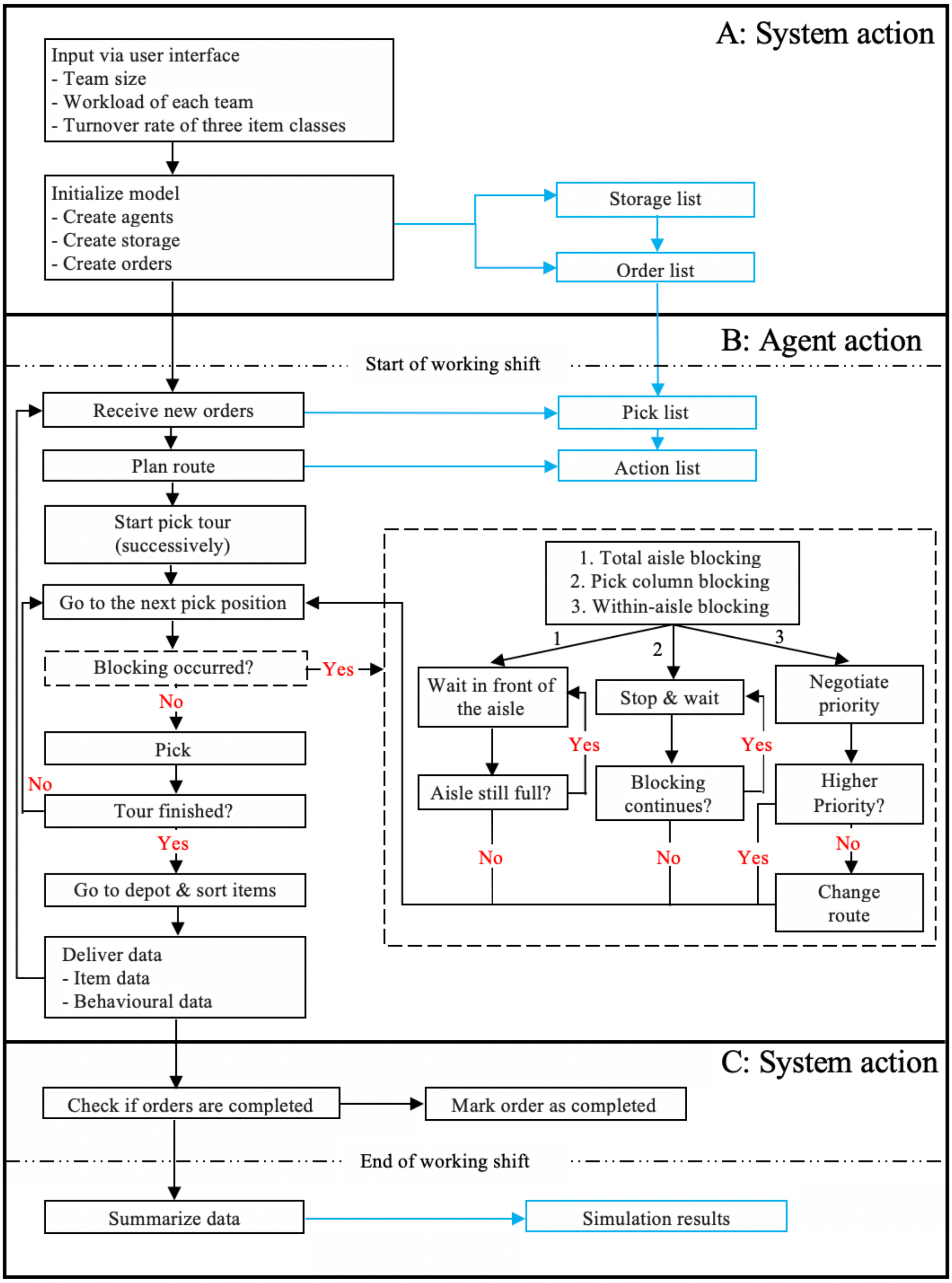

Figure VI-4: Conceptualisation of the simulation model.

Block A prepares the order picking process on the system's side, which mainly includes setting the parameters for the simulation experiment and creating the environment for the picking process. The warehouse applies class-based storage with three item classes (A, B and C) defined by their sales volume. Each item has the same stock quantity. The simulation model stores the items on a storage list and customer orders on an order list. In the simulation model, two basic rules are applied during the creation of orders. First, orders with out-of-stock items will be ignored in the current working shift because the warehouse is unable to meet all their requirements, which corresponds with the real-world situation in which such orders can only be fulfilled after a replenishment process. Second, a turnover rate is assumed so that different sales volumes of the three item classes are guaranteed. The order creation process terminates when the first item class runs out of stock completely. This enables us to create a large number of consistent orders from the stock that is assumed not to be refilled within the simulated period of time (working shift of 8 h) and to fully measure the performance of the HOPS in one working shift without any idle time. For a detailed description of the relevant parameters and assumptions, we refer to Section 3.4.

Based on the two rules stated above, the order generation process is defined as follows:

1) Generate the order size randomly according to the triangular distribution (1, 2, 6);

2) For each item in the order, define the item class (A, B, or C) randomly according to the predefined turnover rate for the three classes;

3) Define the needed item within the remaining stock of the item class randomly according to a uniform distribution;

4) Assign one particular item in stock according to the demand defined in Step 3 to the order. When the stock quantity of one item turns to 0, it will be marked as out-of-stock, so that it does not appear on new orders afterwards;

5) Repeat Steps 1 to 4 until any item class runs completely out-of-stock.

Block B starts with a working shift and is driven by the agents’ actions. The system first assigns pick lists to the agents. Accordingly, the agents plan their pick tours by translating their pick lists into a combination of the eight basic actions 1) “Start”, 2) “End”, 3) “Pick”, 4) “Move on aisle”, 5) “Switch lane”, 6) “Enter aisle”, 7) “Exit aisle” and 8) “Move on cross aisle” (see Figure VI-5).

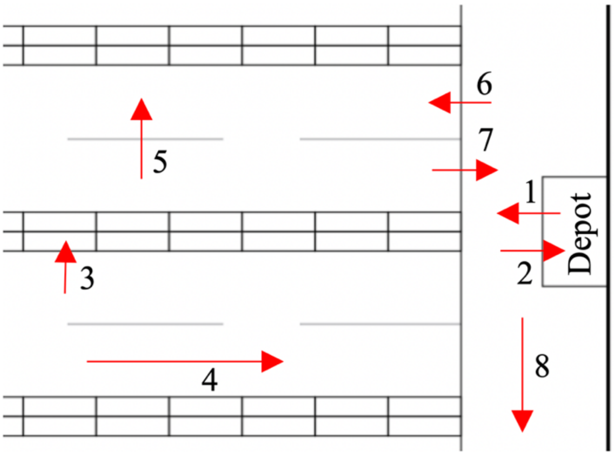

Figure VI-5: Eight basic actions in the process.

The result is an individual action list that serves as a guide for the agent to finish the current pick tour. Each tour starts with the agent leaving the depot. Possible congestion could occur when multiple agents try to start their tours at the same time (Chen et al., 2016). In our case, we try to avoid such congestion by releasing agents successively from the depot. The time interval between each agent leaving the depot is 3 s, which corresponds to the time a human operator would need to move to the first picking aisle (Franzke et al., 2017). The agents move through the aisles and collect all requested items. Then, they return to the depot, sort the items and deliver the necessary data to the system. Subsequently, the agents receive new orders and repeat this procedure until the end of the working shift has been reached.

In addition to this standard cycle, blocking is a relevant parameter for the system efficiency. In many practical cases, operators have to manage picker-blocking situations in which the process is disturbed by the congestion caused by multiple operators in a storage area (e.g. Chen et al., 2016). Earlier research has focused on two main types of picker blocking: 1) blocking within wide aisles, in which operators are always able to pass each other in the picking aisles (e.g. Parikh and Meller, 2009) and 2) blocking within narrow aisles, in which passing is not possible (e.g. Gue et al., 2006). In our study, passing in picking aisles has certain limitations and consequences, meaning that passing causes lane switching and extra travel distance (e.g. Heath et al., 2013). Adopting the classification of picker-blocking situations from Klodawski et al. (2018), blocking events are assigned to three classes in our model (see Figure VI-6), which are described in Table VI-1.

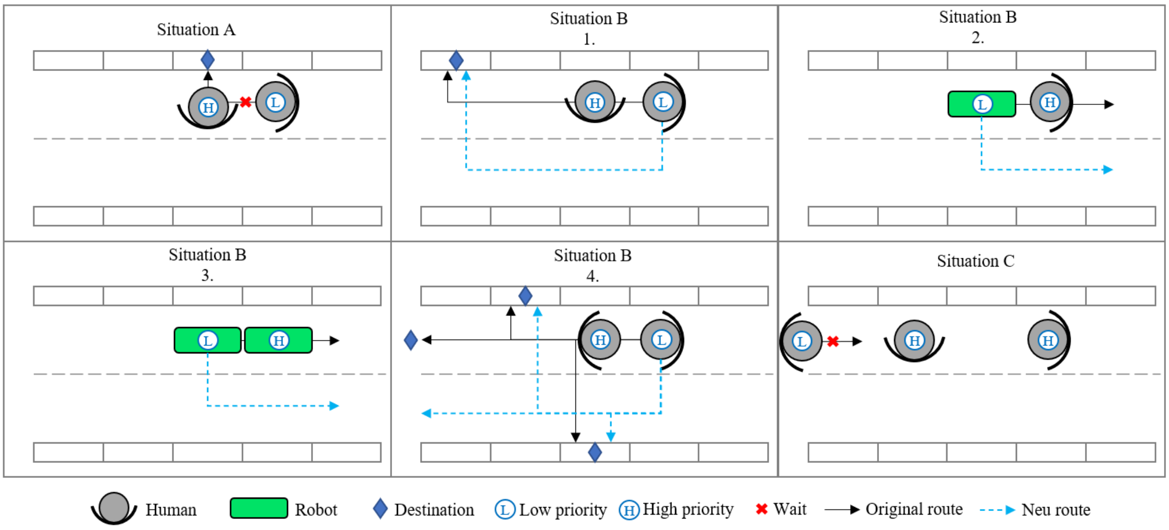

Figure VI-6: Classification of picker-blocking situations.

In addition to blocking, overtaking was also considered. Humans are able to overtake robots within the picking aisles because of their higher travel speed; however, this also requires extra "switch lane" action(s).

Table VI-1: Classification of picker blocking and negotiation rules.

