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REVIEW ARTICLE

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A review of digital assistants in production and logistics: applications, benefits, and challenges

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ABSTRACT

This study presents a systematic literature review to understand the applications, benefits, and challenges of digital assistants (DAs) in production and logistics tasks. Our conceptual framework covers three dimensions: information management, collaborative operations, and knowledge transfer. We evaluate human-DA collaborative tasks in the areas of product design, production, maintenance, quality management, and logistics. This allows us to expand upon different types of DAs, and reveal how they improve the speed and ease of production and logistic work, which was ignored in previous studies. Our results demonstrate that DAs improve the speed and ease of workers' interaction with machines/information systems in searching, processing, and demonstrating. Extant studies describe DAs with different levels of autonomy in decision-making; however, most DAs perform tasks as instructed or with workers' consent. Additionally, we observe that workers find it more intuitive to perform tasks and acquire knowledge when they receive multiple sensorial cues (e.g. auditory and visual cues). Consequently, future research can explore how DAs can be integrated with other technologies for robust multi-modal assistance such as eye tracking and augmented reality. This can provide customised DA support to workers with disabilities or conditions to facilitate more inclusive production and logistics.

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1. Introduction

Researchers and practitioners have tried to design user-friendly human-computer interaction for decades. Finally, graphical user interfaces have been transformed into natural language user interfaces (Følstad and Brandtzæg 2017). Digital assistants (DAs), which are empowered by improved artificial intelligence (AI) systems, such as natural language processing, machine learning, and knowledge representation, can engage in conversations with humans, answer complex questions, perform tasks, provide recommendations, and make predictions (Oracle 2022). These are known as conversational agents, dialogue assistants, chatbots, intelligent personal assistants (IPA), virtual assistants (VA), softbots, or avatars (Maedche et al. 2019; Wellsandt, Hribernik, and Thoben 2021). Some examples are general aids such as Amazon's Alexa, Apple's Siri, and Google Assistant (Maedche et al. 2019), while Alibaba's Xiaomi and JD's JIMI are chatbots to improve customer service (Jiang, Qin, and Li 2022). In 2023, OpenAI released a large language model of a generative pre-trained transformer (GPT)-4 with the ChatGPT application (OpenAI), which demonstrates the potential (and limitations) in providing responses and solutions for a broad range of subjects, such as code generation, image generation, or text writing (Frederico 2023; OpenAI 2023a).

The production and logistics sectors are main drivers for employment and play critical roles in economic growth. The European Union for example employed more than 40.6 million people in its manufacturing, transportation, and storage sectors and generated a value addition of EUR 2509.3 billion (Eurostat 2022a; 2022b). However, production and logistics face challenges such as how to offer highly customised products and services, reduce production and delivery lead times and costs, and plan for uncertainty (Oracle 2021). DAs, in this regard, can be of great assistance. Juniper Research (2023) predicted that chatbot use over two years could save around two and a half billion hours and eight billion dollars.

Owing to the digital transformation that inspired concepts such as Industry 4.0, human workers interact more frequently with smart materials, machines, equipment,

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and computers; process a higher volume of information; and manage more complex tasks (Kagermann, Wahlster, and Helbig 2013; Peruzzini, Grandi, and Pellicciari 2020; Romero et al. 2016). Enabling human workers to interact with cyber physical systems (CPS) through intelligent interfaces, such as DAs, is the key to supporting them in digitalised production and logistics environments, and to realise a human-system symbiosis in an Industry 5.0 context (Choi et al. 2022; Grosse et al. 2023). For example, DAs can enable human workers to chat with machines or information systems straightforwardly (Kassner et al. 2017), retrieve, process, and analyse shop floor information (Gärtler and Schmidt 2021), assist workers in completing tedious tasks, enable human-centric production control (Rabelo, Romero, and Zambiasi 2018), and coach workers to learn new tasks (Rooein et al. 2020).

Despite DAs being prevalent in our private and business lives, the literature has mainly focused on general applications of DAs in diverse industries, including banking, insurance, public transportation, retail, and customer relationship management (Agarwal, Agarwal, and Gupta 2022; Camilleri and Troise 2023; Quarteroni 2018; Silva et al. 2020). The aforementioned potentials of DAs in production and logistics have not yet been comprehensively discussed.

To contribute to closing this gap, this study aims to consolidate knowledge from the scientific literature and investigate how DAs can reduce human effort in production and logistics. They allow workers to be released from routine tasks, have additional control of the work process, and focus on creative and value-adding activities. We do this by performing a systematic literature review with the intention of (1) exploring and conceptualising the applications of DAs in supporting human workers in production and logistics tasks, (2) summarising the existing scientific evidence on the benefits and challenges of adopting DAs, and (3) proposing future research opportunities.

The remainder of this manuscript is structured as follows: Section 2 provides an overview of related literature reviews. Section 3 introduces the conceptual background of the study. Section 4 describes the research methodology used in the literature review, and Section 5 presents the literature review results in detail. Section 6 discusses the main findings of the literature review and syntheses regarding the application, benefits, and challenges of adopting DAs in production and logistics. Section 7 offers suggestions as to future research avenues, and Section 8 concludes the manuscript.

2. Overview of previous literature reviews

A few related literature reviews exist that discuss the use of different types of DAs in a production and/or logistics context. These related reviews are classified in Table 1, and they are briefly summarised in this section to highlight the novelty of our study.

Von Wolff et al. (2019) summarised applications of chatbots in digital workplaces and found that chatbots can be used to support information search tasks and standardise routine processes. Their review primarily focused on digital workplace design in the office instead of physical work (such as manual assembly or materials handling). Wellsandt, Hribernik, and Thoben (2021) discussed the benefits of using DAs in production but did not discuss the potential of DAs in reducing human effort while performing tasks in detail. Pereira et al. (2023) analysed physical and virtual assistance provided by VAs, their main services, and their limitations in an Industry 4.0 context. Rabelo, Zambiasi, and Romero (2023) proposed the concept of softbots 4.0 and discussed their potential to support production with CPS. Colabianchi, Tedeschi, and Costantino (2023) investigated manufacturing chatbots by clarifying their design elements and creating a taxonomy and development guidelines.

Table 1. Summary of related literature reviews.

Review	Review type	Focus area	DAs considered	Sample size
von Wolff et al. (2019)	Systematic literature review	Digital workplace	Chatbots	52
Wellsandt, Hribernik, and Thoben (2021)	Narrative review	Benefits of using DAs in production	DAs	Not clearly identified
Pereira et al. (2023)	Systematic literature review	Characteristics of technical assistance design principles in Industry 4.0; specific services offered by VA; application challenges of VA	Softbots	9
Rabelo, Zambiasi, and Romero (2023)	Narrative review	Control of shop floor composed of cyber physical systems	Softbots	Not clearly identified
Colabianchi, Tedeschi, and Costantino (2023)	Taxonomy development	Conceptual architecture, taxonomy and design guidelines for manufacturing chatbots	Chatbots	Not clearly identified
Our study	Systematic literature review	Human-DA collaborative tasks in the areas of product design, production, maintenance, quality management, and logistics.	DAs	69

Table 1 demonstrates that our present study differs from existing literature reviews by (a) applying a systematic literature search and selection methodology, (b) focusing on different types of DAs, (c) discussing DAs' potential in reducing human effort in production and logistics tasks as well as the associated benefits and challenges, and (d) considering a larger literature sample than the earlier reviews.

3. Conceptual background

In this section we first introduce key concepts relevant to understanding how DAs can support production, and then logistics tasks (sub-sections 3.1 to 3.5). Furthermore, we combine these key elements in our conceptual framework (sub-section 3.6). This forms the basis of our discussion of the relevant literature in the subsequent sections.

3.1. Production and logistics areas

In this study, we consider four production and logistics areas, as stated in Pfohl (2022) and Porter (2011) : *production (manufacturing)*, which transforms raw materials and semi-finished products into finished goods; *maintenance*, which involves functional checks, servicing, repairing, or replacing devices, equipment, and machines to ensure that all assets in industrial plants are in operational condition; *quality management* that ensures that the finished products meet the customers' expectations; and *logistics* that handle demand, storage and distribution of goods. We consider these areas because they are value-creating processes of a typical manufacturing company characterised by the heavy reliance on the interactions between humans and technology (Neumann et al. 2021). In addition, we consider *product design*, including the design, testing, and possible redesign of product versions, because it is extremely interconnected with production. It ensures the manufactured products meet or exceed customer expectations in terms of quality and functionality (Borgianni et al. 2018).

3.2. Human-centricity

Humans are critical, both physically and cognitively, in every production and logistics area. They are endowed with domain knowledge, physical movement capacities, and work experience. In human-system interactions, the total system performance is determined by the symbiosis of the technical and social systems (Trist 1981). Owing to the ongoing digitalisation in production and logistics, human workers interact more often with the virtual world through advanced communication technologies and operate in complex and technology-driven systems. This leads to new challenges for them (Longo, Nicoletti, and Padovano 2017). In this context, terms such as 'Operator 4.0', 'Human-in-the-loop', and 'Logistics Operator 4.0' have been proposed, with the vision of supporting the physical and cognitive work of operators by new technological means (Cimini et al. 2020; Romero et al. 2016; Turner et al. 2021). Additionally, human-centricity, as one of the three pillars of Industry 5.0, highlights the central role of humans in the design of production and logistics systems (Grosse et al. 2023; Ivanov 2023). In this study, we consider the characteristics of workers from the perspectives of endowments and preferences based on the work of Baird and Maruping (2021), who demonstrated that endowments occur when someone wants to free up resources for other pursuits or engage in activities that were previously unattainable to them. In addition, human workers may have preferences in production and logistics, such as learning how to perform assembly operations, monitoring and evaluating shopfloor issues, or simply retrieving query information from a machine or information system (Rabelo, Romero, and Zambiasi 2018).

