algorithms

Review

Artificial Intelligence for Management Information Systems: Opportunities, Challenges, and Future Directions

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Abstract: The aim of this paper is to present a systematic literature review of the existing research, published between 2006 and 2023, in the field of artificial intelligence for management information systems. Of the 3946 studies that were considered by the authors, 60 primary studies were selected for analysis. The analysis shows that most research is focused on the application of AI for intelligent process automation, with an increasing number of studies focusing on predictive analytics and natural language processing. With respect to the platforms used by AI researchers, the study finds that cloud-based solutions are preferred over on-premises ones. A new research trend of deploying AI applications at the edge of industrial networks and utilizing federated learning is also identified. The need to focus research efforts on developing guidelines and frameworks in terms of ethics, data privacy, and security for AI adoption in MIS is highlighted. Developing a unified digital business strategy and overcoming barriers to user–AI engagement are some of the identified challenges to obtaining business value from AI integration.

Keywords: artificial intelligence; machine learning; intelligent process automation; predictive analytics; management information systems; enterprise resource planning; cloud computing; edge computing

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1. Introduction

With the global AI SaaS market expected to grow tenfold in value to over USD two trillion by 2030 [1], artificial intelligence (AI) has become an increasingly popular topic of research and discussion within the management information systems community. It has been claimed that AI technology has the potential to be the most disruptive [2,3] technological force with the largest transformational potential [4] within the organizational and business setting for the next decade. The possibility of AI-driven innovation has been studied for a broad range of applications:

- Computer science [5–7];
- Telecommunications [8,9];
- Education [10–12];
- Medicine [13–17];
- Sustainability [18–20].

The rise of interest in AI research and development has been sparked by a series of accumulating technological advancements with respect to software availability and hardware requirements. The emergence of open-source neural network models, large language models, pre-trained transformers, and the possibility for fine-tuning these models has opened the AI development field to the end user as a developer of AI-driven applications [21]. The extensive and sophisticated computation inherent to AI training procedures has presented an obstacle to the introduction of AI in smaller and medium-sized businesses; however, recent developments in GPU technology (NVIDIA DGX Systems) and analog edge AI products (Mythic AMPs) have made such integration not only feasible but also affordable. The trend toward the accessibility of AI development is further reinforced by the expansion of cloud-based AI services (SAP Core: AI, SAP: Conversational AI, Oracle AI Services, AWS AI services), suited to the automation needs of organizations and businesses across different market segments.

The question of the applicability of large language models (LLMs), generative pre-trained transformers (GPTs), and AI tools in general to large-scale automation for business use has been raised in recent years within the ERP and business management software (BMS) research and development communities [22,23]. Theo Priestley, CEO and founder of the AI analytics platform Metanomic, has commented on the integration of LLMs and GPTs such as Google Bard and ChatGPT as enterprise-grade solutions for data analytics and customer service by ERP providers like SAP, Oracle, IBM, Salesforce, Infor, and NetSuite, outlining the importance of considering the trade-off between cost-effectiveness and competitive advantage. Priestley notes that the use of pre-trained models (Bard, ChatGPT) fine-tuned on customer data might give BMS and ERP providers a competitive advantage in terms of having cutting-edge AI technology; however, API charges for gaining and maintaining access to such models might prove more expensive in the long-term than the development and training of specialized proprietary models by the BMS and ERP providers [24]. Given that LLMs and GPTs are heavily data-driven technologies, bias in training data sets is a rising concern with respect to their application in critical sectors such as healthcare [25] and law enforcement [26], where data privacy and security are a necessity. The announcement of the introduction of generative AI within Google Workspace offers for businesses has sparked a debate on whether the benefits of having personalized AI tools outweigh the issues with information accuracy, copyright violation, and data security [27–29].

Despite the aforementioned concerns, research shows that LLMs and GPTs have been applied with some success in several business sectors [22]: finance and banking, healthcare, e-commerce, and digital marketing, with the focus of the applications again being data summarization and analytics as well as automated customer service solutions. OpenAI lists several successful ChatGPT business integration projects on their "Customer Stories" webpage [30], including GPT-4 for qualitative data analytics (Viable); GPT-3 for insight extraction based on customer feedback (Yabble); and GPT-4 for knowledge base structuring in wealth management (Morgan Stanley). The use of ChatGPT-4 for [30] image recognition and context generation in blind and low-vision communities (Be My Eyes, Virtual Volunteer project), language preservation (Government of Iceland), and customer support and personalized learning in educational platforms (Khan Academy, Duolingo), shows the transformative potential that such AI technologies can have. However, it is pertinent to note that LLMs and GPTs are not a replacement for human intelligence and critical thinking, but rather tools that can support more streamlined and personalized experiences in business [22], research [31], and educational [32] processes.

With new AI tools continuously introduced as automation solutions for organizations and businesses across different market segments, an assessment of the current state of AI technology in management information systems (MIS) can provide valuable insight to researchers and developers. This systematic literature review aims at studying AI technology with respect to its implementation and adoption in MIS and focuses on identifying:

- Existing opportunities and challenges in AI adoption at the organizational level.
- Available tools and platforms for launching AI services.
- The reported business value of integrated AI models.
- Future research directions.

The paper is structured in a popular literature review format. First, a brief theoretical introduction to AI in the context of MIS is presented. Second, relevant preceding literature reviews are considered, and their advantages and limitations are discussed. Third, the research methodology followed in this paper is explained in detail. Finally, the outcomes of the performed literature research are discussed, its limitations are acknowledged, and further research directions are identified.

2. Background and Related Research

A systematic literature review on the inclusion of AI in information systems [4] has pointed out a "lack of clarity concerning the concept and classification of AI" in literature resources, with 54 of the 98 primary literature sources of the study [4] giving no clear definition of the AI relevant to the study, while of the remaining 44 sources, 7 gave a definition of AI without referencing it and 37 used a total of 28 different definitions of AI. This concerning trend of the lack of a unified definition of the distinct qualities of AI has continued in the years after the study was published (2021) and has led to a broadening of the scope of AI to include a vast variety of tools and capabilities. To avoid the inherent vagueness of the term AI, in our study, we have identified a list of capabilities presented in Table 1, which the literature sources we chose as primary have included in their definitions of AI. The selection process used for identifying the primary sources is described in detail in the Materials and Methods section of this review.

Table 1. List of AI capabilities as identified by the referenced primary sources.

Capabilities *	Description
Predictive Analytics	A branch of advanced analytics that makes predictions about future outcomes using historical data combined with statistical modeling, data mining techniques, and machine learning. Companies employ predictive analytics to find patterns in this data to identify risks and opportunities [33].
Intelligent Process Automation	The application of neural networks and related new technologies, including computer vision and cognitive automation, for robotic process automation, i.e., technology that simplifies the processes of building, deploying, and managing software robots (bots), and the processes of deploying and managing context-aware robots in an industrial setting [34].
Machine Learning	The use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyze and draw inferences from patterns in data [35].
Natural Language Processing	NLP combines rule-based modeling of human language (computational linguistics) with statistical, machine learning, and deep learning models to enable computers to process human language in the form of text or voice data and to analyze and synthesize a relevant response in the form of natural language and speech. NLP is the foundation of speech recognition [36].
Machine Vision	All industrial and non-industrial applications in which a combination of hardware and software provide operational guidance to devices in the execution of their functions based on the capture and processing of images [37].
Expert Systems	A computer program that is capable of simulating the judgment and behavior of a human or an organization that has expertise and experience in a particular field [38].

* Studies regarding the use of different AI capabilities in robotics have been summarized within the category of AI capability used by the study.

Since this literature review focuses on the application of AI in management information systems, a relevant definition and scope of the term MIS must also be provided. MIS are information systems used for decision-making, coordination, control, analysis, and visualization of information regarding the processes, people, and technology employed within an organizational setting. MIS is a term unifying various software solutions for automation at the organizational level such as [39]:

- Decision support systems (DSS);
- Executive information systems (EIS);
- Office automation systems (OAS);
- Knowledge management systems (KMS);
- Transaction processing systems (TPS);
- Enterprise resource planning systems (ERP).

The field of MIS relies on the implementation and integration of business analytics (BA) tools to transform aggregated organizational and business data into insights for improving business decisions, as well as employing AI for process automation of repetitive low-value-added tasks [40]. Here, the term business analytics is used to describe a set of disciplines and technologies for solving business problems using data analysis, statistical models, and other quantitative methods, involving an iterative, methodical exploration of organizational and experience data, with an emphasis on statistical analysis, to drive decision-making. AI-powered business analytics tools allow organizations to utilize machine learning algorithms and predictive analytics to identify trends and extract insights from complex data sets across multiple organizational sources [41].