Blocking Situation	Negotiation
Situation a) Pick Column Blocking	*Definition: Agent's next pick position is occupied.* 1. The performing agent has higher priority; the blocked agent stops and waits until the pick position is free.
Situation b) Within-aisle blocking	*Definition: Agent is blocked while moving to the next pick position.* 1. The agent executing "Pick" & "Switch lane" has the highest priority and cannot be interrupted. 2. When a human and a robot move against each other in the same lane, humans have priority over robots and robots switch lanes for humans. 3. When two robots move against each other in the same lane, one randomly selected robot changes lanes. 4. When two humans move against each other in the same lane, their priority is defined according to the next action on their original action list. 4.1 The ones with the next action "Pick" (b1), "Exit aisle" (b2) and "Switch lane" (b3) have high, medium and low priority, respectively in accordance with the number of resulted extra "Switch lane" if the agent changes the picking route (b1 would cause two extra lane switches, b2 one extra lane switch and b3 no extra lane switching). 4.2 If two humans have the same next action to perform, the one closer to the destination has higher priority. 5. The agent with lower priority adjusts the route on the action list and executes the new picking route.
Situation c) Total aisle blocking	*Definition: Agent is blocked at the entrance of the aisle.* 1. Each aisle only allows up to two agents in it at the same time. 2. When an aisle is full, the agents coming next queue at the aisle's entrance. 3. The agents next in the queue can enter the aisle as soon as the aisle has free capacity again.

The model only considers blocking situations within the picking aisles, which means that blocking in cross aisles and the associated negotiation process is not considered (e.g. Franzke et al., 2017). The blocking situations are detected by humans when another agent stands directly in front of the operator. The process of determining the priority is immediately activated to solve the blocking problem. The equivalent process for robots starts when they detect another agent via their sensor within 1.5 m. To simulate the braking process, the robots then move at half-speed in this warning zone and stop when coming too close before the resolution of the blocking starts. Otherwise, if the other agent switches lanes during the half-speed period, the robots will directly switch back to the full-speed mode.

Block C works as an interface between agent actions and simulation results. It is activated at the end of each tour and checks if the orders have been completed, as some orders must be split according to the assignment rules and assigned to two agents (one human and one robot). When the working shift ends, the system terminates all activities immediately and summarises the data for the simulation results. As the main performance measure, the number of items picked in completed orders per shift (throughput) is counted. Furthermore, behavioural data are measured, in particular, the average times for travelling and retrieving and the time to solve blocking situations for each pick tour.

3.4 Simulation parameters and assumptions

The warehouse under study is characterised by several assumptions that rely on relevant literature in this field (e.g. Elbert et al., 2017; Franzke et al., 2017) and observations from real-world cases to guarantee the comparability and transferability of results and the relevance for practice. These characteristics are summarised in Table VI-2.

Customer orders are randomly generated with a size drawn from a triangular distribution (1, 2, 6). The triangular distribution gives the representative order sizes for B2C e-commerce warehouses (Moons et al., 2019). The turnover rate of the three item classes, representing the probability of one item from classes A/B/C being needed, is either 80% / 15% / 5% or 50% / 30% / 20% (e.g. Dijkstra and Roodbergen, 2017). The storage capacity for these item classes is predetermined according to the storage areas A, B and C. All orders have the same priority and will be processed in accordance with the “first come, first served” principle.

Table VI-2: Features of the warehouse.

Characteristic	Configuration	Reference
Warehouse Shape	Rectangular, ten equidistant picking aisles and three cross aisles, as shown in Figure VI-7	Elbert et al. (2017); Franzke et al. (2017)
Aisle Shape and capacity	3 m width; two lanes allowing no more than two agents at the same time in each picking aisle, no restriction on cross aisles	Assumption for the simulation based on observations in practice
Storage zones	Two zones, one with class A items near the depot, the other with class B items in the back of the warehouse	Assumption for the simulation based on observations in practice
Storage assignment	A&B items: in the respective zones inside the golden zone of picking (on 3rd–5th shelf layers) C items: on each shelving unit in both zones outside the golden zone of picking (on 1st, 2nd, & 6th shelf layers)	Based on the golden zone concept (Petersen et al., 2005)
Depot	One central depot in the middle of the front cross aisle	Elbert et al. (2017); Franzke et al. (2017)
Shelf size	Width: 1.5 m, depth: 0.4 m, height: 2.1 m	Based on observations in practice
Shelf capacity	126 items on 6 layers (21×6)	Result of the assumptions on shelf size and item shapes
Items per Shelf Level	21 identical items	Assumption for the simulation
Item Shape	Cubes 200 x 100 x 300 mm (based on typical shoe boxes)	Based on observations in practice
Storage space per item class	Class A: 20%, class B: 30% and class C: 50%	See prior assumptions

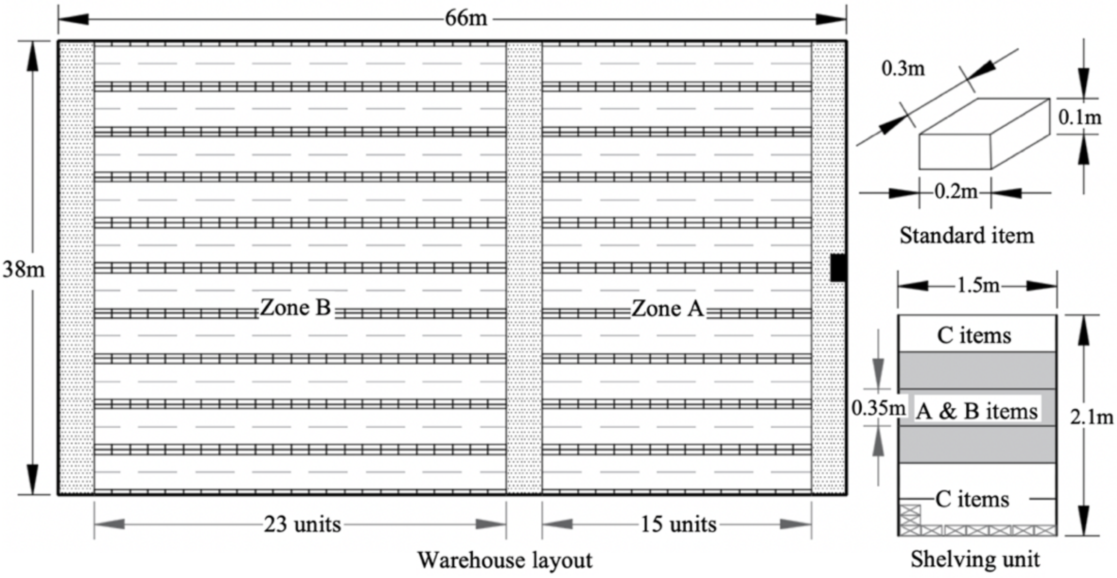

Figure VI-7: Warehouse layout, shelving unit and stored item.

The warehouse operates one eight-hour working shift every day. All customer orders are assumed to be known at the beginning of each working shift, such that no idle time is required to update orders. The investigated main scenario is based on the concept of a HOPS and, thus, the collaboration between humans and robots (Hoffman and Breazeal, 2004). Specifically, a human and a robot team are formed. The order assignment follows each team's pre-assigned workload according to the item classes and respective turnover rates. Thus, each item in stock is pre-assigned to a team based on the item class (A, B, or C) to which it belongs. If the item appears on an order, a member of the team responsible for that item picks it. As a result, some orders are split into two parts, with one part being processed by a human and the other part by a robot that collaborates for order fulfilment. In this scenario, the system performance strongly depends on the coordination of the two teams (team configuration and workload).

The agents, as the executers of the picking process, have the characteristics outlined in Table VI-3. We assume that the retrieval time of humans is variable. According to the golden zone concept, items stored between the height of the human waist and shoulders are easier for them to retrieve (in our model, we assign A and B items to this zone). For C items that are stored outside the golden zone, the retrieval time increases accordingly (+4 s or +8 s).

We made the following assumptions based on market information to assess the operating costs of the system. The monthly costs for one human operator are 3200 EUR. For the robots, the total costs are the sum of the depreciation costs (based on the acquisition costs of 55,000 EUR for each robot with a service life of six years), service costs (0.06 EUR for each selected item) (Magazino GmbH, 2019a) and additional operating costs including maintenance and energy costs (estimated 1000 EUR for each robot yearly).

Table VI-3: Characteristics of the agents.

	Characteristic	**Configuration**	**Source**
Humans	Base area (L×W)	1500 mm × 500 mm	Based on one person equipped with a picking cart
	Batching capacity	8 orders (max. 60 items)	Gong and de Koster (2008)
	Velocity	1 m/s	Giannikas et al. (2017)
	Time for retrieving one item	12 s (for A & B items) 16 s or 20 s (for C items)	Le-Duc and de Koster (2007) Based on the golden zone concept (Battini et al., 2016; Petersen et al., 2005)
	Time for sorting	12 s/order	Estimated based on Marchet et al. (2011)
Robots	Base area (L×W)	1500 mm × 685 mm	Based on TORU data sheet (Magazino GmbH, 2019b)
	Batching capacity	max. 16 items	
	Speed	0.8 m/s	Based on observations in practice
	Time for retrieving one item	20 s/item	
	Time for sorting	20 s/item	
	Range of sensor	1.5 m	

To achieve RO 2, which is to evaluate the potential of HOPSs for an economic improvement of human OPSs under different warehouse operating policies and market characteristics, we investigate the impact of different parameters in the simulation. We study approximately 50 different parameter combinations, as shown in Table VI-4, which are presented in Sections 4 and 5. First, as a benchmark, *basic scenarios* in which only human operators *or* only robots work in the warehouse are considered, including the impact of different routeing policies on the throughput and cost structure of the OPS. Routeing policies influence the pickers' travelling time and are therefore regarded as one of the most important decision problems in order picking (Masae et al., 2020a). As described above, the impacts of differences in turnover rates, as well as the golden zone concept, are also considered. We then study different *collaboration scenarios* based on the HOPS concept, in which the robots and humans share customer orders based on a pre-assignment of item classes to the two teams. Again, the impact of different routeing policies was investigated. Finally, in Section 5, we study the impact of some limiting assumptions we made in the previous experiments to further discuss the potential economic benefits of the investigated HOPS. For every experiment, the number of different parameter configurations is given in column 2 "*# Experiments*" in Table VI-4.