3.3. Digital assistants

DAs are socio-technical systems that help humans perform tasks efficiently (Maedche et al. 2019). Early DAs could only have short conversations, and most of them did not easily learn from interactions (e.g. ELIZA, A.L.I.C.E.) (Wallace 2009; Weizenbaum 1966). With the advancement of AI, especially natural language processing and knowledge representation, DAs allow users to interact intuitively by using their natural language and provide assistance with daily activities (e.g. Apple's Siri, Amazon's Alexa, and IBM's Watson) (Hoy 2018; IBM 2022). In production and logistics, DAs are included in the broader scope of Worker/Operator Assistance Systems, simplifying interactions between workers and complex machines and reinforcing workers' physical and cognitive capabilities (Mark, Rauch, and Matt 2022; Roth, Moencks, and Bohné 2023). This study considers DAs that run on some information technology (laptop, touch panel, smartphone, smart speaker, etc.) and rely on a conversational, graphical, haptic, or multi-modal user interface. This is both for receiving input from and delivering output to users, to support them with information or knowledge to better perform tasks (Diederich et al. 2022; Maedche et al. 2019). We summarise the descriptions of various types of DAs based on the Operations Management and Information Systems literature in Table 2.

Table 2. Overview of different types of DAs.

Digital assistant type	Description	References
Conversational agent	A dialogue system that can support spoken and written natural language as input and output.	van Pinxteren, Pluymaekers, and Lemmink (2020); Knote et al. (2019)
Chatbot	An application system that provides a natural language user interface for human-computer interaction. It can be rule-based or AI-based, and it can be chit-chat or task-oriented.	Følstad and Brandtzæg (2017); Adamopoulou and Moussiades (2020)
Intelligent personal assistant (IPA)	A software agent that helps in interfacing with machines, computers, databases, and other information systems as well as managing commitments and performing tasks in a human-like interaction.	Myers et al. (2007); Santos et al. (2018)
Virtual assistant (VA)	A new way to interact with humans naturally, which can be done in a cognitive, collaborative, and linguistic human-machine manner, to automate routine tasks partially or entirely to increase the productivity and comfort of the users so that they can devote time to other tasks.	Maedche et al. (2019); Schmidt et al. (2018)
Softbot	A new type of frictionless human-computer interaction by skipping fixed and predefined menus commonly accessed via a keyboard and mouse. It is a virtual system that automates tasks and helps humans in the execution of tasks with variable levels of intelligence, autonomy, and proactivity.	Rabelo, Romero, and Zambiasi (2018); Rabelo, Zambiasi, and Romero (2023)
Avatar	Computational agents that represent the real embodiment of people in cyberspace, including human-like auditory and visual characteristics or traits. It can assist users by recording their actions and inputs to the appropriate database or retrieving technical information or historical data for the user.	Brade et al. (2020); Lampen, Liersch, and Lehwald (2020)

3.4. Human-DA collaborative tasks

Depending on the characteristics of the DA, human characteristics, and related production and logistics areas, DAs can reduce the human effort involved in performing various tasks. Referring to the works of Adamopoulou and Moussiades (2020), Maedche et al. (2019), and Neumann et al. (2021), we deductively categorise three macro-task types: *information management* (querying, retrieving, consulting, or analysing information), *collaborative operations*, (tasks in which DAs either instruct or assist human workers or assume the responsibility of completing parts of a joint task) and *knowledge transfer* (the involvement of DAs in reducing human effort for the acquisition of skills during real-life tasks). A more concrete classification of how DAs support humans while performing tasks across different production and logistics areas is discussed after an inductive refinement in the literature review (Section 5).

3.5. Benefits and challenges of using DAs

Inspired by the work of Pereira et al. (2023) and Wellsandt, Hribernik, and Thoben (2021), we summarise the benefits of using DAs in production and logistics from *human* and *task* perspectives. Given that DAs can guide humans in conducting tasks without memorising complex procedures, the cognitive workload of humans can be reduced. Workers can instruct DAs to perform certain tasks leaving them able to focus on abstract tasks instead, and they can also obtain assistance from them in developing skills and competencies. Given that DAs are capable of accessing multiple information systems and providing analytics for decision-making, their use can shorten task completion time and improve task efficiency. They can also support people ubiquitously, thereby increasing flexibility. A more concrete classification of benefits is discussed in Section 6.2.

Our review also aims to synthesise the challenges of using DAs in production and logistics from technological and implementational perspectives. They introduce complexities that can arise from intricate technical systems, for instance, accessing different user interfaces, interpreting structured, semi-structured, or unstructured data, or precise understanding of speech. Apart from technological challenges, companies may also face challenges that hinder the implementation of DAs, such as the integration of DAs into the existing systems as well as regulatory compliance. A more concrete classification of challenges is provided in Section 6.3.

3.6. Conceptual framework

We propose a framework summarising the conceptual background to guide the analysis of the literature sample (see Figure 1). The framework consists of five main elements: (1) production and logistics areas, (2) human-centricity, (3) DAs, (4) human-DA collaborative tasks, and (5) benefits and challenges of adopting DAs. The framework is developed based on the socio-technical systems theory, which explains three key elements: humans that aim to achieve a specific goal; technology that is utilised by humans, in this case, the DAs; and tasks that are jointly accomplished by humans and technology to

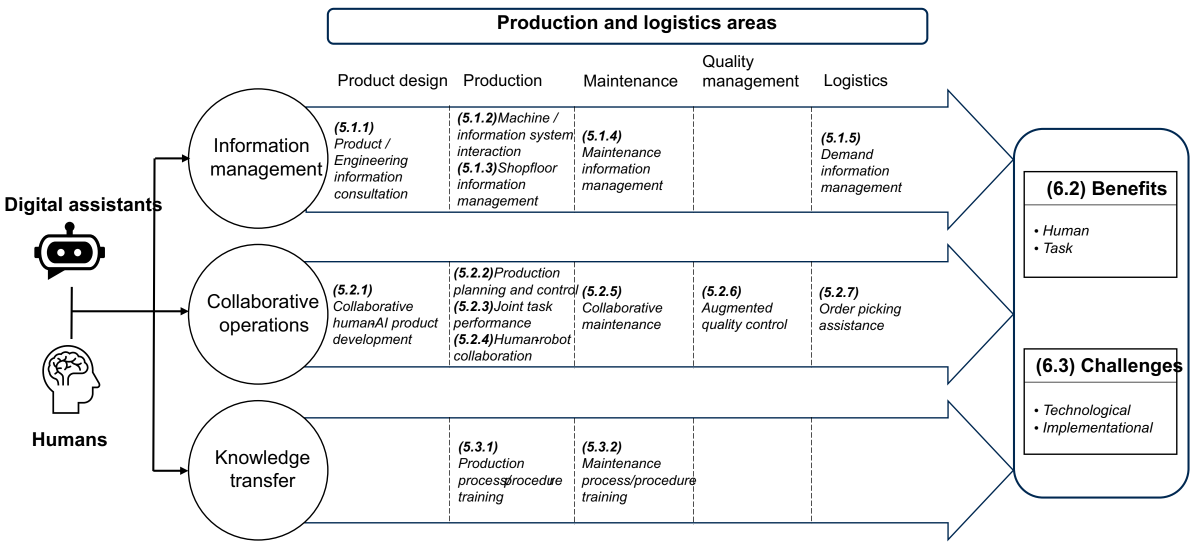

Figure 1. Conceptual framework of human-DA interaction in production and logistics.

Table 3. Groups of keywords used in the literature search.

Group	Keywords
A	Digital assistant∗, AI-based assistant∗, AI based assistant∗, Personal assistant∗, Smart assistant∗, Autonomous agent∗, Interactive agent∗, Conversational agent∗, Conversational system∗, Conversational interface∗, Chatbot∗, Chatterbot∗, Chatterbox∗, Dialog system∗, Dialog agent∗, Dialog assistant∗, Digital agent∗, Smart speaker, Speech based assistant∗, Speech-based assistant∗, Voice assistant∗, Text-based assistant∗, Text based assistant∗, Virtual agent∗, Virtual assistant∗, Virtual coach∗, Avatar∗, Software robot∗, Softbot∗, Operator assistance system∗, Worker assistance system∗
B	Product design, Product development, Engineering design, Production, Manufacturing, Assembly, Machining, Maintenance, Quality management, Quality assurance, Quality control, Quality inspection, Quality check, Logistics, Supply chain, Warehouse∗, Order pick∗, Material∗ handling, Inventory management, Fleet management

achieve the goal (Goodhue and Thompson 1995). The framework was inductively refined during the literature review (for better clarity, subsection numbers in Figure 1 indicate where the respective part of the framework is discussed in further detail). Furthermore, the framework demonstrates DA-related benefits and challenges in production and logistics based on the results of the literature review (Section 6).

4. Systematic literature review methodology

To develop a literature sample for this research, we adopted a four-step approach: (I) identify groups of keywords, (II) search scholarly databases, (III) screen the literature, and (IV) complement the literature sample using a snowball search (Denyer and Tranfield 2009; Gough, Oliver, and Thomas 2017). First, we identified two groups of keywords based on related reviews (Section 2) and the conceptual framework (Section 3). Table 3 lists the identified keywords. Group A keywords are related to DAs. Group B keywords are related to production and logistics, including product design, production, maintenance, quality management, and logistics.

Second, we searched for keywords in the Scopus and Web of Science databases, which are leading databases with comprehensive research coverage in the fields of science, technology, social sciences, arts, and humanities (Birkle et al. 2020; Burnham 2006). We used the Boolean operator ‘AND’ to combine the keywords in Group A with those in Group B and generated the final list of keywords for the search query. Studies published until the end of November 2023 and featuring at least one of the keywords in the article title, abstract, or list of keywords were retrieved for further analysis. This was with the proviso that the articles were written in English and published in peer-reviewed conference proceedings or scientific journals. The initial literature sample consisted of 7,337 papers, with 5,740 from Scopus and 1,597 from Web of Science. After eliminating duplicates, 5,913 papers were consolidated in the initial sample.