Based on the provided definitions of AI capabilities and the defined scope of MIS, a systematic literature review of the existing applications of AI in MIS was prepared and will be presented in this paper. However, before the findings of the review are discussed, it is appropriate to consider previously conducted literature reviews with similar agendas.

Literature studies that have been conducted with respect to the implementation of AI in an organizational or business setting, can be summarized in the following categories based on the main research topic:

- Finance and Accounting [42,43];
- Information management [44];
- Human resource management [45–47];
- Decision-making [48,49];
- Forecasting [50];
- Conversational agents [51].

It is evident that each of the above-mentioned literature reviews has focused on a narrow segment of AI applications in management information systems. Thus, the insight they provide is rich for each individual research topic and at the same time limited to a specific AI application segment, which does not allow for the exploration of business opportunities arising from data exchange in overlapping segments, e.g., the use of forecasting models for predictive financial reporting, the effects of the deployment of digital assistants on decision-making in the organizational setting or the outcomes of the application of conversational agents in the early stages of employee onboarding. In addition, due to the fast pace of AI development and the surge of investments in AI research in recent years, some of the literature reviews conducted on sources up to the year 2020 no longer provide a complete view of the available technology in a specified segment.

Three systematic literature reviews [3,4,52] will also be considered since they approach the literature investigation by incorporating a wide range of AI applications and thus mitigate the segmentation of the resulting insights. A comparison of [3,4,52] with the current systematic literature review is presented in Table 2. It is pertinent to discuss the limitations of previous systematic literature reviews. Highlighting these limitations is helpful to the research community, as well as to the authors of this review in presenting a more thorough view on the key factors affecting the adoption of AI in MIS.

The literature review conducted by Borges et al. [3] cited a total of 41 primary studies from a variety of journals and conferences; however, its focus was on specific AI interactions with organizational strategy, unlike that of the current literature study, which investigates the challenges and opportunities for AI adoption, platforms used, and contributions made by researchers when implementing AI in MIS.

Collins et al. [4] focused their review on the subject definition and business value identification of AI in information systems. Their study provides valuable insight into the concept and classification of AI tools in information systems; however, their journal selection process excluded some valuable literature sources, e.g., the Q1 journal *Knowledge-Based Systems* focused on AI applications in MIS and the Q1 *Journal of Supply Chain Management* focused on information systems research. The review conducted by Rzepka and Berger [38] is narrowly focused on the context of user interaction with AI tools and provides insights into the effects of such interactions; however, it is primarily focused on the outcomes in terms of user behavior rather than business value.

The outlined limitations of previous systematic literature reviews allow for a knowledge gap to be recognized with respect to the identification of key factors affecting the process of AI adoption in MIS. The current literature review aims to minimize this knowledge gap by identifying some of these factors: challenges of AI adoption at the organizational level of automation, existing AI capabilities and platforms, business value, and contributions made by researchers in the field of AI adoption in MIS.

Table 2. Comparison of existing systematic literature reviews and the present review.

Study	Purpose	Chronological Scope of Research	Number of Primary Sources
Borges et al. [3]	To investigate the application of AI in organizational strategy.	2009–2020	41
Collins et al. [4]	To define AI as a subject of research and identify its uses in business information systems.	2005–2020	98
Rzepka and Berger [52]	To study individual user interaction with AI tools in the context of information systems.	1987–2017	91
Our study	To identify challenges and opportunities for the adoption of AI in MIS, discuss existing platforms and tools, and provide directives for future research.	2006–2023	60

3. Materials and Methods

This section presents the research methodology used in this study. A systematic research approach for the purpose of creating literature reviews has the following advantages: transparency and review replicability [53], high quality of the resulting analysis for studies with a clearly formulated research question [54], and the capability to summarize large quantities of research studies [55]. Since we aim at creating a literature review based on specific research questions and identifying key factors for AI application in MIS in a transparent manner from available research sources, the use of the systematic research approach is most suitable.

The quality of a literature review is dependent on the rigor of the search process [56]. Thus, it is considered best to develop the search strategy in concert with the posed research questions. The goal is then to find as many studies as possible that are capable of answering one or more of the research questions [57]. The choice of research questions directly affects the primary source selection. The research questions investigated in this study were identified by the authors based on perceived knowledge gaps in previous literature reviews and the necessity of providing up-to-date answers to questions that have been posed previously by the AI research community in literature reviews [3,4,52] and studies [58,59].

The objective of this systematic literature review is to answer the following research questions:

RQ. 1 *What AI capabilities are utilized by AI researchers?*

RQ. 2 *What types of platforms are utilized by AI researchers?*

RQ. 3 *What kinds of contributions are made by studies of AI in MIS?*

RQ. 4 *What business value has been identified by studies of AI in MIS?*

RQ. 5 *What are the challenges and benefits of the adoption of AI in MIS?*

RQ. 1 aims at providing a contemporary view of what AI capabilities are most frequently utilized by researchers in the field of AI and more specifically its implementation in MIS. The categorization of studies, performed based on RQ1, includes new categories of AI capabilities that were not separately considered by previous reviews, i.e., intelligent process automation and predictive analytics. RQ. 2 focuses on identifying trends with respect to the type of platforms used to deploy AI applications for the purpose of MIS research. RQ. 3 and RQ. 4 are oriented toward defining the contributions that AI researchers have brought to the MIS community in terms of innovation and business value. RQ. 5 aims at identifying some of the challenges and benefits of adopting AI in MIS.

Applying the systematic literature review methodology, as described in [60,61], to the research questions above requires a 3-stage process to be followed to generate a systematic literature review. The first stage (planning the review) and second stage (conducting the review) are described in this section. The last stage—reporting of the review outcomes—is presented in the Results section of this paper. In the Discussion section, possible limitations of the performed systematic literature review are considered and the strategies applied for their mitigation are discussed.

3.1. Planning the Review

A common approach to conducting literature reviews is to use a keyword string search to locate appropriate literature sources from available electronic literature databases. A universally accepted search strategy is to base the search string on the research questions and to include a list of synonyms, alternative spellings, and abbreviations of the search terms [57]. Based on the research questions and considering the theoretical background in artificial intelligence and management information systems domains, this review focused on the following sample key phrase selection for identifying relevant source material: "artificial intelligence", "machine learning", "deep learning", "neural networks", "cognitive enhancement", "speech recognition", "natural language processing", "intelligent process automation", "predictive analytics", "enterprise resource planning", "information management", "expert systems", "knowledge management systems", "business value", "cloud-based platform", "edge AI", and "federated learning". The selected key phrases correspond to the choice of research questions. By focusing the key phrases on recently researched AI capabilities, terminology related to management information systems, and types of platforms for deploying AI applications, the possibility of gathering studies that are relevant to one or more of the posed research questions is increased. However, given the variety of AI capabilities, models, and methods in use by AI researchers and the lack of cohesiveness in the way they are referred to by researchers, a more thorough search strategy was needed. Thus, the initial database search was performed iteratively by including different variations of the key phrases, as well as enriching the search strings with terminology specific to the adoption of AI in MIS. The above-mentioned key phrases were used as the basis for formulating the string search; however, they do not represent the complete and exhaustive list of terms used in the search.

The search for source material was conducted in three research databases: Scopus, Web of Science, and Association of Information Systems e-library; however, all the sources extracted via the AIS e-library were duplicated in the Scopus and Web of Science extractions and the duplicate articles were later discarded.

The following inclusion criteria were identified in accordance with the selected research methodology:

- Journal and conference papers that addressed the intersection between AI and management information systems domains, containing the key phrases defined above in their title, abstract, or keywords.
- Journal and conference papers written in English.
- Journal and conference papers published since 2006, when research studies started focusing on overlapping topics in the AI and MIS research domains.
- Studies that directly answer one or more of the research questions.

The following exclusion search criteria were identified in accordance with the selected research methodology:

- Duplicate articles.

- Use of the key phrases only in the abstract to present the context of the study.
- Unavailability of the full study text as an electronic document.
- Simulation studies (no actual application of AI technology).

As recommended by [61], the data extraction process was planned based on the research questions in order to outline similarities and differences between the research results of the examined studies. Thus, the following main search elements were highlighted: author(s); year when the paper was published; language of publication; source of publication; title; abstract; indexed keywords; AI capability in the organizational context addressed by the paper; challenges of adopting AI in the researched MIS application; research method; and the business value and benefits of the AI application.

3.2. Conducting the Review

Sample search strings used for conducting the literature search in the scientific databases, Scopus, Web of Science, and AIS e-library, are presented in Table 3. The database search was performed in a fragmentary manner with subsequent search strings being increasingly narrowly defined, i.e., using more AND logic connections between search terms and implementing more specific key phrases.