Note that all the experiments are described in a short form with the following logic: turnover rate of the three item classes (80%/15%/5% or 50%/30%/20%) – assignment rules (human/robot) – routeing policy for humans (H) and robots (R) (S: S-shape, LG: Largest gap, Re: Return, X: any of the routeing policies) – golden zone retrieval (GZ 16 s or 20 s, only if relevant). The resulting description is then, for example, 80/15/5-A/BC-H(LG)R(Re)-(GZ16), which means that in this case we study an 80/15/5 turnover rate, human operators are responsible for A items, and robots are responsible for B and C items. The routeing policies implemented here are the largest gap policy for humans and the return policy for robots. GZ indicates golden zone retrieval and 16 represents the time in seconds for searching the pick location, retrieving an item and confirming the pick for items outside the golden zone.

Table VI-4: Parameter configurations of the simulation experiments.

Experiment	***# Experiments***	***Assignment rules (Human/Robot)***	***Turnover rate for three item classes***	***Collaboration***	***Golden zone***	***Routeing (H(X)R(X))***	***Zoning***	***Batching***	***Storage assignment***
1 – Basic runs	2	ABC /- ; - / ABC	80 / 15 / 5	None	Const.	H(S) / R(S)	Const.	Const.	Const.
2 – Routeing impact	4	ABC /- ; - / ABC	80 / 15 / 5	None	Const.	H(Re) / H(LG) / R(Re) / R(LG)	Const.	Const.	Const.
3 – Turnover rate impact	6	ABC /- ; - / ABC	50 / 30 / 20	None	Const.	H(S) / H(Re) / H(LG) / R(S) / R(Re) / R(LG)	Const.	Const.	Const.
4 – Golden zone impact	12	ABC / -	80 / 15 / 5; 50 / 30 / 20	None	+4s / +8s for C items	H(S) / H(Re) / H(LG)	Const.	Const.	Const.
5 – Type of collaboration	4	AB / C; A / BC	80 / 15 / 5; 50 / 30 / 20	Coll.	Const.	H(S)R(S)	Const.	Const.	Const.
6 – Type of collaboration (Appendix, Figure VI-18)	4	BC / A; C / AB; AC / B; B / AC;	80 / 15 / 5	Coll.	Const.	H(S)R(S)	Const.	Const.	Const.
7 – Routeing impact in collaboration	2	A / BC	50 / 30 / 20	Coll.	Const.	H(LG)R(LG) H(S)R(LG)	Const.	Const.	Const.
8 – Impact of cost assumptions (Discussion & Appendix, Figure VI-19)	8	A / BC	80 / 15 / 5; 50 / 30 / 20	Coll.	Const.	H(S)R(S)	Const.	Const.	Const.
9 – Impact of storage assumptions (Discussion)	8	AI / BC; I / ABC	80 / 15 / 5	Coll.	Const.	H(S)R(S)	Const.	Const.	Mixed storage

Const. = Constant; Coll. = Collaborative

3.5 Validation

Simulation models should be validated throughout the entire lifecycle of a simulation study, hence, from the conceptual model to the computer model and the output data. However, there is no single framework or predefined order of activities that is proven to be suitable for every simulation study (Franzke et al., 2017). For this study, because HOPSs are still rarely used in practice, the conceptual model of the simulation was built based on related research and observations in practice and implemented gradually in the simulation software. First, a warehouse with only one picking aisle was built to test if the agents move, stop and pick as planned. Then, all the other components of the warehouse were successively added to ensure that actions like “Enter/Exit aisle” and “Move on cross aisle” were correctly simulated. By using the debugging and breakpoint functions provided by the software, programming errors could be avoided in the codes. Several check functions were added to ensure that the picking process ran as planned. For example, the accuracy of task execution was checked by the system each time the agents removed an item from the shelves or returned to the depot to ensure that the selected items corresponded to customer orders. The implementation of routeing policies and picker blocking situations could be validated by observing the graphical animation of the warehouse and agents during the simulation runs. Moreover, the target values of the agents’ predictable behaviour (e.g. the travel time of each tour) were calculated and compared with the measured values to ensure that the results of the simulation are credible. Finally, we validated the output data using the confidence interval. For each system setting, a number of observations (100 in most cases) were made, such that the 95% confidence intervals for the output data were smaller than 1% of their mean values.

4. Results

This section presents the results of the simulation experiments. The cost analysis was based on the costs per pick (on the y-axis) over the system throughput (on the x-axis, indicating the total number of items picked in completed orders per working shift). The experiments for the different scenarios started from the minimum required number of agents in the system, that is, one human or one robot for the benchmark cases (human or robot OPS) and one human and one robot for the HOPS. Each experiment generated one point (cost-throughput combination) in the coordinate system. By involving one additional agent (human or robot) in the system, additional points were recorded as simulation results. This was repeated until either team finishes all the orders within a daily shift (idle time occurred) or the HOPS no longer achieved cost advantages. In the first case, the cost advantages of the HOPS were only partially analysed as the stock quantity counted as a restriction and the simulation stopped within the eight-hour working shift when the stock was empty. Creating more orders was not possible because replenishment was necessary. Thus, these scenarios were not included in the results. Furthermore, as employing decimal units for the number of agents was not realistic, we combined the cost-throughput combinations resulting from successively increasing the numbers of agents within each scenario into cost curves to estimate the costs per pick within two points. This estimation can be realised in practice, for example, as a temporary working staff in warehouses.

4.1 Benchmark scenarios: Human and robot OPS

In the first step, the case in which only one type of agent (human or robot) works in the warehouse is analysed (Figures VI-8 and VI-9). These scenarios serve as benchmarks for evaluating the HOPSs performance. The figures show increasing costs per pick for all tested scenarios, as higher daily throughput requires more agents in the system, causing more blocking situations (particularly total aisle blocking), which lowers the overall picking speed and effectiveness of assigning additional agents. As can be seen, robots have cost advantages at lower throughputs per working shift; however, they are outperformed by humans when higher throughputs are required. Because robots work slower than humans, they suffer more from blocking for two reasons: 1) Robots remain longer in the picking aisles and in front of pick locations, which may result in longer blocking times. 2) More robots than humans are needed for the same throughput because robots pick slower, leading to a higher blocking frequency. Thus, break-even points can be observed in Figures VI-8 and VI-9 that indicate the number of picks at which the system favourability changes.

As expected, we found that the applied routeing policy had a strong impact on the system performance. For both human OPS and robot OPS, the cost curves show the order LG < S < Re, meaning that the return policy causes the highest costs per pick.

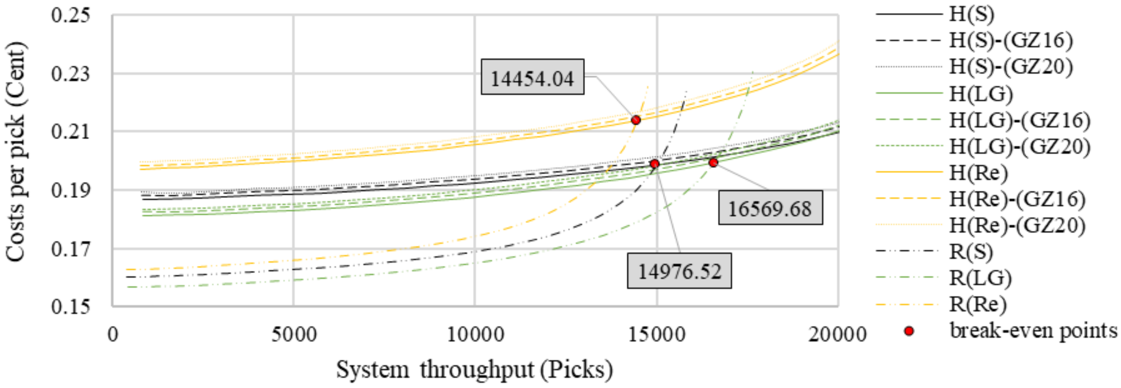

Figure VI-8: Cost curves of human and robot OPS for different routeing policies (turnover rate: 80/15/5).

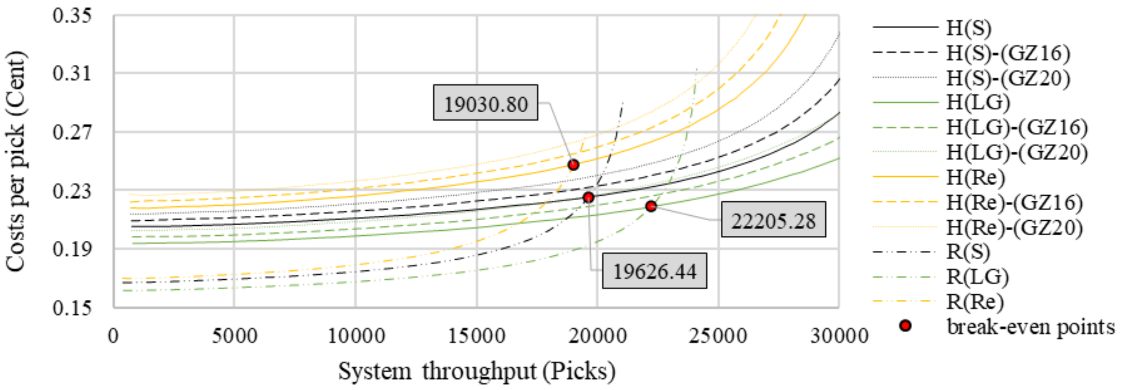

Figure VI-9: Cost curves of human and robot OPS for different routeing policies (turnover rate: 50/30/20).

In contrast to the turnover rate of 80/15/5, the pick positions are distributed more homogenously when analysing a 50/30/20 turnover rate. This leads to a longer average travel time per pick and higher costs for the same total number of picks. In contrast, the change in the turnover rate reduces congestion in the warehouse, which flattens the cost curves and enlarges the range of the robots' cost advantages. We can observe this, for example, in the case of total aisle blocking. The agents are spread out more homogenously in the two zones and in different aisles, reducing the probability of being blocked in front of a fully occupied aisle. In the case of 30 human operators with an S-shape policy for example, the average travel time increases from 18.35 s/pick (80/15/5) to 21.67 s/pick (50/30/20), while the total aisle blocking decreases from 4.80 s/pick (80/15/5) to 3.66 s/pick (50/30/20). For 30 robots with an S-shape policy, the travel time is then 29.73 s/pick (80/15/5) and 34.22 s/pick (50/30/20) and the total aisle blocking 6.65 s/pick (80/15/5) and 4.90 s/pick (50/30/20).

Considering different retrieval times for items stored outside the golden zone in the human OPS (see assumptions in Table VI-3), the average time needed for picking increases accordingly. Because there are more C-items (stored outside the golden zone) to be picked in case of a 50/30/20 turnover rate compared to a 80/15/5 turnover rate, the effect of the golden zone assumptions can be observed more clearly. In particular, the golden zone assumptions counteracted the reduced blocking times for different turnover rates in this scenario.