Third, we screened the titles, abstracts, keywords, and publication sources of the papers to select those that presented research on DAs and their applications in production and logistics. Studies that (1) did not examine a DA according to our definition or (2) did not focus on any of the production or logistics areas defined in Figure 1 were excluded. In the screening process, all authors were involved to avoid selection bias, and any mismatches were discussed and reviewed by the authors. The screening process was recorded in an Excel spreadsheet and

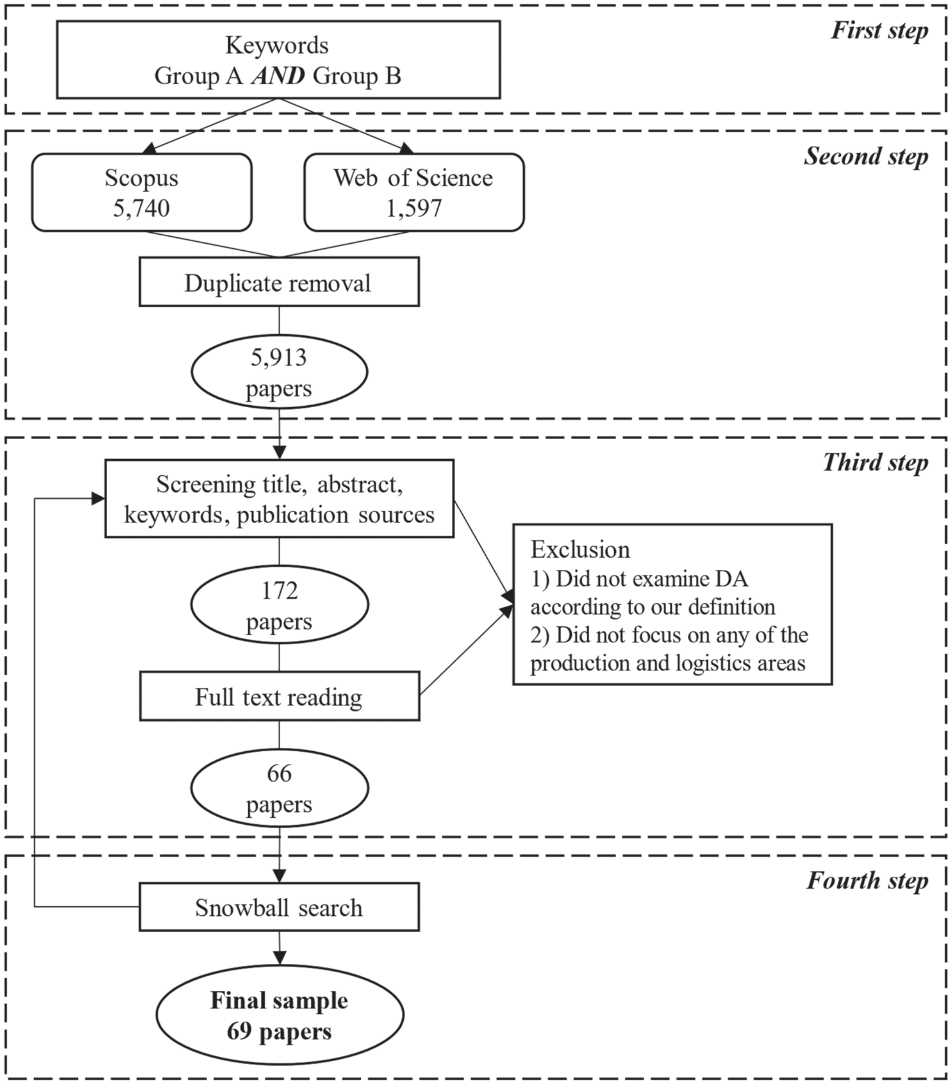

Figure 2. Literature search and selection protocol.

the selected papers were marked and categorised according to their application areas. At this stage, 172 papers were considered suitable for further analysis. Next, the screened papers were downloaded and exported to the Citavi Reference Management Software for full-text reading and annotation. Studies that did not satisfy the above-described selection criteria were excluded from further analysis. Consequently, the sample consisted of 66 papers.

Finally, a snowball search using the reference lists of the sampled papers or citations of the sampled papers was conducted to identify additional papers (Wohlin 2014). As a result, three more papers were identified, thus resulting in a total of 69 papers in the final literature sample. A summary of the literature selection process and results is shown in Figure 2.

After selecting the final literature sample, we carried out descriptive analyses to show how research on DAs in production and logistics had developed over time, as well as the methods adopted in this stream of research (see Figure A1 and Table A1 in the Appendix).

5. Results

This section reviews the literature sample according to the framework developed in Section 3.6. We focus on highlighting the importance of DAs in reducing human effort while performing three types of tasks (information management, collaborative operations, and knowledge transfer) in production and logistics areas (product design, production, maintenance, quality management, and logistics). To structure the results, we also provide a more specific classification of tasks that inductively emerged during the analysis of the literature sample. An overview and categorisation of the 69 sampled papers are provided in Table A2 in the Appendix.

5.1. Information management

5.1.1. Product/Engineering information consultation [Product design]

Using DAs can accelerate collaborative engineering design and enhance customer experience. Choi, Hamanaka, and Matsui (2017) developed a chatbot for a product manual. They demonstrated that users perceived the interaction with the chatbot as more helpful than paper-based instructions. In addition, because users can visualise product-function-related information via a chatbot interface, they can better understand the functions of the product. Trappey et al. (2022) developed a natural language and virtual reality (VR)-enabled engineering consultation chatbot. Their proposed system presents product structures in a VR environment and enables customers to quickly ask questions and receive answers via chatbots. The authors tested the proposed system for an interactive design process and demonstrated that the chatbot could answer users' questions with high accuracy (over 91%) irrespective of the kind of questions. However, the authors found that the developed chatbot sometimes failed to give correct answers owing to an incorrect judgement of the user's intent or subjectivity of the query. Their study revealed that integrating chatbots with VR may help users obtain answers easily while viewing and reconfiguring a product's structure in an immersive environment, thus facilitating vivid design reviews of the product.

5.1.2. Machine/information system interaction [Production]

Compared to various human-machine interfaces such as visual displays, physical interaction, and haptics, DAs help humans interact with machines more intuitively and naturally. For example, workers can communicate with machines by using one-to-one or public messages through text-based chatbots, where machines are interconnected and represented by their social network profiles via a digital twin (DT) (Kassner et al. 2017). Using avatars on the machine controller side may better assist humans in paying attention to unusual events and returning to normal situations. They can be developed with various facial and body characteristics for different information representation scenarios, such as maintenance notifications, warning and alarm messages. The question of whether they can increase safety and long-term user acceptance should be further investigated (Ziegeler and Zuehlke 2005).

In addition to interactions with machines, DAs also facilitate interactions with information systems and help workers monitor operational statuses. For example, Mantravadi, Jansson, and Møller (2020) attempted to accommodate an AI-enabled chatbot to MES for information retrieval. They demonstrated that using an AI-based chatbot for manufacturing order management is quicker than a regular database lookup. Chatbots can also be connected to robot process automation (RPA) to enable users to obtain manufacturing-related information, generate queries, and schedule tasks anytime and anywhere (Do and Jeong 2022). Hüsson, Holland, and Sánchez (2020) demonstrated that using an IPA to explain graphic and tabular information was less effective for long text speech input and information searches from an enterprise resource planning (ERP) system; therefore, IPA was recognised as an addition to traditional input methods (keyboard, mouse). Similarly, Gärtler and Schmidt (2021) compared the effectiveness of a VA with GUI-based solutions (Excel, Power BI) for information extraction and demonstrated that, although the VA can help solve problems with different complexity levels, users are more comfortable in using the VA to solve simple problems and are reluctant to use the same to reach complex goals. To facilitate evaluating the benefits of DAs, Bousdekis et al. (2022) proposed a framework for assessing AI-based DAs from the perspective of the trustworthiness of AI, the usability of DAs, the cognitive workload of human users, and overall business benefits for the company.

5.1.3. Shop floor information management [Production]

In shopfloor management, it is important to keep track of the equipment and item status. In this regard, DAs enable information retrieval, monitoring, and processing of information and facilitate shopfloor control. For example, Afanasev et al. (2019) and Loh et al. (2023) demonstrated the potential of using a dialogue assistant to automate the access and retrieval of production data, and in particular, constantly monitor equipment parameters and notify workers when an anomaly occurs. Reis et al. (2022) used a VA to retrieve information from a database and alert workers based on predefined rules. Their results demonstrated that workers were comfortable using the VA for monitoring production and work shift performance and that the VA was reliable in recognising user requirements even though users had to speak a foreign language during the test. Jwo, Lin, and Lee (2021) designed an interactive shop floor information dashboard and embedded a VA into a mobile API to help workers communicate and control the dashboard through vocal commands. Their results demonstrated that the VA is more flexible and easier to learn than a traditional user interface where the keyboard and mouse are used for dashboard monitoring and control. In addition, it can actively contact the related staff when the real-time data and historical data stored in the dashboard cannot answer the users' questions. Penica et al. (2023) combined a chatbot with smart glasses to allow workers hands-free access to real-time data and instructions. Their test results revealed that the chatbot can facilitate data exchange among machines and that it has a good level of dialogue interpretation.

Additionally, softbots can be used to analyse operational performance and help managers in decision-making. A softbot developed by Abner et al. (2020), for example, supports three types of behavioural modes during communication with end users (reactive, planned, and proactive) and four types of business analytics (description, diagnostics, prediction, and prescription). The authors tested the system in reactive mode in real-time and demonstrated that it can work as an additional module of an MES to analyse shop floor information, identify current operational excellence maturity models, and help managers in decision-making. Furthermore, the authors argued that training is essential for managers to understand the terminology used by the softbot.

In addition to interacting with machines or information systems, DAs can be used to interact with item-level information for product tracking and tracing in a factory. For example, using Amazon Echo 5 as a voice-based DA can enable workers to interact with the DT of the product, helping them to keep track of a product's status and identify its location. However, the use of this type of assistant poses challenges related to low transcription accuracy of speech and factory noise (Wellsandt, Foosherian, and Thoben 2020).

5.1.4. Maintenance information management [Maintenance]

Lean maintenance requires the workforce to focus their attention on their primary task, rather than maintenance data documentation. Compared with paper-based maintenance report generation, using a DA can streamline the process, shorten maintenance task completion time, and generate a higher-quality report. However, technicians may experience increased time pressure when interacting with the conversational agent because they are multitasking and have to maintain the conversation flow (Kernan Freire et al. 2022).