Regarding the Scopus database search, a selection of journals relevant to the field of Management Information Systems was made in order to focus the search on the desired research domain. The journal selection was made based on the SJR impact factor and quartile ranking in the fields of Management Information Systems, Information Systems, and Artificial Intelligence. The selected journals have high SJR impact factors, with the lowest being 1.38 and the highest–4.91 (ranking from 2022), and all of them fall into the Q1 category for Management Information Systems or Information Systems research. The journals *Knowledge-based Systems* and the *International Journal of Information Management* also fall into the Q1 category for artificial intelligence research.

The selected journals are:

1. Management Information Systems Quarterly;
2. Journal of the Association of Information Systems;
3. Knowledge-based Systems;
4. Information Systems Journal;
5. Information Systems Research;
6. Journal of Information Technology;
7. International Journal of Information Management;
8. Journal of Management Information Systems;
9. Journal of Strategic Information Systems;
10. Journal of Supply Chain Management;
11. European Journal of Information Systems;
12. Human Factors and Ergonomics in Manufacturing and Service Industries.

Conference research papers were mainly extracted from the published editions of the International Conference on Information Systems (ICIS), International Conference on Automatics and Informatics (ICAI), and the European Conference on Information Systems (ECIS). The conference selection was based on a mix of indicators, including paper submission and acceptance rates, citation rates, and the visibility and research history of the conference organizing and editorial teams. ICIS and ECIS both hold low paper acceptance rates, with less than 30% of the submitted papers being accepted for publication as of 2022, and implement rigorous editing and reviewing procedures. ICAI, organized by the IEEE Robotics and Automation Society, brings together researchers and industry experts in the fields of information and automation technology and thus provides opportunities for publishing research focused on overlapping topics in the AI and MIS research domains.

A multistage process was implemented to identify and summarize the available literature on AI applications in management information systems. The selection process consisted of the stages, shown in Figure 1, and followed the procedural phases described below.

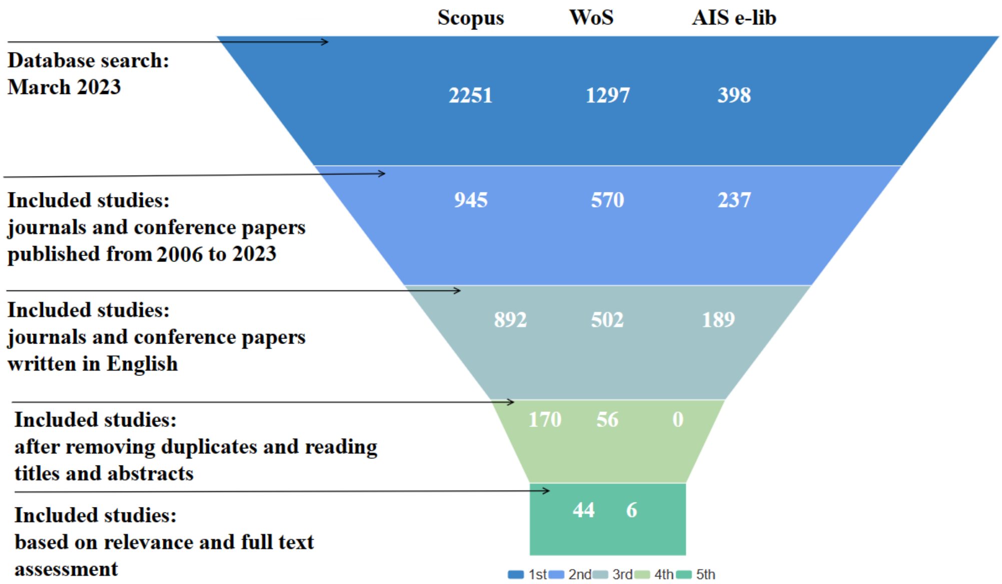

Figure 1. Number of studies at each stage of the selection process.

The procedural phases were the following:

- The key phrases were searched in titles, indexed keywords, and abstracts, without any limitations imposed on the search. In this phase, the following metadata regarding the examined studies were extracted: authors, publication year, title, keywords, abstract, publication source title, language, and document type. The generated article metadata were stored in .csv files and Microsoft Excel spreadsheets.
- The inclusion and exclusion criteria were applied. Duplicated research was removed.
- The selected articles were exported, read, and assessed based on relevancy.
- Relying on the full content of each article selected in the final stage of the selection process, manual information extraction was performed with respect to the defined research questions RQ1–RQ5. The full content of the selected articles was independently read and assessed by both authors, having in mind the defined research questions.

It is important to note that studies were eligible for selection if they presented either empirical data on the application of AI capabilities in MIS or if they were non-empirical studies with clear academic contributions to the MIS research field.

Sample search strings based on the selection of the literature source database are presented in Table 3. The * sign is commonly used in search strings as a symbol to note distinctive word stems to retrieve variations of a term or phrases containing the term with less typing.

Table 3. Sample search strings based on the choice of database.

Database Source	Sample Search String
Scopus	TITLE-ABS-KEY (“AI” OR “artificial intelligence” OR “machine learning” OR “neural networks” OR cognitive* OR automation* OR business* OR augment* OR enterprise*) AND SRCTITLE (“MIS Quarterly: Management Information Systems” OR “INFORMATION SYSTEMS RESEARCH” OR “JOURNAL OF MANAGEMENT INFORMATION SYSTEMS” OR “JOURNAL OF STRATEGIC INFORMATION SYSTEMS” OR “EUROPEAN JOURNAL OF INFORMATION SYSTEMS” OR “INFORMATION SYSTEMS JOURNAL” OR “JOURNAL OF INFORMATION TECHNOLOGY” OR “JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS” OR “INFORMATION AND ORGANIZATION” OR “INFORMATION AND MANAGEMENT” OR “JOURNAL OF SUPPLY CHAIN MANAGEMENT” OR “KNOWLEDGE-BASED SYSTEMS”) AND PUBYEAR $\geq$ 2006
Web of Science (WoS) AIS e-library	TS = (“AI” OR “artificial intelligence” OR “machine learning” OR “neural networks” OR “natural language processing” OR “speech recognition” OR cognitive* OR automation* OR business* OR augment* OR enterprise* OR resource plan* OR expert sys*)

The sources selected as primary, on which the analytical part of this study is based, are listed in the References section as [62–121].

4. Results

The reported outcomes of the literature review are presented in the form of an analysis of the 60 selected primary studies (marked as [62–121] in the References section) based on the identified research questions. Each research question is discussed in a separate section.

RQ. 1 *What AI capabilities are utilized by AI researchers?*

The aim of this question is to categorize the studies based on the main type of AI capability that was investigated in the study. Since it is possible to combine a variety of capabilities in a single AI system or toolbox, such studies were categorized by singling out the main capability used in the research. Figure 2 shows the distribution of AI capabilities utilized in the examined studies.

Figure 2. Distribution of primary studies by AI capability.

Evidently, research efforts are focused on exploring intelligent process automation and machine learning capabilities. A rise in interest in natural language processing and predictive analytics can be noted with respect to the outcomes from previous literature reviews [4], which showed NLP as a relatively unexplored field and did not consider predictive analytics as a large enough field to explore outside of machine learning.

RQ. 2 *What types of platforms are utilized by AI researchers?*

The aim of this question was to identify the types of platforms used by AI researchers for their applications. The classification focuses on isolating whether the application works on a cloud-based platform (SAP Core AI/Conversational AI, Oracle AI services, etc.), an on-premises server, or edge devices, where the data are generated (smartphones, tablets, computers, etc.). The studies which present hybrid architectures are counted in a separate category.

Figure 3 shows that the majority of the examined studies focused on cloud-based or on-premises applications, while only two studies investigated edge device AI applications and one study focused on hybrid architectures. A potential future research direction would be to focus on developing edge AI applications and investigate possibilities for federated learning and heterogenous data silo structures. Edge AI applications allow for greater data privacy and security since the use of federated learning means that the training of a smaller AI model is performed locally on an edge device, where the data are generated, and only aggregated data outcomes are presented for training to the large model based on the cloud. Such implementations also mitigate concerns regarding data accessibility in cases when the cloud service becomes temporarily unavailable.