4.2 Collaborative HOPS with an S-shape routeing policy

We now investigate the case in which humans and robots collaborate in a HOPS. In the first step, it is assumed that all order pickers use only S-shape routeing, which is the most frequently applied policy in practice (Masae et al., 2020a). If we successfully add agents to one team (either humans or robots) for a predefined order assignment rule, we obtain a U-shaped system cost curve, meaning that the costs per pick decline first and then increase from a certain turning point. In this section, we explain this U-shaped pattern, based on which a cost analysis is performed.

4.2.1 U-shaped cost curves

The shape of the cost curves depends on the extent to which the workload is balanced between collaborating teams. Balancing the workload between teams according to team size has a strong impact on the costs per pick for the overall system. For example, when one team processes tasks faster than the other team, a processing backlog occurs on the order list because orders are not completed. This will cause higher picking costs in the following manner: initially, the faster team continues to process its share of orders, and the slower team is not able to keep up with this speed. In practice, partially completed orders can often not be delivered to customers and need to wait for completion in a depot with limited capacity. This decoupling of picked and delivered items leads to an inefficient use of resources and may cause extra handling and storage costs, which may increase the total cost of the system. Additionally, because order pickers are not allowed to stay idle until the other team has caught up, the faster team always continues to process new orders, which may further decrease the speed of the slower team due to additional blocking. In view of the effects mentioned above, ideally, both teams should process their assigned order share from the order list so that the order list is processed evenly, and no resources are wasted by processing partial orders, which cannot be completed by the other, faster team. This can be achieved by avoiding inappropriate team configurations and workload settings.

To quantify and visualise this phenomenon, we define three indicators:

- *The real throughput refers to the number of picks that each team actually performs in every shift.*
- *The effective throughput measures the number of items picked and the completed orders.*
- *The hybrid throughput, compared to the effective throughput, does not measure the total number of completed orders, but only up to the order that the slower team has just finished.*

To minimise the costs per pick, the three indicators should adopt the same value, such that both teams process their order share from the order list equally. In this case, no processing backlog occurs, which indicates that all retrieved items are delivered at the end of the working shift. In the case of a processing backlog, the three indicators differ, such that the real throughput exceeds the effective throughput, which, in turn, is higher than the hybrid throughput. The difference between the real and effective throughputs points directly to a waste of resources by showing how many items were picked without being successfully delivered until the end of the shift. In addition, the difference between the effective and hybrid throughputs indicates a reduction in process efficiency. According to the predefined assignment rules, some orders are the responsibility of only one team. If such orders exist in the processing backlog, the faster team can complete them individually. However, according to the first-come-first-served principle, the faster team can only do this if these orders appear next on the order list. Overall, the three indicators can be used to evaluate the extent to which the workload between the collaborating teams is balanced, which directly impacts the costs per pick.

To illustrate the development of the three indicators and the resulting system costs for different team configurations, an example is displayed in Figures VI-10 and VI-11 with a fixed number of robots (5) and a varying number of humans (1–35) for a given assignment rule (AB/C). Figure VI-11 shows that a five-robot team is too large for a small human team (starting from one human operator), causing an inefficient use of resources and higher costs in the robot team. In Figure VI-10, the differences in the three indicator values of the system (black curves) and the robot team (orange curves) decrease with an increasing number of humans, which can be interpreted as a more balanced workload between the collaborating teams. Starting with eleven human operators, the indicators of the human team (blue curves) begin to show differences again, as do the system indicators. The same behaviour can be observed in the development of the cost curves in Figure VI-11. The system cost curve increases when more than 11 humans (red triangle) work in the system. Note that only an integer number of agents are feasible. Thus, the team configuration of five robots and eleven humans presents a situation in which the three indicators of the system show the minimal difference, which is nearest to the ideal situation from the perspective of a collaboration in which no resources are wasted. Furthermore, this "resource-efficient" team configuration does not necessarily correspond to the minimum cost curve, because a larger number of agents causes more blocking situations, which always results in a reduced process efficiency and, as can be observed in Figure VI-11, a general upward tendency of the cost curves. This partially compensates for the benefits of the resource-efficient team configuration and causes a slight deviation of the cost-optimised configuration, which shows the minimal difference between the three indicators. For example, in the scenario shown in Figures VI-10 and VI-11, the lowest cost point is actually at five robots and ten humans.

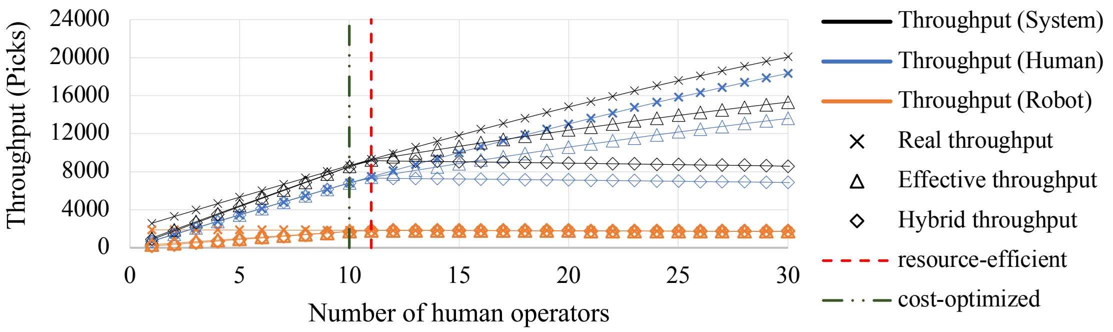

Figure VI-10: Three indicators to evaluate the balance of workload between the collaborating teams (Scenario: 50/30/20-AB/C-H(S)R(S), number of robots: 5, number of humans: 1–35).

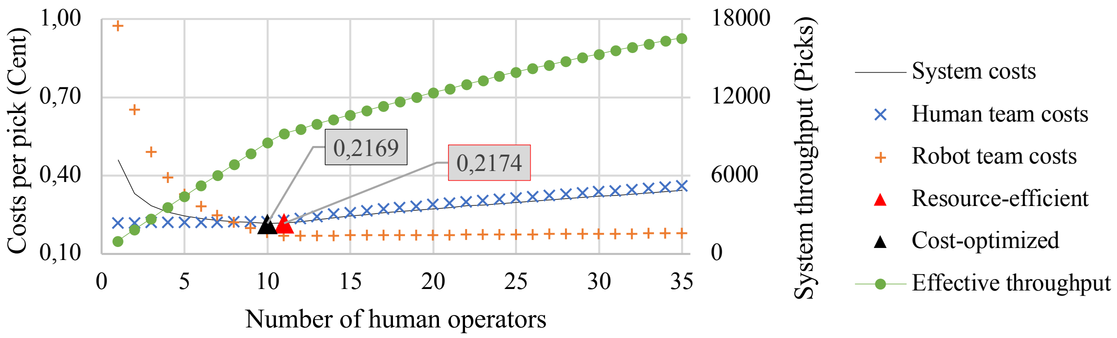

Figure VI-11: U-shaped cost curve of collaborative HOPS (Scenario: 50/30/20-AB/C-H(S)R(S), number of robots: 5, number of humans: 1–35).

The system throughput of the HOPS investigated in this study refers to the effective throughput, which we defined as the number of items picked in completed orders per shift. Thus, the items that are picked but not delivered in one working shift due to the unbalanced workload between the teams directly cause higher costs per pick.

4.2.2 Cost analysis

Based on the previous analysis, we investigate the collaborative HOPS scenarios “AB/C” and “A/BC,” in which items outside the golden zone (C items) and, respectively, the items distant from the depot (B items) are assigned to the robot team. To clearly show the balance of workload between two teams in HOPS (see Section 4.2.1), points with the same robot team size are combined into curves. The aim is to analyse the cost advantages of the HOPS in these scenarios for two different turnover rates (see Figure VI-12). The parts of the cost curves that lead to higher costs per pick than in the human OPS are not shown. As can be seen in Figure VI-12, by assigning only C items to robots (scenarios a and c: “AB/C”), the HOPS cost curves lie partially below the human OPS’s cost curves with golden zone picking consideration. However, cost advantages are not observed: HOPS is outperformed either by humans or by robot OPS. In contrast, if class B items are also assigned to the robot team (scenarios b and d: “A/BC”), cost reductions comparing to the benchmark scenarios can be observed in HOPS (see red break-even points).

To validate this result, we tested the HOPS with other work assignment options, as shown in the Appendix (Figure VI-18), including scenarios in which other duties are assigned to robots (such as picking A items). As can be seen, cost advantages mainly result from assigning B items to robots (scenarios AC/B or A/BC). In other cases, the HOPSs are outperformed either by human OPS (ABC/-) or by robot OPS (-/ABC). For a discussion of these results and the possible benefits of the HOPS, we refer to Section 5.

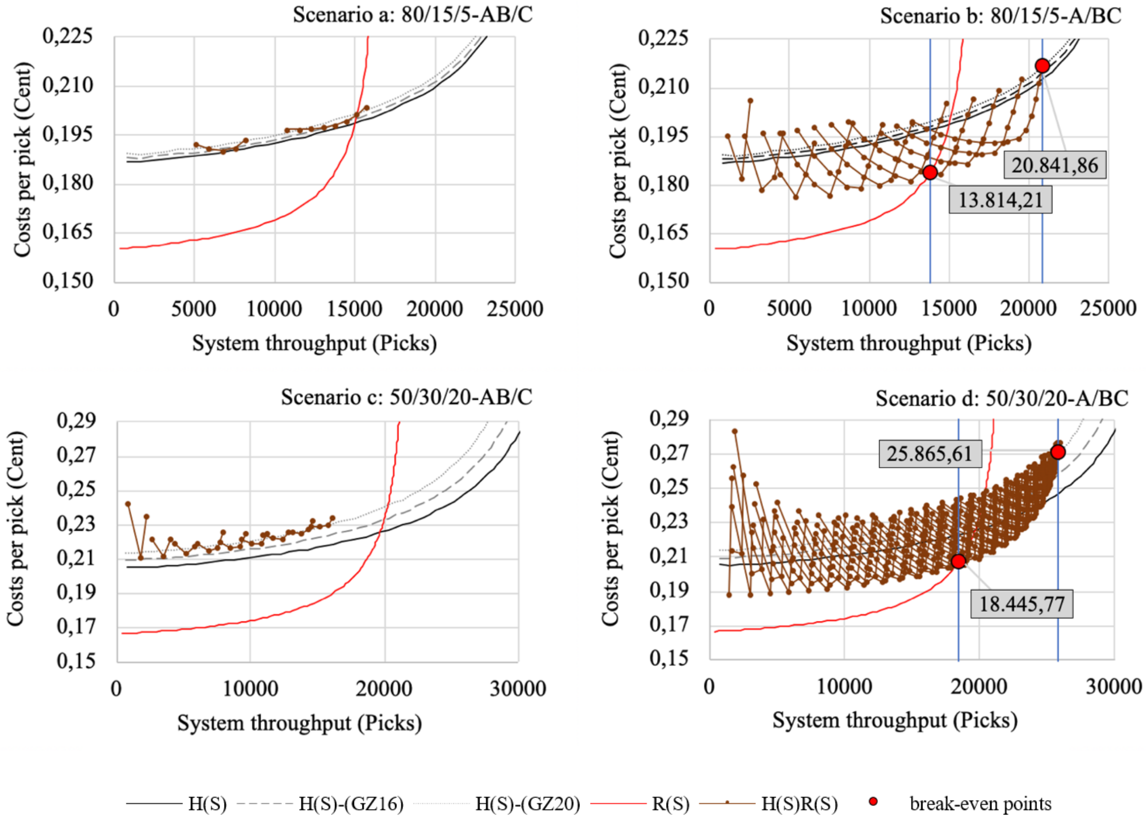

Figure VI-12: Cost analysis of HOPS.