5.1.5. Demand information management [Logistics]

In logistics, understanding the market demand is important for companies to plan their operational strategies for market fulfilment. In this respect, DAs enable companies to connect better with customers and improve their logistics services. Hsiao and Chang (2019) found that embedding a DA into the existing information systems for queries and evaluating customer interaction may add value to logistics services. Companies need to improve their capabilities for organisational, scientific and technological innovation as well as logistics services to successfully adopt DAs. Murciego et al. (2020) proposed an order-processing system targeting older people living in rural areas. They employed an IPA to collect customer demand information and used the collected data to optimise delivery routing. The results demonstrate that the use of an IPA provides new channels for older people to access demand ordering services and that the logistics company can utilise the order and customer location information to optimise the routings and minimise delivery costs. Angelov and Lazarova (2019) presented a distributed chatbot system for order queries in supply chains. The system comprises several services, including a chatbot, natural language processing, and supply chain services, and it can analyse the user's query, and provide information about queried orders and supplies. Kern et al. (2006) described an approach in which softbots can provide information to supply chain managers anytime and anywhere. Their approach was enabled by a decentralised overlay network, thus allowing the assistants to dynamically communicate with each other in the network, exchange information, and negotiate tasks.

5.2. Collaborative operations

5.2.1. Collaborative human-AI product development [Product design]

Moving beyond current scenarios in which humans generate design ideas within a team, AI-enabled DAs can facilitate human-DA collaborative design. In Makokha's (2022) work, the assistant observes the human activity and provides relevant suggestions via text or voice. The author trained language models, based on a publicly available database (Ubuntu) and transcripts of professional designers. Although the models did not perform as expected, the author found that using designer transcripts as a training set provided better conversation quality (Makokha 2022).

5.2.2. Production planning and control [Production]

CPS necessitate the intensive collaboration of workers with smart machines. DAs can assist in these tedious activities and human-centred production planning and control. Rabelo, Romero, and Zambiasi (2018) demonstrated that workers could delegate automatic execution tasks, management of the shop floor process, notifications and summary reports to DAs. Rabelo et al. (2019) then leveraged multiple softbots to enable symbiotic collaboration among workers, CPS, and information systems. Their proof-of-concept study demonstrated that softbots can collaborate to access the MES, query the

ERP system regarding the scheduling of orders, confirm with workers, coordinate orders, trigger alarms, address errors, and adapt communication language automatically to the text input. Rabelo et al. (2021) followed up with a softbot prototype which they found could help users interact with the workstation DT, actuate physical workstations, and proactively perform predefined tasks and communicate results to the user via chatting. Similarly, Li and Yang (2021) developed a VA for sales order generation, material checks, production order generation, and shop floor equipment state monitoring, which reduced repetitive operations and improved productivity. Additionally, they highlighted that owing to ambient noise, the VA needs to filter the noise, which can be time-consuming and may lower efficiency.

Schwartz et al. (2016) described a hybrid scenario in which a team composed of robots, virtual characters, and softbots work collaboratively. A worker here issues task commands via a dialogue engine to the blackboard accessed by robots that then execute the tasks. Softbots aggregate data produced by team members and update databases. The virtual character serves as a natural interface that communicates with the worker. Longo, Nicoletti, and Padovano (2022) presented a knowledge-management platform that supports workers with multiple front-end applications (mobile and wearable devices, AR, and XR) and an AI-enabled DA. In this case, the DA serves as the main interaction tool for workers, which continuously screens the back-end knowledge platform and interacts with workers using a question-answer form, thus providing meaningful knowledge quickly and effectively.

5.2.3. Joint task performance [Production]

DAs can assist workers in performing tasks by providing instructions either directly or in combination with other technologies (e.g. object detection, machine vision). For example, Zimmer et al. (2020) demonstrated the potential of chatbots to assist production ramp-up processes. They argued that the chatbot may here guide workers to perform better by familiarising them with the equipment and processes compared to relying solely on their own knowledge and equipment manuals. Li and Wang (2021) developed an audio-visual humanoid VA that uses a camera and sensory system worn on the human forearm to detect workers' assembly actions, a facial tracking system to detect the worker's facial expression, and a natural language processing system to predict intention. Their proposed VA successfully communicated with co-workers to complete collaborative assembly tasks based on its own judgement of the current assembly situation. Recent studies by Chen et al. (2021) and Chiu et al. (2021) demonstrated the potential of using multi-modal chatbots that combine speech with object detection to classify user intentions to assist users with multi-step assembly tasks. Their test results demonstrate that multi-modal input can capture the user's requirements better and thus provide more accurate assistance to the user than speech information alone. Similarly, Talacio et al. (2021) introduced machine vision techniques as part of their developed IPA to augment the capabilities of speech recognition with image recognition and guide workers in assembly execution. They compared the developed IPA with conventional printed manuals and found that their use helps decrease assembly time and increases worker comfort, particularly beneficial with complex and time-consuming procedures. Behrendt and Strohmeier (2021) proposed a process modelling methodology that can efficiently and accurately synthesise DAs and workers in task information and progress.

5.2.4. Human-Robot collaboration [Production]

DAs can serve as a natural interface that communicates between workers and robots in the production environment. Li et al. (2021), for example, built a VA that adopts generic conversational strategies. They revealed that the prediction accuracy of the VA depends on ambient noise, workers' voice volume, sentence length, and physical distance between the worker and the VA. Using a GPT neural network as the backbone, Li, Zhang, et al. (2022) and Li et al. (2023) constructed a dialogue corpus that accurately supported task-related and small talk dialogue in assembly, internal logistics delivery, and robot positioning and relocation. Li, Hansen, et al. (2022) used a VA that assisted workers in completing internal logistics tasks by communicating with them to obtain task-related information, including the object, recipient, and destination. The VA then identified and instructed a suitably skilled robot to perform the task. Although this study was successful, Li, Chrysostomou, and Yang (2023) found the DA had some interpretation latency and inaccuracy that could lead to safety issues in multi-robot working scenarios (e.g. the recent deadly incident where an industrial robot failed to differentiate between a human and a box[1]). Ye, You, and Du (2023) fine-tuned ChatGPT into a worker's robot assistant when controlling a robot arm, demonstrating that this increased the assembly task performance and enhanced the trust of humans. This was owing to its naturalness in communication and its capabilities in memorising previous decisions. However, the authors noted that in case of miscommunication, the robot assistant may become too assertive.

5.2.5. Collaborative maintenance [Maintenance]

In maintenance, DAs can assist workers in searching for maintenance-related information and provide instructions. In an early study, Nyrkko et al. (2007) illustrated a dialogue system to support three types of dialogues: (1) metacommunication (greeting, goodbye), (2) providing information and feedback (inform, agree/disagree, partial information), (3) and asking questions (ask what, answer yes, or no). Ade et al. (2020) later developed an AI-enabled chatbot for maintenance procedural consultations. Their study demonstrated that the chatbot could effectively help workers navigate the procedural steps linearly, return to the previous step, and repeat the step by identifying the context based on a previous conversation. They concluded that the chatbot could serve as a tool for safety and performance improvement, owing to its ability to navigate a large number of procedural steps and its effective engagement with the worker. Wellsandta et al. (2020) developed concepts for using DAs to support manufacturing maintenance. They collected the requirements of maintenance stakeholders (i.e. maintenance coordinator, maintenance technician, and machine operator), and identified function modules of DAs (i.e. process monitoring, task execution, reporting, problem-solving, and maintenance planning). They emphasised that solving interoperability issues and convincing stakeholders to trust DAs remains a challenge for the implementation. Wellsandt et al. (2021) proposed a novel approach to integrate human knowledge in the design of DAs for supporting predictive maintenance. They identified five stages of human intervention for predictive maintenance, including sense, detect, predict, decide, and act. They demonstrated that DAs can provide data required by the technician, configure the data visualisation based on the communication with the technician, recommend maintenance solutions, and offer instructions to guide inspection or repair. Wellsandt, Klein, et al. (2022) argued that to integrate DAs successfully in the company, the benefits and limitations of their use should be clearly communicated to managers, the company-level data should be free from biases, errors, inaccuracies and mistakes, and also that the employees should be trained to adapt human-AI collaborative working scenarios. Aceta, Fernández, and Soroa (2022) and Aceta et al. (2022) developed a semantics-based task-oriented dialogue system to assist workers in maintenance tasks using natural language. Their usability test demonstrated that users could obtain accurate information from the system and complete a high share of the maintenance dialogue in a short time. Moreover, they perceived lower cognitive demands and higher security when interacting with the dialogue system.

DAs can be combined with other technologies to complete maintenance tasks efficiently. For instance, Abate et al. (2008) demonstrated the possibility of using an avatar to guide workers towards collaborative maintenance. They proposed a framework consisting of a behavioural engine for retrieving human biometric data and creating a virtual model, a visualisation engine for managing all visual components, and an avatar for assisting workers in failure search and repair. They argued that the proposed avatar was more effective than a conventional screen-based interface because it provided the maximum possible level of adaptivity to users' needs and assisted workers proactively. Zambiasi et al. (2022) demonstrated that participants found merit in combining a DA with AR for task guidance, as it reduced their efforts so that they could concentrate on conducting tasks correctly. Serras et al. (2020a) and Serras et al. (2020b) augmented kinesthetic–bionic interactive technologies using data collected from device sensors to enhance domain knowledge creation. The results of their usability study demonstrated that novices found the system intuitive to use and that they felt more confident under multi-modal guidance. More importantly, the system was perceived as highly efficient for users with cognitive impairments because the cognitive workload is lower if such a system is used. Fleiner et al. (2021) argued that conversational user interfaces are not sufficiently robust for maintenance guidance because of the ambient noise that interferes with voice recognition. Therefore, they proposed a set of user-defined gestural inputs (hand and head) as a complement to text- and voice-based communication. Their usability study revealed that gestures can be used as an alternative in noisy environments and that the participants preferred gestures for simple actions, whereas speech was more suitable for abstract actions.