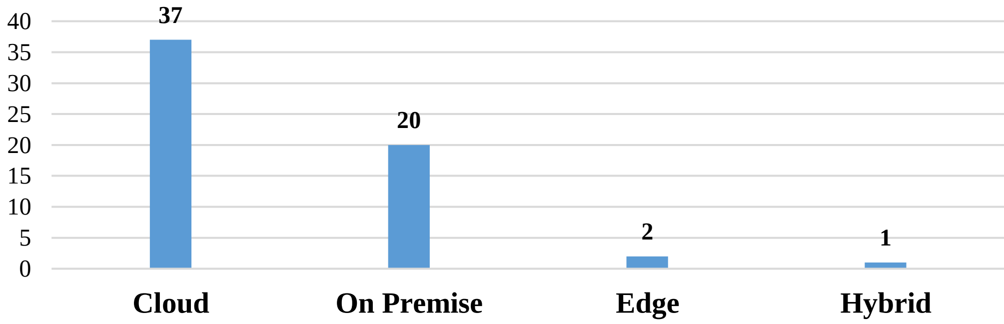

Figure 3. Distribution of primary studies by platform type.

The choice of platform for AI integration can have a significant effect on data privacy and security and thus can be used to help organizations comply with the increasing number of data regulation and protection laws and policies implemented by the European Union (EU). One such instance is the General Data Protection Regulation (GDPR), which came into effect for all EU and EEA (European Economic Area) member countries on 25 May 2018. The GDPR requires organizations to implement appropriate technical and organizational measures to ensure the security of personal data generated on edge devices. AI can support GDPR compliance by automating data protection tasks and identifying potential data breaches in real time. Some considerations regarding the impact of AI on data privacy and protection have been summarized in [122].

RQ. 3 *What kind of contributions are made by studies of AI in MIS?*

The aim of this research question is to identify and categorize the contributions of the primary studies and thus single out categories in which academic discourse on AI in MIS should be encouraged. There are five contribution categories, namely: framework, method, and technique; lessons learned; model or tool; guidelines; and implication or advice. A graphical representation of the contributions of the 60 primary studies is presented in Figure 4. Analysis of the 60 primary studies also shows that contributions were largely made as lessons learned (29 studies) and models or tools (15 studies), whereas advice or implication (7 studies), methods (6 studies), and guidelines (3 studies) comprised a smaller amount of the examined sample. Where more than one type of contribution was identified, the main contribution, as stated by the authors of the given primary study, was assumed as the type of contribution to be counted for that study.

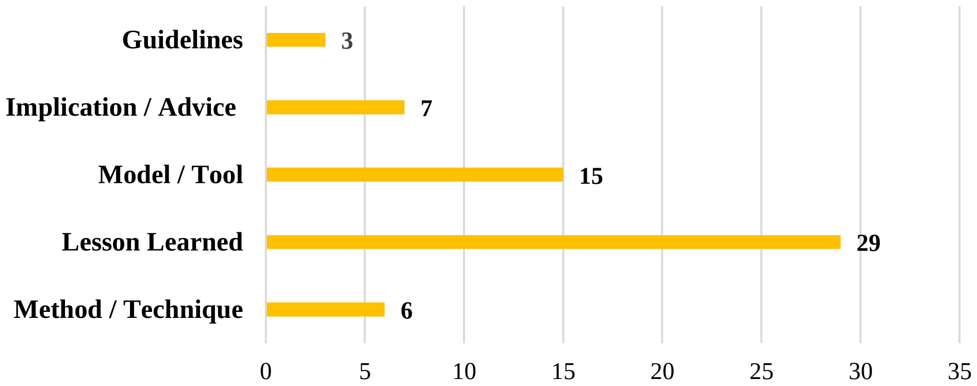

Figure 4. Distribution of primary studies by type of research contribution.

It is important to note that contributions of the type 'lessons learned' are context-specific, and given the large variety of applications that are examined, accumulating universally applicable knowledge from these types of contributions is time-consuming. The need for more studies focusing on guidelines and frameworks, especially in terms of ethics, data privacy, and security for AI adoption in MIS is highlighted. A rise in research studies contributing models and tools is evident, in contrast with reported outcomes from previous literature reviews [4], which called on the research community to contribute more specifically to the categories of models and tools.

RQ. 4 *What business value has been identified by studies of AI in MIS?*

As noted in previous literature reviews [4,123], the qualitative approach to the classification of AI applications in MIS based on the type of business value generated by the research is more appropriate than arbitrary measurements of business value in a specified currency, which are subject to inaccuracies due to the rapid pace of market changes in the technology domain. The following business value types are defined:

- Process Automation, i.e., the value generated due to the automation of business processes and elimination of low-value-added tasks from human workflows.
- Analytical Insight, i.e., the value generated due to business insight based on predictive data analytics and forecasting techniques.
- Cognitive Interaction, i.e., the value generated due to the engagement of employees or customers with digital assistants, AI tools and interfaces, or NLP agents.

A visual representation of the distribution of primary studies based on business value type is presented in Figure 5.

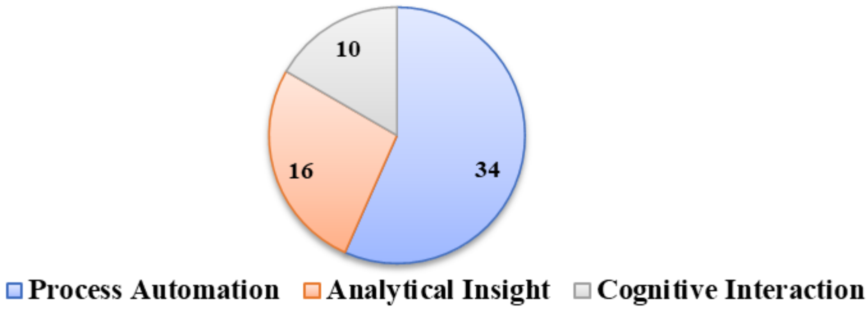

Figure 5. Distribution of primary studies by business value type.

Future research efforts can shift focus away from process automation and toward applications that generate value with respect to analytical data insights and cognitive interaction.

RQ. 5 *What are the challenges and benefits of the adoption of AI in MIS?*

The identified benefits and challenges within the primary research studies are summarized in Table 4. The classification is based on the source of generated business value.

Table 4. Challenges and benefits of adoption of AI in MIS.

Source of Business Value	Benefits	Challenges	Primary Sources
Process Automation	Ease of implementation and rapid return on investment. Allows human resources to focus their attention on value-added tasks.	To achieve benefits through the use of AI in automation, a unified digital business strategy must be developed and implemented at all company locations. Decision logic and business rules must be integrated.	[63–72] [74–81], [84,87,88,90] [92,94], [95], [101–106,108] [116,117]

Table 4. *Cont.*

Source of Business Value	Benefits	Challenges	Primary Sources
Analytical Insight	Deep learning and machine learning techniques can extract patterns from large volumes of generated data at a speed that a human being cannot achieve. AI tools are much more suited than human operators to perform predictive analytics for high-velocity data generation domains.	Some AI technologies rely on human experts to establish a working hypothesis and to identify relevant features, but the fear of job elimination can drive human operators to be unwilling to share knowledge and provide expertise for AI model creation.	[85,86], [97,98], [100,107], [109–113,115] [118–121]
Cognitive Interaction	AI applications can create competitive advantages by improving customers' experience and engagement through digital assistants and conversational agents. Onboarding and on-the-job learning processes can be supported by intelligent AI assistants built to provide responses to prompt-like queries.	Resulting changes in workforce structure and possible job reductions with respect to instructors and HR specialists. Overall lack of confidence in AI decisions, recommendations, and responses, based on negative previous experience. Barriers to engagement with intelligent digital assistants: access to the Internet and to AI tools (hidden by paywalls and subscriptions) as well as at least a basic understanding of prompting techniques and general technical competence.	[62,73,82,83,89, 91,93,96,99,114]

5. Discussion

5.1. Summary of Findings

In the framework of the conducted systematic literature review, the authors identified, classified, and analyzed 3946 studies on the subject of adopting AI in management information systems that were published between 2006 and March 2023. Of these, 60 were identified as primary studies after an exhaustive sorting and filtering process.

The presented systematic literature review aims at filling a knowledge gap created by previous literature reviews in the field of artificial intelligence adoption in management information systems. While previous systematic literature reviews have focused on specific aspects of the influence of AI on organizational-level automation and information systems, such as the impact of AI on organizational strategy [3], and studied individual user interactions with AI tools [52], this review focuses on creating a contemporary overview of research contributions in the field of AI adoption in MIS and their practical implications.