4.3 Collaborative HOPS with different routeing policies

As stated in Section 4.1, the applied routeing policies affect the system throughput and costs per pick. In this section, we investigate the effect of two routeing policy combinations on the HOPS performance: H(S)R(LG), H(LG)R(LG). The S-shape policy (H(S)R(S)) serves as a benchmark. Figure VI-13 presents two example cases, in which 15 robots (assignment rule: AB/C), 45 robots (assignment rule: A/BC) and a varying number of humans collaborate. As can be seen, LG again, appears to be a better policy for both teams. It generally leads to lower costs per pick than S, similar to the results in benchmark cases. This finding also holds in other cases (other robot team sizes) investigated in this simulation experiment.

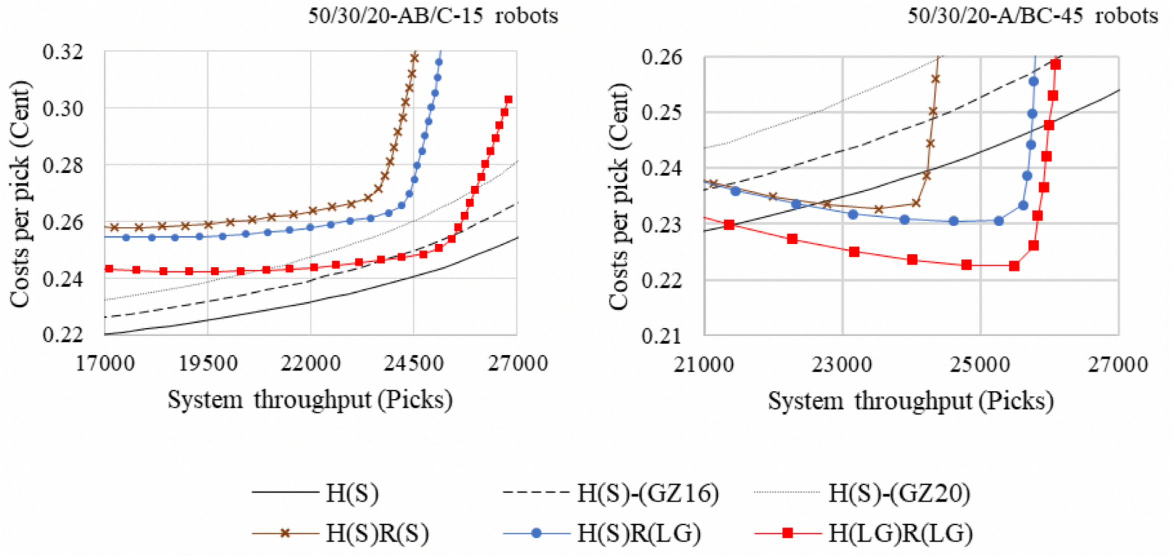

Figure VI-13: Exemplary cost curves of HOPS for different routeing policy combinations for a varying number of humans and a given number of robots.

To quantify the cost advantages of the HOPS for different team configurations, we plotted curves representing each routeing policy combination assuming that it is not realistic to employ decimal units for the number of agents (see Figure VI-14). The results (cost-throughput combinations) were obtained by varying the size of either collaborating team by one agent each time, as one agent is the smallest unit when measuring different system performances. Among the two types of agents in the HOPS (humans and robots), robots have a lower speed of processing orders. Adding one robot to the system results in a comparatively smaller increase in system throughput. This entails that when we investigate the simulation results for a fixed robot team size, more system throughputs and the corresponding costs per pick can be sampled to analyse the system performance of the current routeing policy combination. Therefore, we start by defining the cost-optimised number of humans for each robot team size. The resulting team configurations point to the number of humans that minimise the system's costs per pick for each fixed robot team. These are denoted as "optimal points" in Figure VI-14. Connecting all optimal points leads to a saw-toothed curve (blue curve). As mentioned above, robots work slower than human operators. Hence, for different sizes of the robot team, the same number of humans can be cost optimal. However, the effectiveness of adding a further human depends on the current robot team's capacity to support the additional picks by the additional human to complete orders, which leads to a better or worse workload balance. We then fixed the human team size among the optimal points and defined the cost-optimised robot team. Those achieving the lowest costs per pick for each human team size are selected again (“optimal+ points”). Combining these points, we see a relatively smooth curve representing the costs of a particular routeing policy combination.

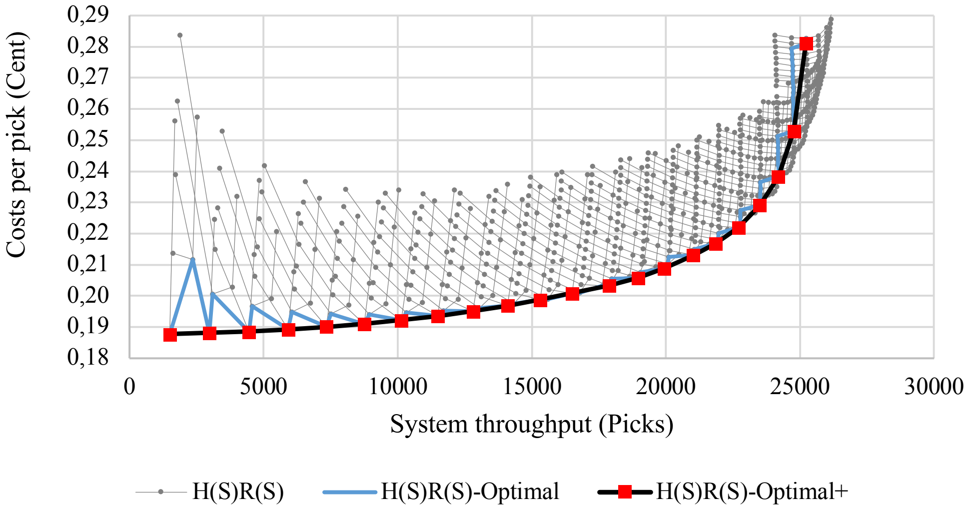

Figure VI-14: Logic of creating a representative cost curve for each routeing policy combination.

To quantify the cost advantages of a HOPS, the “50/30/20-A/BC” scenario is chosen for the subsequent analysis (see Figure VI-15), as it is the only scenario that is not restricted by the inventory quantity we defined for the analysis. The cost curves derived using the above-mentioned method correspond to the previous findings: with the order of H(LG)R(LG) < H(S)R(LG) < H(S)R(S), LG is preferred in the current HOPS for both teams. We conclude that the HOPS can provide further cost advantages. With varied routeing policy combinations, it can be observed that the HOPS always outperforms the two benchmark OPSs for a certain range of system throughput.

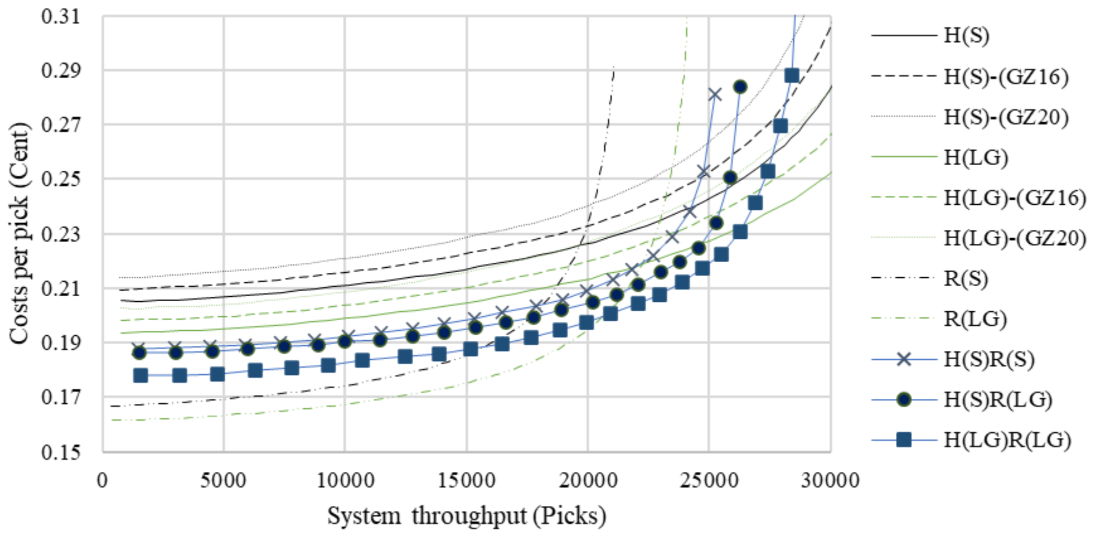

Figure VI-15: Comparison of representative cost curves for different routeing policy combinations (scenario: 50/30/20-A/BC).

5. Discussion

The previous analyses showed that the investigated collaborative HOPSs are generally capable of reducing the costs per pick compared to purely manual or purely robot OPS. However, we also found that HOPSs outperformed the benchmark OPSs only for a relatively small number of parameter configurations. In this section, we discuss some main assumptions made throughout the analyses to gain deeper insights into the possible benefits of HOPSs in real-world applications and to identify future research opportunities for HOPSs.

5.1 Cost advantages

Our earlier analyses showed that HOPSs outperformed the two benchmark OPSs only for a small range of system throughputs. This result was induced by some of the assumptions made in the simulation. So far, we investigated an ideal situation in which the robots are able to pick all items without additional costs and without making mistakes. In a practical situation, this would imply that goods have to be packaged (in standardised boxes) prior to storage to allow robot picking. In e-commerce, in which small batch sizes are usually retrieved (Yang et al., 2020), this might be a plausible solution. Nevertheless, this additional cost, together with the increased capital tied up in inventory, needs to be considered.