5.2.6. Augmented quality control [Quality management]

DAs augment workers' capabilities for quality control by simplifying the retrieval and processing of quality data. Bousdekis et al. (2021) investigated a scenario in which quality data were collected and processed using prescriptive analytics such that defects and corresponding root causes could be quickly detected and mitigating actions could be defined. In this case, the DA provides descriptive, predictive, and prescriptive information to workers, thus enabling them to easily manage quality issues and make decisions based on the given analytics results. Wellsandt, Foosherian, et al. (2022) summarised how DAs can augment workers by interacting with data analytics for quality testing. Users can retrieve existing information (eventually with customised parameters) and instruct the DA to add quality reports for further data learning, or the DA can proactively remind the user and provide relevant suggestions. The DA ensures that workers spend less time preparing, processing, and understanding data, and their cognitive capabilities are augmented.

5.2.7. Order picking assistance [Logistics]

DAs can provide remote instructions for order pickers. For example, Wang et al. (2020) investigated the effect of avatars with different body representations (whole body, hand and arm, and hand only) on the quality of remote instructive order picking tasks in terms of efficiency, performance, workload, usability, and performance. The results illustrated that all three types of avatars transferred the instructions accurately; the avatar with a body representation outperformed the other types of avatars in terms of perceived workload by the participants and the time taken to respond to the instructions.

5.3. Knowledge transfer

5.3.1. Production process/procedure training [Production]

In a production environment, DAs assist workers in learning new tasks. Tanaka et al. (2003) developed an assembly training system based on bidirectional verbal and nonverbal communication between humans and avatars. Verbal data from humans were collected and processed via a language processing system. Position sensors and data gloves were used to detect the pointing actions of the humans. Based on these data, the avatar can understand the user's intention, recognise the object that the user is referring to, and give instructions on how a specific assembly operation should be performed. Kernan Freire et al. (2023b) demonstrated the potential of using a DA to support transferring tacit knowledge from experienced workers to novices. They argued that using a DA can automatically prompt experienced workers to begin a reflection session by providing contextual information, generating visualising graphs and communicating in a natural way. Although usually, large language models-enabled DAs can interpret workers' questions accurately, their use also induces ethical concerns that are related to privacy and knowledge security, as well as the validation of the knowledge bias collected by the DA (Kernan Freire, Foosherian, et al. 2023; Kernan Freire et al. 2023a).

Researchers have also focused on the design of avatars by integrating AR/VR for effective training. Pace et al. (2019) compared the effectiveness of a human avatar and an abstract metaphor in assembly guidance, but could not identify a significant difference between the two interfaces in terms of the user's perception of efficiency, learnability, or satisfaction. Moreover, a large humanoid avatar may cause difficulties for the participants in visualising the real objects owing to the narrow field-of-view of the AR wearable device, thereby increasing occlusion problems with overlapping virtual objects. Lampen, Liersch, and Lehwald (2020) provided insights into the possibility of using an AR avatar for implicit imitation learning in manual assembly. Their results demonstrated that workers could learn ergonomic motions by imitating an avatar without decreasing the assembly performance. Furthermore, Brade et al. (2020) evaluated the effect of different avatar representations (hands only, full body) on perceived presence and acceptance during manual assembly training in a VR environment. Their results illustrated that participants perceived a high 'sense of physical space' and 'engagement' during the task when an animated avatar appeared; however, there was no significant difference in the impact of different avatars on task performance. They concluded that the details of animated avatars could be reduced to focus on the body parts that are important in fulfilling the given tasks.

In addition to using avatars for training assistance, Rooein et al. (2020) demonstrated how a chatbot can be used as a navigator for tailored learning for workers. Their chatbot especially filled the gap between novice workers' knowledge of the factory's business processes and the complex notions of business process descriptions. Casillo et al. (2020) and Clarizia et al. (2021) also developed a chatbot for novice training based on text information processing and elaboration of user needs. Their results exhibited improved learning paths, although the dialogue capabilities of the chatbot could be further improved. Longo, Nicoletti, and Padovano (2017) introduced a DA to enable the interaction and assistance of workers by providing knowledge about components, machines, tasks, procedures, and processes via vocal exchange. They found that workers assisted by the DA had better task performance and that the system led to a stronger learning effect.

5.3.2. Maintenance process/procedure training [Maintenance]

DAs can transform multi-modal data into easily understandable information to support maintenance staff in learning complex tasks. In contrast to the existing AR-based mentoring systems, Zhu et al. (2014) combined a VA with AR and pose-tracking to guide users during maintenance tasks using multi-modal cues. In the developed system, the VA processes visual, audio, and location data to interpret context information and provide precise technical assistance to the user. As a result, novices can perform complex maintenance tasks without any technical manuals or instructor support; simultaneously, the burden on the instructor is reduced as the novices' task performance need not be monitored. Barbosa et al. (2018) demonstrated that VAs and DT can be combined to automatically detect equipment errors, compare them with historical data, and provide maintenance suggestions to technical staff. When compared with traditional maintenance routines, their proposed method enables

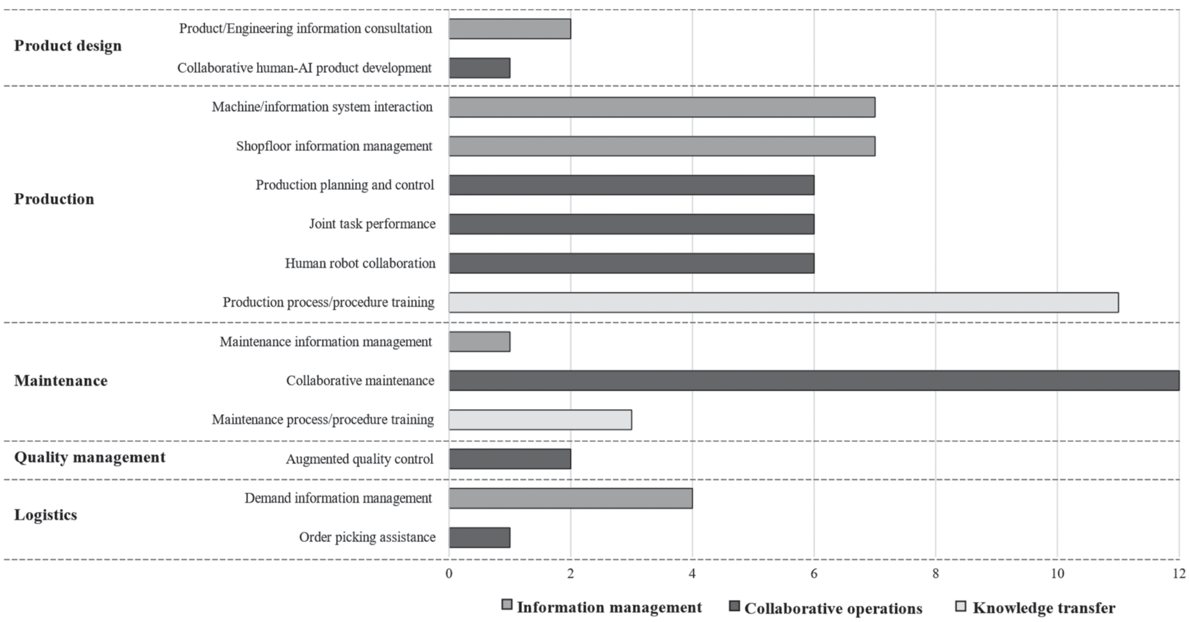

Figure 3. Application of DAs across different production and logistics areas.

the online monitoring of equipment, facilitates the visualisation of equipment and its components, and makes it easier for maintenance staff to learn how to conduct maintenance by receiving instructions from the VA. Recently, Zambiasi et al. (2023) demonstrated the potential of using a softbot as an intelligent tutor in training workers in an immersed industrial metaverse environment. In particular, their proposed system can adapt itself to support both normal workers and workers with hearing or colour-blind disabilities in three maintenance training scenarios (reactive, planning, proactive), leading to more inclusive workplaces.

6. Discussion

6.1. Different application maturity levels of DAs

The applications of DAs in the production and logistics literature are summarised in Figure 3, which demonstrates that production and maintenance are the most popular areas. The literature investigates the use of DAs in reducing human effort while performing different types of tasks in this area, summing up to 59 papers. Additionally, they are the only two areas in which the literature highlights how DAs can help workers gain knowledge and learn new skills.

Furthermore, certain studies have focused on product design (3 papers, 4.3%), quality management (2 papers, 2.9%), or logistics (5 papers, 7.2%). With respect to product design, the literature indicates the substantial potential of DAs as an effective tool to build communication channels between designers and customers and help designers generate new ideas collaboratively. In terms of quality management, the literature has focused on using DAs to collect and analyse quality-related data and remind workers about quality issues. Regarding logistics, existing literature uses DAs to facilitate demand queries from the customer's end to improve logistics service.

6.2. Benefits of using DAs

This study summarises the benefits of using DAs from two perspectives: humans and tasks. Regarding benefits for humans, some works demonstrated that DAs can reduce the cognitive workload of humans from different perspectives. First, DAs can streamline the shopfloor information by actively collecting data and thus decrease the information overload for shopfloor management (Abner et al. 2020; Aceta et al. 2022; Aceta, Fernández, and Soroa 2022; Kern et al. 2006; Longo, Nicoletti, and Padovano 2022). Second, when technicians are being assisted by DAs for collaborative maintenance, they do not need to memorise complex procedures but can feel more confident and perceive less mental workload in performing the tasks (Ade et al. 2020; Serras et al. 2020a; Zambiasi et al. 2022). Third, as humans differ in terms of skills and personality, DAs can provide customised assistance to enhance humans' decision-making capabilities in production planning and control (see e.g. Abner et al. (2020); Longo, Nicoletti, and Padovano (2022)), quality control (Bousdekis et al. 2021; Wellsandt, Foosherian, et al. 2022), and demand management (Hsiao and Chang 2019; Kern et al. 2006). Moreover, using DAs can reduce the physical workload of humans. For instance, humans

Table 4. Benefits of adopting DAs in production and logistics.