This review grouped the selected primary studies based on the AI capabilities identified in the researchers' own definitions of AI. This sorting procedure was implemented due to a concerning trend of a lack of cohesiveness in the definition and scope of artificial intelligence functionalities used in the research community, which was also identified by a previous systematic literature review [4]. While the majority of the research is focused on the application of AI for intelligent process automation, there is a notable increase in the number of studies focused on predictive analytics and natural language processing. A previous literature review on AI in information systems research [4] reported that NLP was a relatively unexplored field and did not consider predictive analytics as a large enough field to explore outside of machine learning; however, in recent years, the focus of research has evidently shifted toward providing business insight based on predictive analytics and developing NLP models for human–AI interaction.

While most AI implementations are facilitated by using cloud or on-premises data centers for the necessary training and data aggregation, an exciting new research trend has focused on AI applications at the edge of industrial networks and the development of federated learning methodologies. This trend has not been brought up in previous systematic literature reviews in the field of AI adoption in management information systems.

The presented literature review identified five contribution categories within the examined AI research sources, namely framework, method, and technique; lessons learned; model or tool; guidelines; and implication or advice. The identified contribution categories were used for the classification of the 60 primary studies. The classification shows that the majority of contributions were made in the 'lessons learned' category, which generates context-specific contributions, and given the diversity of applications that are examined, accumulating universally applicable knowledge from this type of contribution is considered very time-consuming. The need for more studies focusing on guidelines and frameworks for the adoption of AI in MIS is highlighted, especially in terms of ethics, data privacy, and security. An evident rise in research studies contributing to AI models and tools has been identified. Such research contributions have a lasting impact since, if properly conducted and documented, these tools can be used by the research community to further investigate their applicability to unsolved problems in a variety of practical fields.

The review utilizes a qualitative approach to the classification of AI applications in MIS, based on the type of business value generated by the research, rather than quantifying business value by generated revenue. The resulting three categories of generated business value are process automation, analytical insight, and cognitive interaction. While most of the primary studies contribute business value in the form of process automation, there is a recognizable shift in research focus toward cognitive insight applications such as chatbots and AI-driven digital assistants. Key benefits and challenges arising from AI adoption in management information systems were also identified.

5.2. Study Contributions

This study aims at providing a contemporary overview of the existing AI applications, focusing on the organizational level of automation and management information systems. The review encompasses sources from 2006 to 2023, providing the most up-to-date literature review in the field of AI adoption in MIS.

By identifying the most researched AI capabilities, this study provides practitioners with an indication as to which AI technologies could become most widespread in industrial and organizational settings in the near future. This is an important practical implication for businesses, which strive toward the automation and digitalization of their operations. Additionally, this review should enable industry practitioners in their research efforts directed toward finding studies that can contribute to solving specific challenges of the adoption of AI in MIS.

This study discussed previous systematic literature reviews with similar agendas [3,4,52]. An attempt has been made to introduce improvements to the review process compared to previous reviews by:

- Including a larger variety of journals (*Knowledge-based Systems, Journal of Supply Chain Management, Human Factors and Ergonomics in Manufacturing and Service Industries*) and conferences (ICAI) that were not part of the scope of previous reviews.
- Discussing recent developments in AI, more specifically the impact of large language models and generative pre-trained transformers on the business use of AI.
- Classifying AI services and tools based on the type of hosting platform: cloud, edge, or hybrid, whereas previous systematic literature reviews focused mainly on cloud implementations.

Furthermore, suggestions for future research directions, based on the performed literature review, are discussed in the last subsection of the Discussion section.

5.3. Study Limitations

After summarizing the findings and contributions of this study, it is important to note some threats to the validity of the conducted research, inherent bias factors, and mitigation strategies that were used to counterbalance those threats.

With respect to construct validity, i.e., the extent to which the research procedure accurately assesses the subject matter, the threat of mismatching the source material and the aim of the literature review was mitigated by implementing a thorough selection process (Figure 1).

Regarding internal validity, i.e., establishing true causal relationships and ensuring that the reported outcomes were not a result of an unmeasured factor, any resulting threats were alleviated by the fact that this review does not focus on establishing statistical causal relationships but merely identifies key factors in the adoption of AI applications in MIS.

Pertaining to conclusion validity, i.e., the inherent bias of the researcher when interpreting the extracted information, the following mitigation techniques were employed: a full audit trail for the selection process from the original number of studies to the selected primary studies is provided, a strict selection procedure is followed, and conclusions drawn from the analysis of the selected 60 primary studies have been agreed upon by both authors.

Although strategies were employed to mitigate the threats to the validity of this literature review, we acknowledge that the manner of journal and conference source selection as well as the applied exclusion and inclusion criteria might limit the scope of the performed literature review.

5.4. Suggestions for Future Research

Given the large amounts of data generated by devices operating in organizational networks, informational security and data privacy in the organizational setting are key future research directions [124,125]. Context-specific practical considerations when implementing organizational-level automation must be considered [126–128]. Discussing the challenges arising from AI adoption in management information systems helped with formulating additional future research directions. Researchers have increasingly focused their efforts on investigating the opportunities for applying AI tools and models to tasks related to process automation, as shown in the Results section of this study and previous literature reviews [4]. An interesting and relatively unexplored topic for future research would be the examination of the overlap between digital twin technology and intelligent process automation in smart factories. Research on how AI-powered robots and intelligent UAVs would affect customer and healthcare services is still lacking, with most of the research efforts focusing on the impact of such technology on logistics [129,130], delivery [131–134], and warehousing tasks [135–139].

Additionally, the following suggestions for future research in the field of AI implementation in MIS were identified based on the analysis of the currently available literature sources:

- Process automation and business logic definition across different cloud ERP platforms: SAP, Oracle.
- ML and computer vision applications for robotization in smart factory deployment.
- Intelligent workflow modeling and business process template generation.
- Impact of process automation on employee engagement.
- Business strategies for the successful inclusion of LLMs and GPTs in the work environment.
- Generative AI for CAD modeling and industrial design.
- Intelligent quality assurance practices for generative AI design applications.
- Human experience management: effects of the use of AI assistants in onboarding procedures.
- Predictive analytics and process automation for human experience management.
- Sales forecasting and client targeting.
- Social media data analytics for advertisement targeting.

- Strategies to assess job reduction threats and mitigate the fear of adoption of AI technologies.
- Operational data analytics and bottleneck forecasting for production planning.
- Natural language robot control for large-scale process automation.
- Application of NLP and large language models for controlling unmanned aerial vehicles.
- Quality control in automated production scenarios.
- Intelligent warehouse management and product life-cycle tracking.
- AI techniques and tools for threat and malware detection.
- Data privacy and informational security for AI applications.
- Cost analysis of edge vs. cloud-based AI applications.

The suggested future research directions, identified by the authors in the process of analyzing the existing research in the field of AI adoption in MIS, can be of use to both the research and business sectors in deciding on future research and development efforts.

In conclusion, this paper presents a systematic literature review of the existing research in the field of the application of artificial intelligence in management information systems. A classification of AI capabilities observed across the reviewed literature sources is developed. Previous related research is considered, and relevant findings and limitations are discussed. An in-depth view of the applied research methodology is provided. The primary source selection process is detailed. Key phrases and search strings are proposed. The study focuses on the integration of emerging AI technologies at the organizational level of automation and identifies research opportunities and challenges; existing capabilities and platforms; business value and research contributions; and future research directions.

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References

1. Thormundsson, B. *Global Artificial Intelligence Market Size 2021–2030*; Statista: Hamburg, Germany, 2023.
2. Devanport, T. *The AI Advantage: How to Put the Artificial Intelligence Revolution to Work*; The MIT Press: Cambridge, MA, USA, 2018; pp. 61–66.
3. Borges, A.F.; Laurindo, F.J.; Spínola, M.M.; Gonçalves, R.F.; Mattos, C.A. The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *Int. J. Inf. Manag.* **2020**, *57*, 102225. [CrossRef]
4. Collins, C.; Dennehy, D.; Conboy, K.; Mikalef, P. Artificial intelligence in information systems research: A systematic literature review and research agenda. *Int. J. Inf. Manag.* **2021**, *60*, 102383. [CrossRef]
5. Moghekar, R.; Ahuja, S. Face recognition: Literature review with emphasis on deep learning. *J. Theor. Appl. Inf. Technol.* **2019**, *97*, 3332–3342.
6. Ohri, K.; Kumar, M. Review on self-supervised image recognition using deep neural networks. *Pac. Asia J. Assoc. Inf. Syst. Knowl.-Based Syst.* **2021**, *224*, 107090. [CrossRef]
7. Verma, K.K.; Singh, B.M.; Dixit, A. A review of supervised and unsupervised machine learning techniques for suspicious behavior recognition in intelligent surveillance system. *Int. J. Inf. Technol.* **2019**, *14*, 397–410. [CrossRef]
8. Morocho-Cayamcela, M.E.; Lee, H.; Lim, W. Machine Learning for 5G/B5G Mobile and Wireless Communications: Potential, Limitations, and Future Directions. *IEEE Access Pract. Innov. Open Solut.* **2019**, *7*, 137184–137206. [CrossRef]
9. Hassanien, A.E.; Darwish, A.; Abdelghafar, S. Machine learning in telemetry data mining of space mission: Basics, challenging and future directions. *Artif. Intell. Rev.* **2019**, *53*, 3201–3230. [CrossRef]