Additionally, we assumed that the robots pick with zero errors and are fail-safe. However, in real warehouse applications, errors may occur in which robots need the support of a human operator. The number of interventions would likely increase in the system throughput the robot team is responsible for, leading to additional costs for the robot team that are not yet included in the model.

To simulate these additional costs, we assumed higher costs per pick for the robot team, as follows. Because humans can pick all the items (not only standardised ones), no additional costs for the human team were considered. For the case of the turnover rate of 80/15/5 A/BC, the number of items and picks the robot team was responsible for was smaller than those in the 50/30/20 case, leading to fewer additional costs for pre-packaging and interventions. Figure VI-16 shows that the cost curves of the robot OPSs shift upward, while the costs for human OPSs remain unchanged.

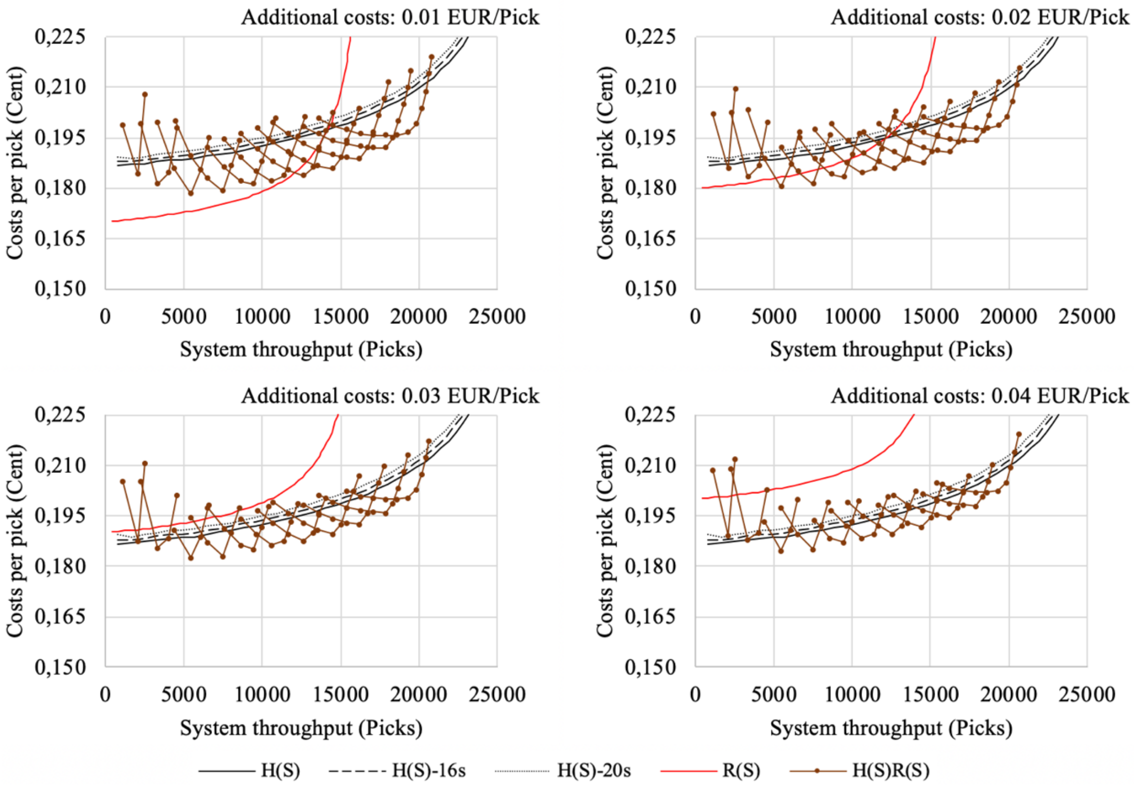

Figure VI-16: Cost analysis of HOPS with additional costs per pick for the robot team (scenario: 80/15/5-A/BC).

As can be seen, this increases the range of system throughputs for which the collaborative HOPS outperforms the human and robot OPSs. This is because the HOPS is less sensitive to increased robot costs than is the pure robot OPS. Increasing the number of items picked by the robots also increases the additional costs considered in this scenario. This leads to the case in which the collaborative HOPS is beneficial for nearly all system throughputs. Organisationally, this system configuration leads to a warehouse in which humans operate in a fast-moving area near the depot and within the golden zone area, whereas robots pick items farther away from the depot and from high and low shelf levels that imply a longer retrieving time according to the golden zone concept. As can be seen in the Appendix (Figure VI-19), the effect is different in the case of a throughput of 50/30/20. Owing to break-even points that differ in this scenario, the range in which the HOPS is preferable is smaller.

5.2 Mixed storage warehouses

As mentioned above, robots may not be able to grasp all the items stored in the warehouse. Instead of pre-packaging these items (e.g. putting them into cardboard boxes the robots can pick), they could alternatively be assigned to human operators. In this section, we simulate a situation in which a set of items can only be picked by humans. These robot-incompatible items (denoted as I) occur randomly in the three item classes and are stored together with other standard packed items. The share of these incompatible items ranges between 10% and 70% of the storage quantity (scenarios a–d in Figure VI-17). In addition to the human OPS (ABC/-) and the robot OPS (-/ABC) as benchmarks, two assignment rules are investigated: 1) AI/BC, in which humans are responsible for picking A items as well as the items not graspable for robots in classes B and C, while robots pick the graspable items in classes B and C; 2) I/ABC, in which only items incompatible for robot picking are assigned to humans, whereas the robot team is responsible for picking all other items. The results are presented in Figure VI-17. Note that the robot OPS serves only as a benchmark scenario for cost analysis. Owing to the existence of robot-incompatible items, the robots are unable to finish some of the orders, so that a pure robot OPS does not apply here.

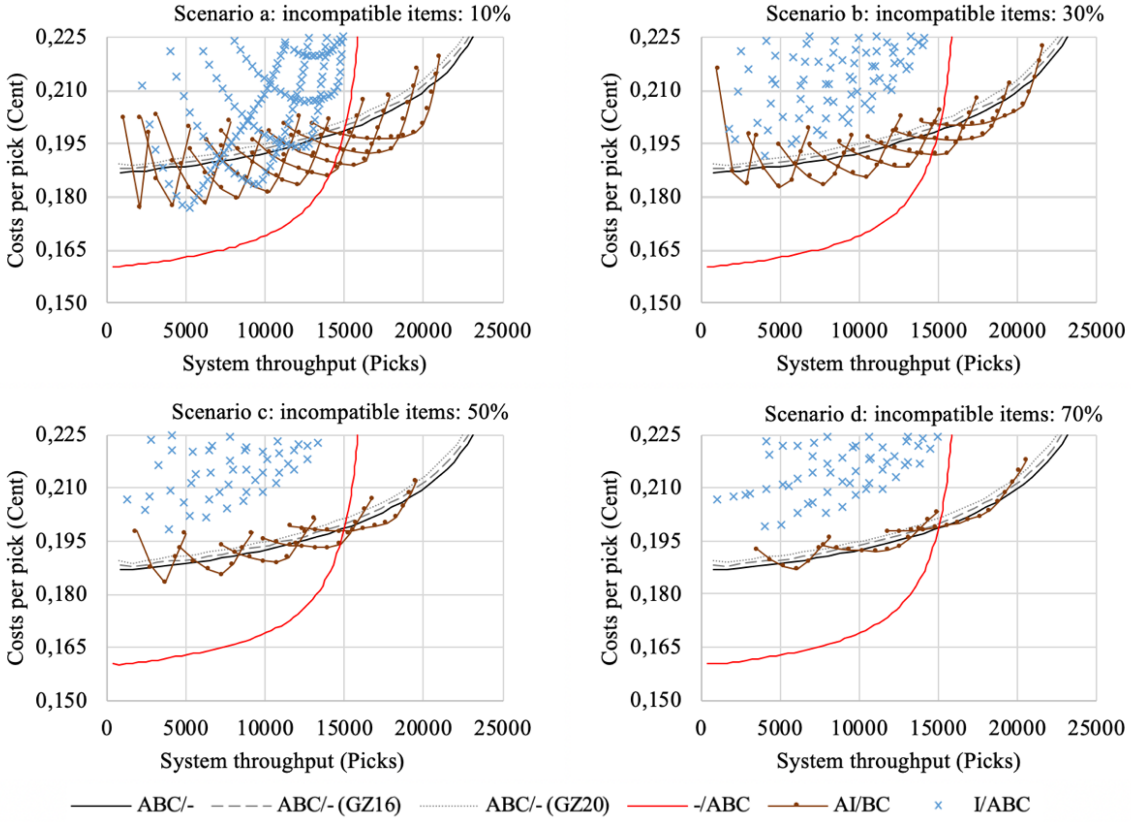

Figure VI-17: Cost analysis of HOPS in a mixed storage warehouse with turnover rate 80/15/5 and S-shape routeing policy (costs per pick over system throughput).

These scenarios are comparable to those investigated in Section 4.2. In AI/BC, humans take over parts of the robots' responsibilities in A/BC, as some items in classes B and C are incompatible with robots. With an increased percentage of incompatible items, the cost curve of the HOPS converges to the human OPS (ABC/-) cost curve.

In contrast, I/ABC is comparable to -/ABC, if the share of incompatible items is low. As can be observed in scenario a, the lower bound of the cost curves is similar to the cost curves of the robot OPS (-/ABC), meaning that cost advantages of the HOPS over human OPS (ABC/-) can only be observed at lower system throughputs. By increasing the number of incompatible items, the workload of humans increases, causing an increase in deviations of the cost curve compared to that of the basic scenario -/ABC. In I/ABC, warehouse zones A, B and C are not pre-assigned to one team, leading to more frequent blocking between humans and robots. Hence, the resulting OPS cannot benefit from the robot OPS's lower costs per pick at a lower throughput, and it also leads to longer blocking times in the human team caused by robots. For instance, a cost-optimised team configuration of 10 robots and

13 humans (see definition in Section 4.2.1) leads to total aisle blocking of 3.57 s/pick in I/ABC with 70% of incompatible items, whereas in the human OPS with the same number of agents (23 humans), the total aisle blocking is 2.67 s/pick. For this reason, I/ABC is, in the tested scenarios, always outperformed by either human OPS or the HOPS with the assignment rule AI/BC. This suggests that, in mixed storage warehouses, our previous statements still hold. A HOPS with assignment rule AI/BC, modified from A/BC, still leads to cost advantages, especially compared with I/ABC, in which humans only perform picks of which robots are incapable.