Benefits			ID
Human	Reduce cognitive workload	Decrease information overload	[15, 21, 28, 40, 46, 47]
		Reduce unnecessary memory of task procedures	[42, 49]
		Enhance decision-making capabilities	[11, 15, 18, 21, 23, 24, 27, 43, 44, 45, 53, 54, 66]
	Reduce physical workload	Enable hands-free operations	[17, 25, 26, 35, 36, 37, 39, 40, 42, 43, 44, 45, 51, 68]
		Improve motion ergonomics	[61]
	Improve psychosocial condition	Increase joy of use and engagement	[3, 4, 7, 15, 18, 21, 23, 24, 27, 28, 29, 34, 37, 39, 53, 54, 68]
	Improve human skills	Improve quality of learning and training	[3, 13, 24, 28, 33, 34, 36, 42, 48, 49, 50, 51, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69]
Task	Improve task efficiency	Facilitate data collection and visualisation	[2, 3, 4, 5, 6, 8, 11, 12, 13, 14, 15, 17, 19, 21, 23, 24, 25, 28, 29, 33, 34, 37, 39, 40, 42, 43, 44, 45, 48, 49, 50, 53, 60, 63, 66, 67]
		Facilitate seamless interaction with machine/information system	[2, 3, 5, 7, 9, 10, 11, 12, 13, 14, 15, 21, 24, 25, 26, 27, 28, 33, 34, 35, 36, 37, 38, 39, 40, 43, 44, 45, 49, 50, 52, 53]
	Increase task flexibility	Increase flexibility in completing tasks	[2, 3, 13, 15, 21, 24, 25, 26, 27, 28, 37, 39, 43, 44, 45, 48, 56, 64, 65]

can delegate DAs in actuating physical workstations or robots to realise hands-free operation (see e.g. Li et al. (2021); Rabelo et al. (2021)). From a psychosocial point of view, our results indicate that owing to the easy-to-learn and -use character of DAs (see e.g. Murciego et al. (2020); Trappey et al. (2022)), as well as the human-like conversation generated by DAs (Ade et al. 2020; Jwo, Lin, and Lee 2021; Li, Zhang, et al. 2022), people enjoy using DAs and engage more in working on the actual tasks (see e.g. Talacio et al. (2021); Gärtler and Schmidt (2021)). In addition, as DAs are endowed with knowledge and a strong digital structure, humans can get assistance from them in retrieving missing information and be guided by them for unfamiliar tasks. Consequently, DAs are useful for training, particularly for novices (see e.g. Behrendt and Strohmeier (2021); Rooein et al. (2020)).

Regarding benefits for tasks, our results demonstrated that DAs are powerful in interacting with machines, robots, and information systems (e.g. ERP and MES), which facilitates access to information from multiple sources, decreases lead times for information search, and improves task flexibility and efficiency (see e.g. Jwo, Lin, and Lee (2021); Kassner et al. (2017); Li, Hansen, et al. [2022]). The benefits of using DAs that emerged from our literature analysis are summarised in Table 4 (note that 'ID' refers to the paper identification code as exhibited in the third column of Table A2 in the Appendix).

6.3. Challenges of using DAs

This study summarised the challenges of using DAs from both technological and implementational perspectives. Owing to the emerging nature of implementing DAs in production and logistics, some technical aspects of DAs are still not mature enough to guarantee smooth interactions between DAs and humans, such as the reliability of speech-to-text (STT) processing (Gärtler and Schmidt 2021; Wellsandt, Foosherian, and Thoben 2020) and accuracy of text modelling and handling of more complex interactions (Abner et al. 2020). In production and logistics, human workers often perform tasks subject to time pressure, and the response speed of DAs therefore needs to be sufficiently fast to maintain low latency during interactions (Barbosa et al. 2018; Bousdekis et al. 2021; Hsiao and Chang 2019). As a reliable STT is based on a large amount of audio data and its transcription, STT model training is inevitably time-consuming and there is a lack of adaptability when using DAs in different application scenarios. Moreover, although companies such as Google and Amazon provide STT solutions, the training data for these solutions are not sufficiently transparent, thus raising ethical concerns (Bousdekis et al. 2021; Wellsandta et al. 2020). Moreover, substantial effort is required to translate the analytical results into easy-to-understand information for human workers (Abner et al. 2020; Bousdekis et al. 2021).

Adoption of DAs in production and logistics also presents implementation-related challenges. Several researchers have pointed out that noise in industrial environments reduces the performance, particularly of speech-based DAs (Bousdekis et al. 2021; Ghofrani and Reichelt 2019; Li et al. 2021; Li and Yang 2021; Serras et al. 2020a; 2020b; Ziegeler and Zuehlke 2005). In addition, testing DA prototypes in real-world settings is essential to validate their effectiveness (Bousdekis et al. 2022; Kassner et al. 2017; Kern et al. 2006; Kernan Freire et al. 2022; Makokha 2022; Mantravadi, Jansson, and Møller 2020; Rabelo, Romero, and Zambiasi 2018; Rabelo, Zambiasi, and Romero 2019) as well as cost-performance issues, especially for small- and medium-sized companies (Wellsandt, Klein, et al. 2022; Wellsandta et al. 2020). Moreover, the adoption of DAs must consider data security

Table 5. Challenges of adopting DAs in production and logistics.

Challenges		ID
Technological challenges	Speech-to-text (STT) processing reliability	[10, 16, 18, 39, 40, 53, 58, 68]
	Text modelling accuracy	[15, 43, 69]
	Training data transparency	[43, 53]
	Data interpretability	[15, 43, 53]
Implementation challenges	Noise in industrial environments	[8, 26, 35, 39, 50, 51, 53]
	Effectiveness test of DAs in real-world scenarios	[3, 4, 7, 17, 21, 22, 23, 24, 37, 39, 43, 45, 59, 69]
	Compatibility with existing legal and ethical framework	[4, 9, 16, 53, 57, 58, 59]

requirements and their compatibility with legal frameworks, which include – but are not limited to – data ownership, data processing scope, and user consent management (Afanasev et al. 2019; Bousdekis et al. 2021; Kernan Freire et al. 2023a; Mantravadi, Jansson, and Møller 2020; Wellsandt, Foosherian, and Thoben 2020). The challenges of using DAs are summarised in Table 5 (note that 'ID' refers to the paper identification code as exhibited in the third column of Table A2 in the Appendix).

7. Future research opportunities

7.1. Using augmented analytics to support human workers

We indicated that DAs can be embedded in management systems (e.g. ERP, MES) or other interfaces (e.g. API, dashboard) for information search and demonstration, which enables human workers to communicate with machines quickly and straightforwardly. However, our literature review identified only a few studies that describe the analytical potential of DAs and that mention the difficulties of translating analytical results into easy-to-understand information for humans (Abner et al. 2020; Bousdekis et al. 2021; Wellsandt, Foosherian, et al. 2022). We believe that DAs are more powerful when they are combined with other digital technologies, for instance, CPS, IoT, Cloud, RPA, or DT, such that real-time analytics regarding the status of materials or equipment can be constantly visualised and interpreted by humans. For example, empirical studies could investigate the usage of DAs to explain the real-time analytics and predictive analytics data on the shop floor, specifically concerning shop floor workers' understanding of the data and resulting consequences.

> ***Proposition 1**. Future studies should explore the synergetic use of DAs, CPS, IoT, and DT in providing transparent, understandable, and predictive analytics and validate their benefits in the real-world.*

Our review also found that only a few studies explored the use of softbots for obtaining more accurate shop floor information (Abner et al. 2020; Kern et al. 2006). For example, if a softbot has access to all relevant shop floor data, managers have access to this information without searching and checking different systems. Li, Chrysostomou, and Yang (2023) conducted a lab experiment to demonstrate the possibilities of using VAs to obtain task-related information from humans and issue commands to suitable robots for completing internal logistics delivery tasks. The workers communicated their specific need to fulfil a task to the VA, which then selected the best fitting robot to complete the task. Different types of DAs may provide different types of support to managers and workers, and it needs to be further investigated how humans can best benefit from using the correct type of DA in their daily activities.

> ***Proposition 2**. Future studies should identify how DAs can augment the decision-making capabilities of different target groups by providing customised analytics, as well as identifying the most suitable DA approach for specific production and logistics tasks (i.e. investigating the best possible DA-Task-Fit).*

In addition, our results highlighted the difference between novice and experienced workers: novices often interact with DAs in a step-by-step approach, while experienced workers use DAs to obtain only a certain part of the information (Ade et al. 2020). Against this background, we encourage future studies to investigate how DAs can provide customised support to different worker groups by considering factors including (but not limited to) domain experience and task difficulty. For example, DAs can be used for training new employees based on their individual learning paths (Casillo et al. 2020; Clarizia et al. 2021).

> ***Proposition 3**. To augment workers effectively, worker-related characteristics, such as learning or individual experience should be considered in the design and implementation of DAs.*

7.2. Hybrid decision-making and teamwork in production and logistics

Our results reveal that DAs have different levels of automation for supporting decision-making, and in most cases, they perform actions as instructed by workers or generate recommended options to implement a task with the consent of workers. Only a few studies have shown the full autonomy of DAs in decision-making. This finding aligns with that of Endsley (2017), who argued that the autonomy level depends on system reliability. As DAs in production and logistics still face challenges related to understanding worker intentions, they require human intervention and are not completely autonomous. Given that humans and DAs have individual rights and responsibilities in completing joint tasks, and task performance is a cooperative effort between human workers and the surrounding system (Abate et al. 2008), additional research is needed to clarify the distribution of tasks between workers and DAs.

> ***Proposition 4***. *Future research should identify suitable thresholds of automation levels of DAs in the decision-making process and their association with task characteristics.*

Considering the opportunities outlined above, further consideration of human-related factors in hybrid teamwork is a fruitful avenue. Beyond considering the task performance and overall business benefits of the company, future work should also consider what means are effective to increase the communication trust between humans and DAs and ascertain the extent to which humans actually want information about the guidance they receive. It also remains an open question as to how the level of trust in the guidance can be increased. Moreover, although our review revealed that DAs can reduce the cognitive workload of humans owing to their natural communication and information streamlining capabilities (Kernan Freire et al. 2023a), some studies noted that when input information is inaccurate or incomplete, humans may need to spend additional cognitive effort on assessing the input of DAs to ensure the flow of tasks (Wellsandt, Klein, et al. 2022). Moreover, there is a need to investigate the potential increasing effects on users' cognitive workload when formulating the commands (i.e. output) for the DA. Finally, current studies evaluate the effectiveness of DAs in hybrid teamwork only for a short-term horizon, and there is a lack of studies investigating the long-term use of DAs, which deserve further empirical evidence.