10. Alenezi, H.S.; Faisal, M.H. Utilizing crowdsourcing and machine learning in education: Literature review. *Educ. Inf. Technol.* **2020**, *25*, 2971–2986. [CrossRef]
11. Ventura, S.M.; Castronovo, F.; Nikolić, D.; Ciribini, A.L. Implementation of virtual reality in construction education: A content-analysis based literature review. *J. Inf. Technol. Constr.* **2022**, *27*, 705–731. [CrossRef]
12. Sharadgah, T.A.; Sa'di, R.A. A Systematic Review of Research on the Use of Artificial Intelligence in English Language Teaching and Learning (2015–2021): What are the Current Effects? *J. Inf. Technol. Educ. Res.* **2022**, *21*, 337–377. [CrossRef]
13. D'Souza, S.; Prema, K.V.; Balaji, S. Machine learning in drug–target interaction prediction: Current state and future directions. *Drug Discov. Today* **2020**, *25*, 748–756. [CrossRef]
14. Ebrahimighahnavieh, A.; Luo, S.; Chiong, R. Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. *Comput. Methods Programs Biomed.* **2020**, *187*, 105242. [CrossRef] [PubMed]
15. Orgeolet, L.; Foulquier, N.; Misery, L.; Redou, P.; Pers, J.-O.; Devauchelle-Pensec, V.; Saraux, A. Can artificial intelligence replace manual search for systematic literature? Review on cutaneous manifestations in primary Sjögren's syndrome. *Rheumatology* **2020**, *59*, 811–819. [CrossRef] [PubMed]
16. Abu-Amara, F.; Bensefia, A.; Mohammad, H.; Tamimi, H. Robot and virtual reality-based intervention in autism: A comprehensive review. *Int. J. Inf. Technol.* **2021**, *13*, 1879–1891. [CrossRef]
17. Liu, X.; Wang, H.; Li, Z.; Qin, L. Deep learning in ECG diagnosis: A review. *Knowl.-Based Syst.* **2021**, *227*, 107187. [CrossRef]
18. Nishant, R.; Kennedy, M.; Corbett, J. Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *Int. J. Inf. Manag.* **2020**, *53*, 102104. [CrossRef]
19. Khakurel, J.; Penzenstadler, B.; Porras, J.; Knutas, A.; Zhang, W. The Rise of Artificial Intelligence under the Lens of Sustainability. *Technologies* **2018**, *6*, 100. [CrossRef]
20. Pappas, I.O.; Mikalef, P.; Giannakos, M.N.; Krogstie, J.; Lekakos, G. Big data and business analytics ecosystems: Paving the way towards digital transformation and sustainable societies. *Inf. Syst. e-Bus. Manag.* **2018**, *16*, 479–491. [CrossRef]
21. Taori, R.; Gulrajani, I.; Zhang, T.; Dubois, Y.; Li, X.; Guestrin, C.; Hashimoto, T.B. Alpaca: A Strong, Replicable Instruction-Following Model, Stanford: Center for Research on Foundation Models 2023, Online Publication. Available online: https://crfm.stanford.edu/2023/03/13/alpaca.html (accessed on 30 April 2023).
22. George, S.; George, H.; Martin, G. A Review of ChatGPT AI's Impact on Several Business Sectors. *Part. Univ. Intl. Innov. J.* **2023**, *1*, 9–23. [CrossRef]
23. Chui, M.; Manyika, J.; Miremad, M. What AI can and can't do (yet) for your business. *McKinsey Q.* **2018**, *1*, 97–108.
24. Lee, G. Bard for Business? Google Enters the Chatbot Game, ERP Today Magazine 2023, Online Publication. Available online: https://erp.today/bard-for-business-google-enters-the-chatbot-game/ (accessed on 15 March 2023).
25. Parikh, R.B.; Teeple, S.; Navathe, A.S. Addressing Bias in Artificial Intelligence in Health Care. *JAMA* **2019**, *322*, 2377–2378. [CrossRef]
26. Raaijmakers, S. Artificial Intelligence for Law Enforcement: Challenges and Opportunities. *IEEE Secur. Priv.* **2019**, *17*, 74–77. [CrossRef]
27. Bhardwaz, S.; Kumar, J. An Extensive Comparative Analysis of Chatbot Technologies-ChatGPT, Google BARD and Microsoft Bing. In Proceedings of the 2023 2nd International Conference on Applied Artificial Intelligence and Computing (ICAAIC), Salem, India, 4–6 May 2023; pp. 673–679. [CrossRef]
28. Kristen, E. Generative Artificial Intelligence and Data Privacy: A Primer, Congressional Research Service, as R47569. 2023. Available online: https://crsreports.congress.gov (accessed on 30 May 2023).
29. Harris, L. Generative Artificial Intelligence: Overview, Issues, and Questions for Congress, as IF12426. 2023. Available online: https://crsreports.congress.gov (accessed on 18 June 2023).
30. OpenAI, Online Resource: OpenAI Customer Stories. Available online: https://openai.com/customer-stories (accessed on 13 July 2023).
31. Siad, S.M. *The Promise and Perils of Google's Bard for Scientific Research*; International Centre for Advanced Mediterranean Agronomic Studies: Bari, Italy, 2023. [CrossRef]
32. Xiaoming, Z. *ChatGPT: The Game-Changer for the Digital Marketing Channels*; AI4STEM Education Center, University of Georgia: Athens, GA, USA, 2023; Available online: https://ssrn.com/abstract=4389098 (accessed on 10 May 2023).
33. Delen, D. *Predictive Analytics: Data Mining, Machine Learning and Data Science for Practitioners, Pearson Business Analytics Series*, 2nd ed.; Pearson FT Press: London, UK, 2020.
34. Bornet, P.; Barkin, I.; Wirtz, J. *Intelligent Automation: Learn How to Harness Artificial Intelligence to Boost Business & Make Our World More Human, Kindle Edition*; Independently Published: Morrisville, NC, USA, 2020. [CrossRef]
35. Müller, A.C.; Guido, S. *Introduction to Machine Learning with Python: A Guide for Data Scientists*, 1st ed.; O'Reilly Media: Newton, MA, USA, 2016.
36. Clark, A.; Fox, C.; Lappin, S. *The Handbook of Computational Linguistics and Natural Language Processing*, 1st ed.; Wiley-Blackwell: Hoboken, NJ, USA, 2013.
37. Jain, R.; Kasturi, R.; Schunck, B.G. *Machine Vision*; Indo American Books: New Delhi, India, 2016.
38. Damyanov, C. *Cybernetics Basics: Elements of AI*; Academic Publishing House of the University of Food Technologies: Plovdiv, Bulgaria, 2010; Volume 4, p. 176.