5.3 Further assumptions

Further assumptions made throughout the analysis relate to the warehouse itself. One assumption limits the vertical pick range to 2.1 m and six shelf levels. However, robots are generally capable of picking items from shelf levels that human order pickers cannot reach. In warehouses without a second floor, it is common that there is free space between the top of a shelf and the ceiling that is not utilised, because humans can only grasp up to a certain height. HOPSs can utilise this space without the need to reconstruct warehouse buildings. Assuming that a robot can pick from shelf levels up to 2.8 m, two additional levels could be utilised, leading to an additional 33% of storage space compared to a six-level shelf. This can provide an advantage for a HOPS compared to a human OPS.

In addition, we assumed in our analyses that robots only work during shifts in which humans work as well. In practice, however, night shifts and extended working hours are common, and, in our case, such extra shifts could be assigned to the robot team with minimal support from human operators. With this configuration, for example, urgent orders can be handled and directly prepared for shipping during the night shift. Additionally, a continuous output around the clock could be handled by the robot system without employing humans for the entire time (and extra pay for night work). If this is complemented by high peak loads, fully automated systems would be oversized for most of the time and would be inefficient. In such scenarios, a HOPS can employ humans for peak hours and robots for a basic continuous output.

HOPSs can also contribute to human well-being and improve ergonomics. Several studies have investigated how economic profitability and improvements in operator well-being can be jointly obtained in an order picking context (see, for an overview, Sgarbossa et al., 2020). In HOPSs, interactions with robots have the potential to improve ergonomics, motivation and job satisfaction, because HOPSs enlarge and enrich the work tasks of humans instead of trivialising them (Neumann et al., 2021). In addition, humans can become supervisors and trouble shooters for the robot team. Concerning physical ergonomics, humans could benefit from shorter travel distances, because long distances are outsourced to robots and from better grasping conditions because of the consistent use of the golden zone concept for human operators. Moreover, robots can also be used for tasks in user-unfriendly environments or periods, for example, for preparing orders during night shifts or in particular climate or spatial conditions. These impacts have the potential to improve physical, mental and psychosocial ergonomics at work.

Overall, HOPSs can lead to further benefits for companies beyond a reduction in costs. HOPSs could be particularly useful for successfully managing the transition to fully autonomous OPSs. For example, if enterprises are not willing or capable of investing in a fully autonomous robot OPS, it is possible to increase the number of picking robots over a longer period of time and apply a HOPS for the transition period.

5.4 Limitations and future research needs

This study has limitations that could be addressed in future research. First, the warehouse environment was assumed to be constant over all the experiments except for the sensitivity analysis. However, the order size, warehouse layout and other aspects can impact the simulation and lead to different results. Second, limiting assumptions regarding zoning, batching, storage assignment and routeing were necessary in our study. Some of these parameters have not been investigated and could be extended in future studies. Third, the interaction rules were chosen to be plausible, generalisable and applicable in the simulation. However, in specific configurations, other rules that impact parameters, such as the strength of the picker-blocking effects on the overall system performance, might be used. Finally, the robot's capabilities are assumed to be fixed. Varying the robot's characteristics, such as the batch size the robot is able to transport before returning to the depot, might lead to different results and varied HOPS benefits.

Despite these limitations, our results highlight the potential of using HOPSs. Owing to the real-world restrictions that autonomous pick-robots still face, future research is necessary to investigate these systems in detail. We identified three clusters of future research needs on HOPSs according to the dimensions of the TOE framework.

Technology: We studied the use of a specific technology, that is, an autonomous pick robot, whose characteristics were derived from relevant literature and market information. However, as outlined in Section 2.1, there are various HOPSs that can be applied to diverse technologies. For example, AGVs are frequently investigated in terms of RMFS; however, only first advanced interaction scenarios are derived in which human order pickers and AGVs collaborate in a shared workspace – that means, HOPSs are not yet in the focus of research. Future research could thus extend the scenarios identified in the literature search and investigate further interaction scenarios, as well as investigate the impact of different decision problems such as the number of AGVs applied, the routeing, batching and zoning policies and their impacts on one another in different combinations. Additionally, the assumed robot characteristics could be investigated more deeply, for example, in terms of speed, pick quality, or in light of the assumptions discussed in Sections 5.1 to 5.3.

Organisation: We studied different routeing policies and assignment strategies for both teams. However, these investigations only built the first set of impact factors. Relevant questions for future work could be, for example, how the system behaviour changes if different zones, batching, or storage assignment strategies are used. Further, future research could investigate how other pick-assignment strategies influence the results. In addition, we only discussed, but did not explicitly study, possible ergonomic benefits for human operators in a HOPS, which represents an interesting field for future research. Finally, HOPSs also have the potential to impact strategic decisions, for example, for change management within a continuous development toward fully autonomous warehouses.

Environment: The assumptions made for the warehouse were constant for all experiments in terms of size and shape within this study. However, the size and shape of a warehouse depend on the tasks to be fulfilled and, thus, differ for large e-commerce retailers, small city hubs, or production facility warehouses. Future research could investigate how the size and shape of the warehouse impacts the performance of a HOPS. Future research could also investigate how the customer structure impacts HOPS performance. For example, we assumed that all orders are known at the beginning of the shift and work by following the first-come-first-served policy. Hence, it would be interesting to investigate how varying workloads, including peak loads and idle phases, impact the achieved results. How does a different order size impact the results?

6. Conclusion

This work introduced the concept of hybrid order picking systems, which apply automation technologies, in the investigated case an autonomous pick robot, to cooperate or collaborate with human operators in order picking in a shared workspace. To investigate whether a HOPS can lower the cost of order picking, a simulation study of different collaborative HOPS scenarios was carried out focusing on different demand frequencies, routeing policies and collaboration strategies. The results can be summarised as follows. From an economic perspective, HOPSs are generally capable of improving order picking operations in terms of throughput and costs, although the benefits are limited to certain system throughputs. The throughput range for which a HOPS is beneficial depends on the quantity and item classes assigned to the robot and the human team. In our study, HOPSs performed well in cases in which B and C items were assigned to the robot team. The main aspects responsible for this result are the effects of zoning and blocking. Additionally, the team configuration has a major impact on the quality of collaboration, meaning that both teams, humans and robots, must be able to process their part of the collaborative order picking task to not generate a backlog for the other team and minimise the overall costs.

Our sensitivity analyses showed that two model assumptions are especially critical for the relative performance of HOPSs. First, we have shown that a small increase in costs for the robot team results in the HOPS outperforming the pure robotic and human OPSs in terms of cost for almost all system throughputs. Because we investigated an idealised warehouse in the simulation, for example, by assuming that all items are graspable for the robots and no human intervention is necessary throughout robot picking, higher costs for robot picking (than those initially assumed in the simulation) are plausible in practice. Additionally, the HOPS is generally capable of making a larger warehouse height usable and may thus significantly increase the usable storage space. Hence, this study makes an important managerial contribution: for practitioners, this study shows, using approximately 50 parameter configurations, how a HOPS generally performs in contrast to completely manual and automated OPSs by applying autonomous pick robots and which interactions seem to be important. With the sensitivity analysis, additional information about real-world applications is obtained and can be used for the initial evaluation of a HOPS within a company. While considering a HOPS for future applications, simulations can be performed for the specific case of a company and based on the results achieved in this study.

With the results obtained, the first study that allows the evaluation of a possible benefit of HOPSs to certain warehouse types is available to practitioners and researchers. With the diversity of parameter configurations considered, a broad investigation was provided, which is among the first to investigate HOPSs from an economic and processual perspective.

Appendix

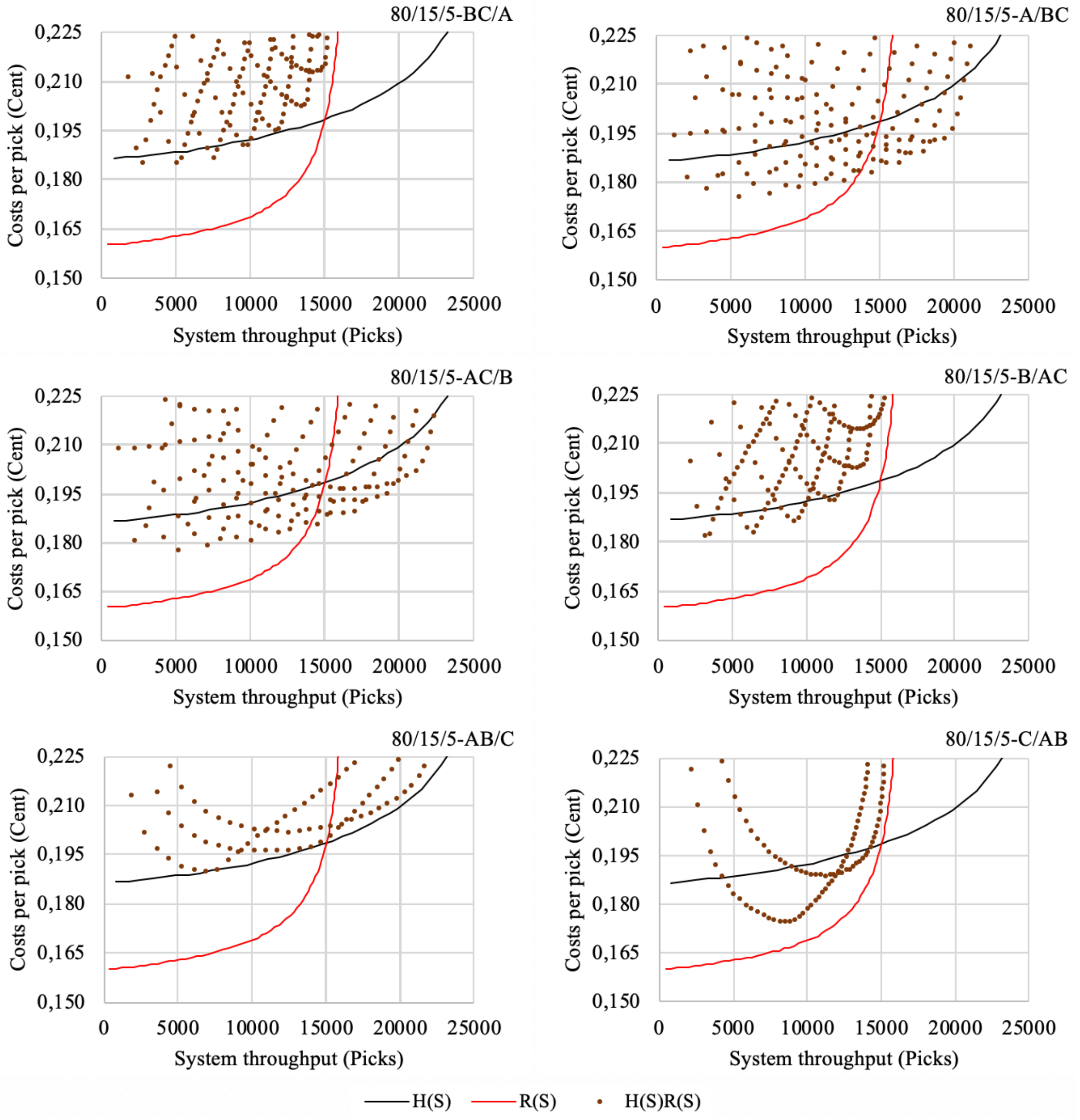

Figure VI-18: Cost analysis of HOPS with other work assignment options.