> ***Proposition 5***. *Hybrid human-DAs teamwork should be evaluated considering workers' intentions, trust levels, comfort, satisfaction, and cognitive workload to achieve human-DA symbiosis in production and logistics tasks. Furthermore, a long-term evaluation is necessary.*

7.3. Multi-modal worker assistance

Our results indicated that DAs can be combined with tracking technologies (e.g. motion tracking, object tracking, facial tracking, and eye tracking) to predict workers' intentions beyond performing a task and providing assistance (Chen et al. 2021; Talacio et al. 2021). However, the use of DAs and tracking technologies to assist workers is still in its initial phase and is only applied to a few tasks, such as assembly and maintenance guidance. Given that the quality of communication between workers and DAs is often influenced by ambient noise, multi-modal inputs enable more robust assistance in task completion.

> ***Proposition 6***. *Future research needs to explore further areas where multi-modal assistance can be applied, such as production ramp-ups, material handling, and order picking.*

This study also demonstrated that workers find it more intuitive and natural when DAs and AR/VR are integrated for assembly/maintenance guidance and training. In this regard, workers' aural, oral, and visual perceptions are activated; as a result, they are more confident while performing tasks (Serras et al. 2020a; 2020b). The evolution of DAs in recent times has been rapid. Accordingly, enabling human workers to learn and master complex tasks is no longer a barrier. However, the design of a competency development pathway such that workers can obtain customised skills with the support of DAs and AR/VR remains a challenge.

> ***Proposition 7***. *Future research should investigate how to generate domain knowledge to refine the usage scenarios of DAs, discover to what extent workers can rely on the input given by DAs, when human expert intervention is necessary, and ascertain who is responsible for the losses due to task operational errors.*

7.4. DAs as facilitators for an inclusive workforce in production and logistics

Many countries are facing demographic changes in terms of age, gender, and cultural background combined with workforce shortages. Our results demonstrated that DAs can provide task assistance, automate information processing, and potentially interpret and communicate in different languages (Reis et al. 2022). It is therefore essential to explore the potential of DAs in supporting older workers and reconciling cultural background issues. Moreover, labour market participation remains a challenge for people with disabilities (Eurofound 2021) who often face difficulties in securing jobs in production and logistics (Mark et al. 2019). An inspiring example of using a DA to support people with disabilities is 'Be My Eyes'. Here ChatGPT-4 acts as the 'eyes' of visually impaired people transforming images into text, so that real-world information can be obtained immediately (OpenAI 2023b). We encourage future research to develop concepts and use case scenarios for the inclusion of people with disabilities in production and logistics.

Proposition 8*. Future studies should explore opportunities for leveraging DAs in production and logistics to achieve an inclusive workforce that involves older workers, people with varying cultural backgrounds, and those with disabilities.*

7.5. Methodological insights

Approximately 60% of the studies reviewed by us developed concepts and qualitatively demonstrated the use of DAs. The remainder used quantitative or mixed methods to assess the usefulness of DAs, only a few of which were conducted in the field (see the summary of methods adopted in the literature sample in Table A1 in the Appendix). As field studies usually provide higher practical validity, we encourage future studies to test the practical feasibility and benefits of DAs. Our review also demonstrates that only a few studies combine performance measures (e.g. task success rate using DAs) with established questionnaires, such as the system usability scale (SUS), subjective assessment of speech system interfaces (SASSI), and NASA Task Load Index (NASA-TLX), while a larger number of studies used simple self-developed questionnaires. DAs in production and logistics normally rely on a conversational, graphical, or multi-modal user interface. Additionally, user satisfaction and experience are crucial for the adoption of DAs. Future studies may thus consider using multiple questionnaires to obtain a more comprehensive analysis of user experience when interacting with DAs. Moreover, our review demonstrates that most extant studies focus on production and maintenance, while fewer works investigate product development, quality management, and logistics despite their obvious relevance for the company. We thus call for more empirical studies to explore the potentials of DAs in these areas. Furthermore, although we did not identify studies in our literature sample that investigate DAs from an Operations Research perspective, we see fruitful opportunities in this field. DAs can be used to support decision-making in production and logistics, which is ultimately connected to solving different planning problems (e.g. assignment or routing problems in intralogistics). Interesting questions include which of these problems should be solved by the DA and which by a central IT system, and what methods are best suited to a quick decision-making process.

Proposition 9*. More empirical research, for example, surveys, experiments, qualitative interviews, and case studies, is required to better understand workers' acceptance and usage of DAs, as well as their resulting actions. In addition, researchers should develop planning models and solution procedures that enable DAs to provide quick decision support. Moreover, research should not only focus on production and maintenance, but extend to other areas such as product development, quality management, and logistics.*

8. Conclusion

We presented a systematic literature review based on a sample of 69 papers and summarised existing scientific evidence on the applications, benefits, and challenges of using DAs in production and logistics. Based on a conceptual framework, we categorised three main tasks, namely information management, collaborative operations, and knowledge transfer. We performed a detailed analysis of how DAs support human workers in performing tasks across the areas of product design, production, maintenance, quality management, and logistics. We observed that research on DAs mainly concentrated on production and maintenance, and that only a few works investigated product design, quality management, and logistics. We discussed the potentials of DAs from the perspective of augmented analytics, hybrid team decision-making, and multi-modal assistance. Additionally, we highlighted the role of DAs in facilitating inclusive production and logistics. From a methodological perspective, we found that existing studies frequently used conceptual or qualitative methods to develop concepts and assess the benefits of DAs; however, additional field studies and comprehensive measurements of DAs are also essential in this line of research.

This study offers support to researchers and managers who are identifying the starting points in this emerging research field, by providing a comprehensive analysis of the various tasks that DAs can perform to help human workers in production and logistics. The objective of this study was to ensure that DAs improve the connection between workers, machines, and information systems, and effectively process information to support decision-making. Furthermore, we demonstrated that DAs could provide appropriate assistance in collaborative operations. Additionally, if they are jointly used with tracking technologies (e.g. motion tracking and eye tracking) and assistive technologies (e.g. AR and VR), they can provide robust assistance to workers. Managers can utilise the results of this study to further explore the possibilities of using DAs to assist workers in their daily tasks. These include combining DA and DT in shop floor management, using a DA and a scanner for order picking, and using a DA along with AR/VR for task guidance and training. Moreover, practitioners can use DAs to engage diverse workforces (e.g. older workers, people with different cultural backgrounds, or people with disabilities) in production and logistics. A few commercially available DAs already exist that can support production and logistics managers, such as *SAP Conversational AI*, *Oracle Digital Assistants*, and *ChatGPT Enterprise*. We expect new start-ups to enter this highly innovative area in the near future.

Some of the limitations of this study are: first, we may have missed some keywords during the database search and omitted a fraction of the literature not included in the Scopus and Web of Science databases. However, we conducted a snowball search as a complementary step to limit potential oversight. Second, subjectivity bias may have occurred during the literature sample selection. To address this shortcoming, we cross-checked the literature that presented DAs related to the framework among the authors.

Note

1. https://economictimes.indiatimes.com/news/international/us/an-industrial-robot-fails-to-differentiate-between-a-human-and-a-box-kills-a-man/articleshow/105100480.cms

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Data availability statement

Data is available on request from the authors.

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Appendix

Table A1. Methods adopted in the literature sample.

Paper type		Number	Percentage
Conceptual		10	14.5%
Total		10	14.5%
Empirical			
	Qualitative	29	42.0%
	Quantitative	24	34.8%
	Mixed method	6	8.7%
Total		59	85.5%
Overall		69	100%

Table A2. Overview of the literature sample.

Task types	Production and logistics areas	ID	Authors	DA category	Input from human	Output from DA	Automation level of task (referred to Endsley 2017)	Joint use with other technologies
Information management								
	Product design							
Product/Engineering information consultation		1	Choi, Hamanaka, and Matsui (2017)	Chatbot	Text	Text, graphic	Batch process	Social network
		2	Trappey et al. (2022)	Chatbot	Text	Text, graphic	Batch process	VR
	Production							
Machine/information system interaction		3	Kassner et al. (2017)	Chatbot	Text	Text, command to robot	Action support	DT, Cloud, Social network
		4	Ziegeler and Zuehlke (2005)	Avatar	NA	Avatar	Information cueing	–
		5	Mantravadi, Jansson, and Møller (2020)	Chatbot	Text	Text	Decision support	–
		6	Do and Jeong (2022)	Chatbot	Text	Text	Batch process	RPA
		7	Hüsson, Holland, and Sánchez (2020)	IPA	Speech	Speech, text, graphic	Decision support	–
		8	Gärtler and Schmidt (2021)	VA	Speech	Text, speech	Batch process	–
		9	Bousdekis et al. (2022)	DA	Speech	Speech	Automated decision-making	–
Shopfloor information management		10	Afanasev et al. (2019)	Dialogue assistant	Speech	Speech	Shared control	DT, CPS, Cloud
		11	Loh et al. (2023)	Chatbot	Text	Text	Batch process	–
		12	Reis et al. (2022)	VA	Speech	Speech	Action support	–
		13	Jwo, Lin, and Lee (2021)	VA	Speech	Text, graphic	Decision support	IoT
		14	Penica et al. (2023)	Chatbot	Speech	Speech, graphic	Decision support	AR, IoT, RFID,
		15	Abner et al. (2020)	Softbot	Text	Text, graphic	SA support, action support, decision support	IoT, Cloud
		16	Wellsandt, Foosherian, and Thoben (2020)	DA	Speech	Speech, graphic	SA support	DT, Cloud, IoT
	Maintenance							
Maintenance information management		17	Kernan Freire et al. (2022)	CA	Speech	Speech	Shared control	RFID
	Logistics							
Demand information management		18	Hsiao and Chang (2019)	DA	Speech	Speech	Automated decision-making	–
		19	Murciego et al. (2020)	IPA	Speech	Text, speech	Batch process	Cloud
		20	Angelov and Lazarova (2019)	Chatbot	Text	Text	Batch process	–
		21	Kern et al. (2006)	IPA	NA	NA	Supervisory control	–
Collaborative operations								
	Product design							