39. Laudon, K.; Laudon, J. *Management Information Systems: Managing the Digital Firm*, 17th ed.; Pearson: London, UK, 2021; ISBN 9780136971276.
40. Ustundag, A.; Cevikcan, E.; Beyca, O.F. (Eds.) *Business Analytics for Professionals*; Springer: Cham, Switzerland, 2022. [CrossRef]
41. Harvard Business Review. *HBR Guide to Data Analytics Basics for Managers*; Harvard Business Review Press: Cambridge, MA, USA, 2018; ISBN 9781633694293.
42. Henrique, B.M.; Sobreiro, V.A.; Kimura, H. Literature review: Machine learning techniques applied to financial market prediction. *Expert Syst. Appl.* **2019**, *124*, 226–251. [CrossRef]
43. Sezer, O.B.; Gudelek, M.U.; Ozbayoglu, A.M. Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Appl. Soft Comput.* **2020**, *90*, 106181. [CrossRef]
44. Pandl, K.D.; Thiebes, S.; Schmidt-Kraepelin, M.; Sunyaev, A. On the Convergence of Artificial Intelligence and Distributed Ledger Technology: A Scoping Review and Future Research Agenda. *IEEE Access* **2020**, *8*, 57075–57095. [CrossRef]
45. Gélinas, D.; Sadreddin, A.; Vahidov, R. Artificial intelligence in human resources management: A review and research agenda. *Pac. Asia J. Assoc. Inf. Syst.* **2022**, *14*, 1.
46. Mihova, T.; Ivanova, I.; Angelov, K. Impact of HRM activities digitisation on the competitiveness of industrial enterprises. *AIP Conf. Proc.* **2022**, *2449*, 070002. [CrossRef]
47. Mihova, T.; Ivanova, I. Industry 4.0–Challenge to Human Resources. *Environ. Technol. Resour. Proc. Int. Sci. Pract. Conf.* **2021**, *2*, 112–115. [CrossRef]
48. Ding, R.-X.; Palomares, I.; Wang, X.; Yang, G.-R.; Liu, B.; Dong, Y.; Herrera-Viedma, E.; Herrera, F. Large-Scale decision-making: Characterization, taxonomy, challenges and future directions from an Artificial Intelligence and applications perspective. *Inf. Fusion* **2020**, *59*, 84–102. [CrossRef]
49. Rossmann, L.; Wald, A. The Automation of Management Decisions: A Systematic Review and Research Agenda of the Factors Influencing the Decision to Increase the Level of Automation. *Int. J. Inf. Technol. Decis. Mak.* **2023**, *22*, 1–34. [CrossRef]
50. Zhu, X.; Zhang, G.; Sun, B. A comprehensive literature review of the demand forecasting methods of emergency resources from the perspective of artificial intelligence. *Nat. Hazards* **2019**, *97*, 65–82. [CrossRef]
51. Diederich, S.; Brendel, A.B.; Morana, S.; Kolbe, L.; Dresden, G.T. On the Design of and Interaction with Conversational Agents: An Organizing and Assessing Review of Human-Computer Interaction Research, Information and Management. *J. Assoc. Inf. Syst.* **2021**, *23*, 96–138. [CrossRef]
52. Rzepka, C.; Berger, B. User interaction with AI-enabled systems: A systematic review of IS research. In Proceedings of the Thirty Ninth International Conference on Information Systems, San Francisco, CA, USA, 13–16 December 2018.
53. Leidner, D.; Kayworth, T. Review: A Review of Culture in Information Systems Research: Toward a Theory of Information Technology Culture Conflict. *MIS Q.* **2006**, *30*, 357. [CrossRef]
54. Petticrew, M.; Roberts, H. How to Appraise the Studies: An Introduction to Assessing Study Quality. *Syst. Rev. Soc. Sci. A Pract. Guide* **2008**, *5*, 125–163. [CrossRef]
55. Fink, A. *Conducting Research Literature Reviews: From the Internet to Paper*, 5th ed.; SAGE Publications Inc.: Thousand Oaks, CA, USA, 2019.
56. Vom Brocke, J.; Simons, A.; Niehaves, B.; Riemer, K.; Plattfaut, R.; Cleven, A. Reconstructing the giant: On the importance of rigour in documenting the literature search process. In Proceedings of the 17th European Conference on Information Systems, Verona, Italy, 8–10 June 2009; pp. 2206–2217.
57. Kitchenham, B.; Charters, S. Guidelines for performing Systematic Literature Reviews in Software Engineering. In *EBSE Technical Report*; Keele University: Newcastle, UK; University of Durham: Durham, UK, 2007.
58. Karger, E. Combining Blockchain and Artificial Intelligence–Literature Review and State of the Art. In Proceedings of the 41st International Conference on Information Systems, (ICIS), Making Digital Inclusive: Blending the Local and the Global, Hyderabad, India, 13–16 December 2020.
59. Chen, L.; Jiang, M.; Jia, F.; Liu, G. Artificial intelligence adoption in business-to-business marketing: Toward a conceptual framework. *J. Bus. Ind. Mark.* **2021**, *37*, 1025–1044. [CrossRef]
60. Tranfield, D.; Denyer, D.; Smart, P. Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
61. Kitchenham, B. *Procedures for Performing Systematic Reviews*; Keele University: Newcastle, UK, 2004; pp. 1–26. ISSN 1353-7776.
62. Lee, W.-I.; Shih, B.-Y.; Chen, C.-Y. A hybrid artificial intelligence sales-forecasting system in the convenience store industry. *Hum. Factors Ergon. Manuf.* **2012**, *22*, 188–196. [CrossRef]
63. Nagy, B.; Hegedűs, I.; Sándor, N.; Egedi, B.; Mehmood, H.; Saravanan, K.; Lóki, G.; Kiss, Á. Privacy-preserving Federated Learning and its application to natural language processing. *Knowl.-Based Syst.* **2023**, *268*, 110475. [CrossRef]
64. Raza, A.; Tran, K.P.; Koehl, L.; Li, S. Designing ECG monitoring healthcare system with federated transfer learning and explainable AI. *Knowl.-Based Syst.* **2022**, *236*, 107763. [CrossRef]
65. Zhao, Y.; Zhang, J.; Cao, Y. Manipulating vulnerability: Poisoning attacks and countermeasures in federated cloud–edge–client learning for image classification. *Knowl.-Based Syst.* **2023**, *259*, 110072. [CrossRef]
66. Punia, S.; Shankar, S. Predictive analytics for demand forecasting: A deep learning-based decision support system. *Knowl.-Based Syst.* **2022**, *258*. [CrossRef]

67. Zohdi, M.; Rafiee, M.; Kayvanfar, V.; Salamiraad, A. Demand forecasting based machine learning algorithms on customer information: An applied approach. *Int. J. Inf. Technol.* **2022**, *14*, 1937–1947. [CrossRef]
68. Alabi, O.; David, A. Model for forecasting electronic fraud threats on selected electronic payment channels using linear regression. *Int. J. Inf. Technol.* **2022**, *14*, 2657–2666. [CrossRef]
69. Yang, H.; Li, P.; Li, H. An oil imports dependence forecasting system based on fuzzy time series and multi-objective optimization algorithm: Case for China. *Knowl.-Based Syst.* **2022**, *246*, 108687. [CrossRef]
70. Seong, N.; Nam, K. Forecasting price movements of global financial indexes using complex quantitative financial networks. *Knowl.-Based Syst.* **2022**, *235*, 107608. [CrossRef]
71. Rinta-Kahila, T.; Penttinen, E.; Lyytinen, K. Organizational transformation with intelligent automation: Case Nokia Software. *J. Inf. Technol. Teach. Cases* **2021**, *11*, 101–109. [CrossRef]
72. Farinha, D.; Pereira, R.; Almeida, R. A framework to support Robotic process automation. *J. Inf. Technol.* **2023**, 02683962231165066. [CrossRef]
73. Parthasarathy, S.; Kar, A.K. Implementing cognitive automation for employee management in Ganitec University of Science and Technology. *J. Inf. Technol. Teach. Cases* **2022**, *12*, 16–22. [CrossRef]
74. Oshri, I.; Plugge, A. Introducing RPA and automation in the financial sector: Lessons from KAS Bank. *J. Inf. Technol. Teach. Cases* **2022**, *12*, 88–95. [CrossRef]
75. Stoykova, S.; Hrischev, R.; Shakev, N. Intelligent Robotic Process Automation for Small and Medium-sized Enterprises. In Proceedings of the 2022 International Conference Automatics and Informatics (ICAI), Varna, Bulgaria, 6–8 October 2022; pp. 223–228. [CrossRef]
76. Stoykova, S.; Hrischev, R. Bot Development for Intelligent Automation in ERP Systems. In Proceedings of the 2022 International Conference Automatics and Informatics (ICAI), Varna, Bulgaria, 6–8 October 2022; pp. 183–188. [CrossRef]
77. Meyer, G.; Adomavicius, G.; Johnson, P.E.; Elidrisi, M.; Rush, W.A.; Sperl-Hillen, J.M.; O'Connor, P.J. A Machine Learning Approach to Improving Dynamic Decision Making. *Inf. Syst. Res.* **2014**, *25*, 239–263. [CrossRef]
78. Nissen, M.E.; Sengupta, K. Sengupta Incorporating Software Agents into Supply Chains: Experimental Investigation with a Procurement Task. *MIS Q.* **2006**, *30*, 145. [CrossRef]
79. Yin, H.H.S.; Langenheldt, K.; Harlev, M.; Mukkamala, R.R.; Vatrapu, R. Regulating Cryptocurrencies: A Supervised Machine Learning Approach to De-Anonymizing the Bitcoin Blockchain. *J. Manag. Inf. Syst.* **2019**, *36*, 37–73. [CrossRef]
80. Afiouni, R. Organizational Learning in the Rise of Machine Learning. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
81. Baier, L.; Jöhren, F.; Seebacher, S. Challenges in the deployment and operation of machine learning in practice. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, 8–14 June 2019; ISBN 978-1-7336325-0-8.
82. Basu, S.; Han, W.; Garimella, A. Impact of Artificial Intelligence on Human Decision Making on ICO Platforms. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
83. Beath, C.; Tarafdar, M.; Ross, J. OneBankAssure: Customer Intimacy through Machine Learning. In Proceedings of the International Conference on Information Systems–Bridging the Internet of People, Data, and Things (ICIS), San Francisco, CA, USA, 13–16 December 2018.
84. Chatterjee, S.; Saeedfar, P.; Tofangchi, S.; Kolbe, L. Intelligent road maintenance: A machine learning approach for surface defect detection. In Proceedings of the 26th European Conference on Information Systems: Beyond Digitization–Facets of Socio-Technical Change (ECIS), Portsmouth, UK, 23–28 June 2018.
85. Dellermann, D.; Lipusch, N.; Ebel, P.A.; Popp, K.M.; Leimeister, J.M. Finding the Unicorn: Predicting Early Stage Startup Success through a Hybrid Intelligence Method. In Proceedings of the 38th International Conference on Information Systems–Transforming Society with Digital Innovation (ICIS), Seoul, Republic of Korea, 10–13 December 2017.
86. Ghanvatkar, S.; Rajan, V. Deep Recurrent Neural Networks for Mortality Prediction in Intensive Care using Clinical Time Series at Multiple Resolutions. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
87. Harfouche, A.; Quinio, B.; Skandrani, S.; Marciniak, R. A Framework for Artificial Knowledge Creation in Organizations. In Proceedings of the 38th International Conference on Information Systems-Transforming Society with Digital Innovation (ICIS), Seoul, Republic of Korea, 10–13 December 2017.
88. Krenzer, A.; Stein, N.; Griebel, M.; Flath, C. Augmented Intelligence for Quality Control of Manual Assembly Processes using Industrial Wearable Systems. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
89. Kuehl, N.; Scheurenbrand, J.; Satzger, G. Needmining: Identifying micro blog data containing customer needs. In Proceedings of the 24th European Conference on Information Systems (ECIS), Istanbul, Turkey, 12–15 June 2016.
90. Lang, F.; Fink, A. Decision support for negotiation protocol selection: A machine learning approach based on artificial neural networks. In Proceedings of the 22nd European Conference on Information Systems (ECIS), Tel Aviv, Israel, 9–11 June 2014.
91. Leyer, M.; Schneider, S. Me, you or ai? How do we feel about delegation? In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, 8–14 June 2019.