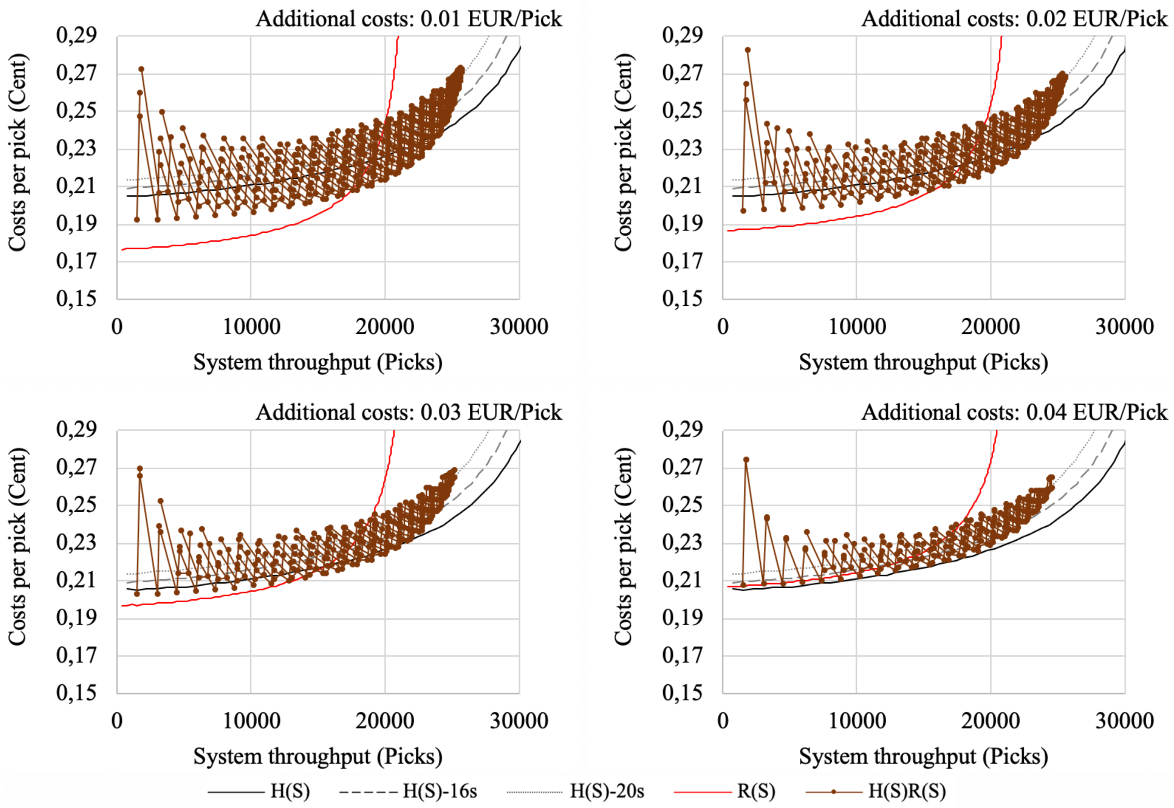

Figure VI-19: Cost analysis of HOPS with additional costs per pick for the robot team (scenario: 50/30/20-A/BC).

VII. Final Conclusion

This cumulative dissertation dealt with the impacts of Logistics 4.0 from a human-centred perspective. Increasing demands are challenging logistics processes and new technologies are enabling more efficient and complex processes that are also impacting how humans work in this still labour-intensive industry. Therefore, new possibilities as well as impacts of this development were investigated in five articles in this cumulative dissertation.

According to the four overarching research questions formulated in the introduction of this cumulative dissertation, we found the following answers: Concerning the first research question, *what Logistics 4.0 is and what the current state of research on Logistics 4.0 is,* Article 1 of this cumulative dissertation developed a definition of Logistics 4.0 based on the concept of Industry 4.0 that includes the technological developments as well as the paradigmatic shift including sustainability issues that also include social targets. The reviewed literature on Logistics 4.0 was analysed in depth to detail the conceptual framework and identify future research directions. Major lacks in Logistics 4.0 research concern empirical research as well as including human factors related research. These findings were proven later in this cumulative dissertation with a content analysis presented in Article 3. This content analysis focused on the extent to which human factors are considered in research on Industry 4.0 – which can be considered a more general term compared to Logistics 4.0. The obtained results support the findings of the systematic literature review and underline the need for further research.

Pursuing this finding, research question 2, *how the developments towards Logistics 4.0 affect intralogistics employees' work characteristics,* was investigated in Article 2 of this cumulative dissertation. To answer this question, 16 semi-structured interviews in seven companies were performed and evaluated according to their Intralogistics 4.0 maturity. Based on this data, the impacts of the Intralogistics 4.0 maturity on work characteristics were derived. The findings show differences between the impacts of automation technologies that affect work characteristics negatively in most cases and digital technologies that show potentials for enrichment of jobs and thus also to improve work characteristics. These findings also complement the results of Article 1 and the content analysis of Article 3 that human factors are important to consider but currently under-researched in the development towards Logistics 4.0 and Industry 4.0.

In the third article, research question 3 on *how jobs can systematically be analysed in the development towards Industry 4.0 and Logistics 4.0,* was focused on. Therefore, a comprehensive analysis tool based on five theoretical building blocks was developed. This analysis tool enables a systematic consideration of human factors impacts prior to and during an Industry 4.0- or Logistics 4.0-element implementation, also considering negative side effects and indirect effects.

Lastly, research question 4, *how order picking changes in the development towards Logistics 4.0 and what impact this might have on social and economic factors of the order picking process,* was answered in Articles 4 and 5 of this cumulative dissertation. Focusing on the first aspect of the research question, how order picking might change in Logistics 4.0, Article 4 provides insights into what is called Order Picking 4.0. Therefore, a framework was developed which considers supportive and substitutive technologies and the respective level of automation, leading to four clusters of order picking systems, three of which were systematically reviewed. Findings show that hybrid order picking systems, in which humans and robots work together in a shared workspace for the task fulfilment, are still under-researched, although they provide promising opportunities concerning economic and social targets. Hence, Article 5 focused on the design and investigation of one instance of hybrid order picking systems, in which autonomous picking robots and human workers pick items out of shelves in a shared workspace at the same time. The simulation study and the discussion of assumptions of these systems show potential for economic profitability, while the system is designed to limit physical effort and improve work characteristics.

With these research articles, the initiated change of the human work system in logistics by Logistics 4.0 is investigated in depth. The changes of the work system for humans and the lack of research addressing this are investigated and a tool to analyse the impacts for an active management is provided. Then, a partial process, order picking, is investigated from a sociotechnical point of view and analysed from an economic, processual and human factors perspective.

The five articles apply different methods to fulfil the research goals: By means of two systematic literature reviews the state of the art in research is investigated in depth for Logistics 4.0 and Order Picking 4.0. A content analysis of the literature of Industry 4.0 proves the lack of human factors consideration in research on Industry 4.0. Semi-structured interviews provide insights into the perceived reality of operators in intralogistics processes of different companies and a simulation study shows how different teams, humans and robots, and process parameters impact the economic preferability of hybrid order picking systems.

Besides its scientific impact, this dissertation also has important managerial and practical implications that are of major importance in this practice-oriented field of research. Especially four aspects should be stressed again: First, this dissertation provided a broad overview on Logistics 4.0 applications, thus enabling practitioners to derive a holistic vision of an individual future logistics system based on certain applications reviewed in Article 1 of this cumulative dissertation. Second, Article 2 provided important insights into the intralogistics employees' perceived work characteristics and derived interrelations between these and the Intralogistics 4.0 maturity. Thereby, enterprises are provided with insights on how work systems might change when implementing certain Logistics 4.0 elements and which aspects might be relevant to consider – this knowledge is essential to manage the transition of work systems from a human-centred perspective. Third, this is complemented by the systems framework which enables a hands-on analysis of technology implementation in the context of Industry 4.0 and Logistics 4.0 as provided in Article 3 of this cumulative dissertation. The ease of use of this tool as well as its general applicability make it interesting for enterprises to use to prevent negative effects of technology implementation ensuring a successful implementation. Lastly, the review on Order Picking 4.0 in connection with the deeper investigation of hybrid order picking systems are also helpful for practitioners. The review on Order Picking 4.0 and its underlying sociotechnical order picking system framework can support the identification of potentially relevant order picking systems as well as the benchmarking of order picking processes. In addition, the simulation study of a hybrid order picking system has important practical implications, because it is among the first studies that investigate a holistic order picking system applying autonomous picking robots together with human order pickers in a shared workspace. The results indicate for which enterprises this solution might be interesting, how such a system behaves under certain restrictions and gives insights on the cost-efficiency of such a system for enterprises that might consider applying autonomous order picking robots.

Overall, this cumulative dissertation shows how workers are affected by and how work systems change in Logistics 4.0 and provides insights and support for research and practice. In this ambition, this dissertation also guides towards what is called Industry 5.0, a concept recently presented by the European Commission (Breque et al., 2021). In that report, the authors define Industry 5.0, in contrast to Industry 4.0, which would refer to digitalisation and the use of artificial intelligence, as an industrial system that is not only profit-driven, but also human-centred, resilient and sustainable. This sheds light on the human worker with regard to technological developments and calls for "placing the wellbeing of the industry worker at the centre of the production process" (Breque et al., 2021) within the boundaries of our planet, thus complementing the techno-centric perspective of Industry 4.0 that was identified in this dissertation. In this regard, this cumulative dissertation not only contributes to the stream of human-centric work in Industry 5.0, but also includes main aspects of the approach in the working definitions of Logistics 4.0 and Order Picking 4.0 and thus implements this view in the foundations of this research.

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