Collaborative human-AI product development		22	Makokha (2022)	DA	Speech	Speech	Automated decision-making	–
	Production							
Production planning and control		23	Rabelo, Romero, and Zambiasi (2018)	Softbot	Text, speech	Text	Decision support	CPS
		24	Rabelo, Zambiasi, and Romero (2019)	Softbot	Text, speech	Text, speech	Automated decision-making	CPS
		25	Rabelo et al. (2021)	Softbot	Text	Text, graphic	SA support, Action support, Decision support	DT, Cloud
		26	Li and Yang (2021)	VA	Speech	Speech, graphic, command to robot	Action support	–
		27	Schwartz et al. (2016)	Softbot	Speech, motion, eye movement	Speech, graphic, avatar, command to robot	Action support	DT, IoT, Motion tracking, Eye tracking, Object tracking
		28	Longo, Nicoletti, and Padovano (2022)	DA	Speech	Speech, text, graphic, video	Decision support	AR, VR, MR, DT, IoT
Joint task performance		29	Zimmer et al. (2020)	Chatbot	Text, haptic	Text	Action support	–
		30	Li and Wang (2021)	VA	Speech, motion	Speech, command to robot	Automated decision-making	Facial tracking, motion tracking, eye tracking
		31	Chen et al. (2021)	Chatbot	Speech	Speech, graphic	Batch process	Computer vision, objects tracking
		32	Chiu et al. (2021)	Chatbot	Speech	Speech, graphic	Batch process	Computer vision, objects tracking
		33	Talacio et al. (2021)	IPA	Speech	Speech, graphic, video	Shared control	Computer vision, motion tracking, objects tracking
		34	Behrendt and Strohmeier (2021)	DA	Speech	Speech, video	Rigid system	Motion tracking, eye tracking, objects tracking
Human-robot collaboration		35	Li et al. (2021)	VA	Speech	Speech, command to robot	Action support	–
		36	Li, Zhang, et al. (2022)	VA	Speech	Speech, command to robot	Action support	Computer vision
		37	Li et al. (2023)	VA	Text	Text, command to robot	Action support	–
		38	Li, Hansen, et al. (2022)	Dialogue assistant	Text, speech	Text, speech, command to robot	Automated decision-making	–
		39	Li, Chrysostomou, and Yang (2023)	VA	Speech	Speech, command to robot	Action support	–
		40	Ye, You, and Du (2023)	Chatbot	Text	Text, command to robot	Shared control	VR
	Maintenance							
Collaborative maintenance		41	Nyrkko et al. (2007)	DA	Text, speech	Text, speech, graphic	SA support	–
		42	Ade et al. (2020)	Chatbot	Speech	Speech	Shared control	–
		43	Wellsandta et al. (2020)	DA	Speech	Speech	Action support	–
		44	Wellsandt et al. (2021)	DA	Speech	Speech, graphic	Blended decision	–
		45	Wellsandt, Klein, et al. (2022)	DA	Speech	Speech, graphic	Blended decision	–

(*continued*)

Table A2. Continued.

Task types	Production and logistics areas	ID	Authors	DA category	Input from human	Output from DA	Automation level of task (referred to Endsley 2017)	Joint use with other technologies
		46	Aceta, Fernández, and Soroa (2022)	Dialogue assistant	Speech	Command to robot	Decision support	–
		47	Aceta et al. (2022)	Dialogue assistant	Speech	Speech	Decision support	–
		48	Abate et al. (2008)	Avatar	Speech, motion	Avatar	SA support	AR, object tracking
		49	Zambiasi et al. (2022)	Softbot	Text, speech	Text, graphic	Shared control, rigid system	AR
		50	Serras et al. (2020a)	Dialogue assistant	Speech	Speech, graphic	Action support	AR
		51	Serras et al. (2020b)	Dialogue assistant	Speech, motion, eye movement	Speech, graphic	Automated decision-making	AR, motion tracking, object tracking
		52	Fleiner et al. (2021)	CA	Speech, motion	Text, speech, graphic	Action support	Facial tracking, motion tracking
	Quality management							
Augmented quality control		53	Bousdekis et al. (2021)	DA	Speech	Text, speech, graphic	Decision support	–
		54	Wellsandt, Foosherian, et al. (2022)	DA	Speech	Text	Action support, decision support, rigid system	
	Logistics							
Order picking assistance Knowledge transfer		55	Wang et al. (2020)	Avatar	Motion	Avatar	Information cueing	AR, object tracking
	Production							
Production process/procedure training		56	Tanaka et al. (2003)	Avatar	Speech, motion	Speech, avatar	Action support	Motion tracking
		57	Kernan Freire et al. (2023b)	DA	Text, speech	Text, speech, graphic	Decision support	–
		58	Kernan Freire, Foosherian et al. (2023)	DA	Text, speech	Text, speech	Decision support	–
		59	Kernan Freire et al. (2023a)	DA	Text	Text, graphic	Decision support	–
		60	Pace et al. (2019)	Avatar	Speech, eye movement	Avatar	Shared control	AR, VR
		61	Lampen, Liersch, and Lehwald (2020)	Avatar	Motion	Avatar	Information cueing	AR, motion tracking
		62	Brade et al. (2020)	Avatar	Motion	Avatar	Information cueing	VR
		63	Rooein et al. (2020)	Chatbot	Text, speech	Text, video	Decision support	–
		64	Casillo et al. (2020)	Chatbot	Text	Text, graphic	Rigid system	–
		65	Clarizia et al. (2021)	Chatbot	Text	Text, graphic	Rigid system	–
		66	Longo, Nicoletti, and Padovano (2017)	DA	Text, speech	Speech, graphic	Action support	AR, VR, DT, IoT, Cloud
	Maintenance							
Maintenance process/procedure training		67	Zhu et al. (2014)	IPA	Text, speech, haptic, motion, eye movement	Speech, graphic, video	Blended decision	AR, motion tracking, eye tracking, object tracking
		68	Barbosa et al. (2018)	VA	Haptic	NA	Shared control	DT, IoT
		69	Zambiasi et al. (2023)	Softbot, avatar	Text, motion	Text, speech, graphic, avatar	Rigid system	Cloud, metaverse

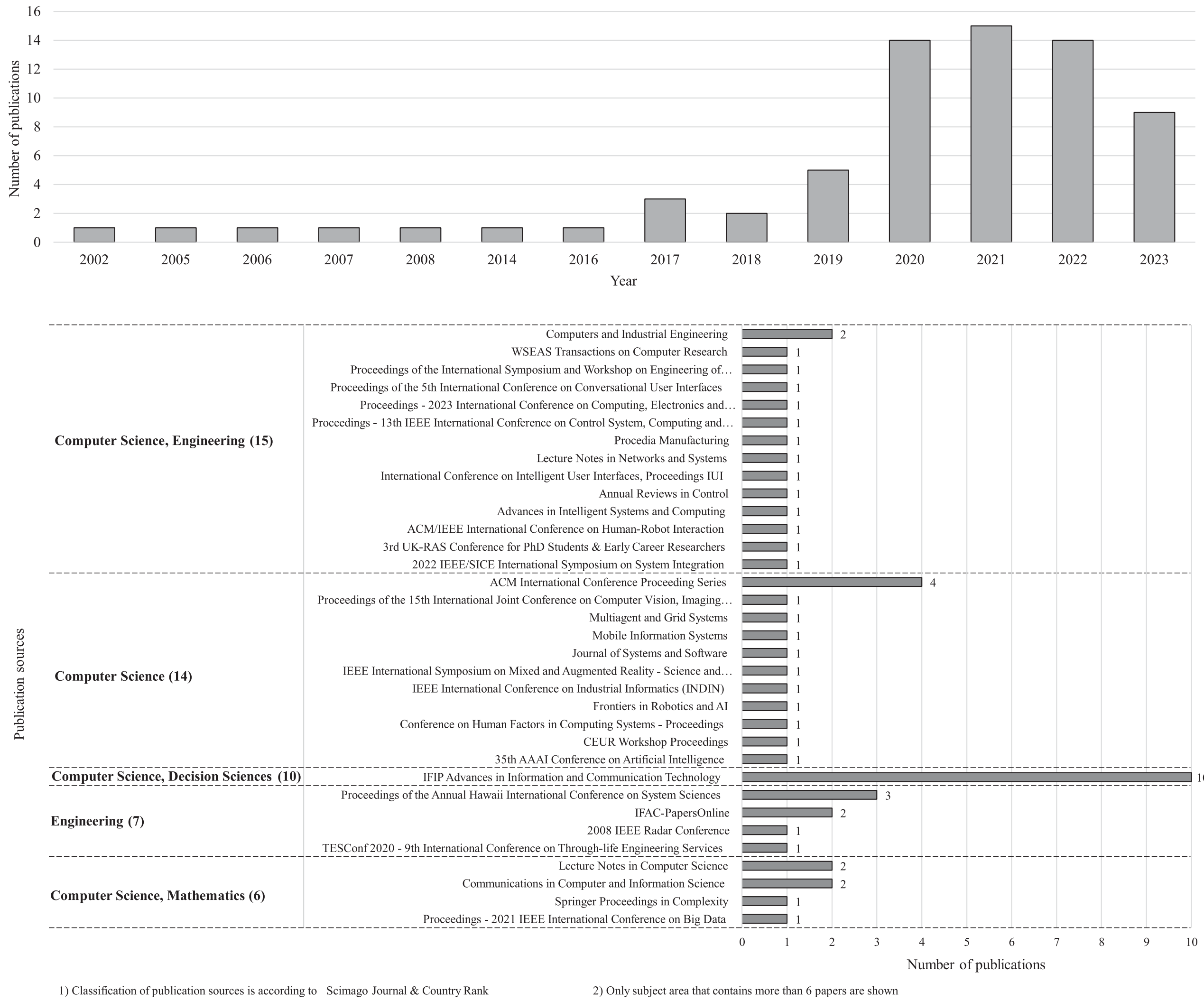

Figure A1. Publication numbers over time and per source.