92. Lou, B.; Wu, L. Artificial Intelligence and Drug Innovation. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
93. Maroudas, G.; Louvieris, P. Exploring factors that determine consumer attitude toward use of intelligent software agents. In Proceedings of the 14th European Conference on Information Systems (ECIS), Göteborg, Sweden, 12–14 June 2006.
94. Merkert, J.; Mueller, M.; Hubl, M. A Survey of the Application of Machine Learning in Decision Support Systems. In Proceedings of the 23rd European Conference on Information Systems (ECIS), Münster, Germany, 26–29 May 2015.
95. Monu, K.; Woo, C. Intelligent Agents as a Modeling Paradigm. In Proceedings of the 26th International Conference on Information Systems (ICIS), Las Vegas, NV, USA, 11–14 December 2005.
96. Nagar, Y.; Malone, T. Making Business Predictions by Combining Human and Machine Intelligence in Prediction Markets. In Proceedings of the 32nd International Conference on Information Systems (ICIS), Shanghai, China, 4–7 December 2011.
97. Pumplun, L.; Tauchert, C.; Heidt, M. A new organizational chassis for artificial intelligence-exploring organizational readiness factors. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, 8–14 June 2019.
98. Rhue, L. Beauty's in the AI of the Beholder: How AI Anchors Subjective and Objective Predictions. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
99. Pandey, S.; Sharma, S.; Wazir, S. Mental healthcare chatbot based on natural language processing and deep learning approaches: Ted the therapist. *Int. J. Inf. Technol.* **2022**, *14*, 3757–3766. [CrossRef]
100. Böttcher, T.P.; Weking, J.; Hein, A.; Böhm, M.; Krcmar, H. Pathways to digital business models: The connection of sensing and seizing in business model innovation. *J. Strat. Inf. Syst.* **2022**, *31*, 101742. [CrossRef]
101. Huang, T.; Fu, R. Prediction of the driver's focus of attention based on feature visualization of a deep autonomous driving model. *Knowl.-Based Syst.* **2022**, *251*, 109006. [CrossRef]
102. Stević, Z.; Korucuk, S.; Karamaşa, Ç.; Demir, E.; Zavadskas, E.K. A Novel Integrated Fuzzy-Rough MCDM Model for Assessment of Barriers Related to Smart Logistics Applications and Demand Forecasting Method in the COVID-19 Period. *Int. J. Inf. Technol. Decis. Mak.* **2022**, *21*, 1647–1678. [CrossRef]
103. Yan, T.; Zhou, T.; Zhan, Y.; Xia, Y. TFDPM: Attack detection for cyber-physical systems with diffusion probabilistic models. *Knowl.-Based Syst.* **2022**, *255*, 109743. [CrossRef]
104. Wickramanayake, B.; He, Z.; Ouyang, C.; Moreira, C.; Xu, Y.; Sindhgatta, R. Building interpretable models for business process prediction using shared and specialised attention mechanisms. *Knowl.-Based Syst.* **2022**, *248*, 108773. [CrossRef]
105. Park, S.; Yang, S.-J. Interpretable deep learning LSTM model for intelligent economic decision-making. *Knowl.-Based Syst.* **2022**, *248*, 108907. [CrossRef]
106. Tofangchi, S.; Hanelt, A.; Li, S. Advancing Recommendations on Two- Sided Platforms: A Machine Learning Approach to Context-Aware Profiling. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
107. Traumer, F.; Oeste-Reiß, S.; Leimeister, J.M. Towards a Future Reallocation of Work between Humans and Machines-Taxonomy of Tasks and Interaction Types in the Context of Machine Learning. In Proceedings of the 38th International Conference on Information Systems-Transforming Society with Digital Innovation (ICIS), Seoul, Republic of Korea, 10–13 December 2017.
108. Urbanke, P.; Uhlig, A.; Kranz, J. A Customized and Interpretable Deep Neural Network for High-Dimensional Business Data-Evidence from an E- Commerce Application. In Proceedings of the 38th International Conference on Information Systems-Transforming Society with Digital Innovation (ICIS), Seoul, Republic of Korea, 10–13 December 2017.
109. Van Den Broek, E.; Sergeeva, A.; Huysman, M. Hiring Algorithms: An Ethnography of Fairness in Practice. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
110. Wang, H.; Huang, J.; Zhang, Z. The Impact of Deep Learning on Organizational Agility. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
111. Wang, H.; Li, C.; Gu, B.; Min, W. Does AI-based Credit Scoring Improve Financial Inclusion? Evidence from Online Payday Lending. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
112. Wang, Q.; Liu, X.; Huang, K. Displaced or Augmented? How does Artificial Intelligence Affect Our Jobs: Evidence from LinkedIn. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
113. Weterings, K.; Bromuri, S.; Van Eekelen, M. Explaining customer activation with deep attention models. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm & Uppsala, Sweden, 8–14 June 2019.
114. Wuenderlich, N.V.; Paluch, S. A Nice and Friendly Chat with a Bot: User Perceptions of AI-Based Service Agents. In Proceedings of the 38th International Conference on Information Systems–Transforming Society with Digital Innovation (ICIS), Seoul, Republic of Korea, 10–13 December 2017.
115. Zhang, K.; Luo, X. Leveraging Deep-learning and Field Experiment Response Heterogeneity to Enhance Customer Targeting Effectiveness. In Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany, 15–18 December 2019.
116. Mahroof, K. A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *Int. J. Inf. Manag.* **2019**, *45*, 176–190. [CrossRef]

117. Abubakar, A.M.; Behravesh, E.; Rezapouraghdam, H.; Yildiz, S.B. Applying artificial intelligence technique to predict knowledge hiding behavior. *Int. J. Inf. Manag.* **2019**, *49*, 45–57. [CrossRef]
118. Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *Int. J. Inf. Manag.* **2019**, *48*, 63–71. [CrossRef]
119. Fan, C.; Zhang, C.; Yahja, A.; Mostafavi, A. Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *Int. J. Inf. Manag.* **2019**, *56*, 102049. [CrossRef]
120. Gloor, P.; Fronzetti-Colladon, A.; De Oliveira, J.M.; Rovelli, P. Put your money where your mouth is: Using deep learning to identify consumer tribes from word usage. *Int. J. Inf. Manag.* **2020**, *51*, 101924. [CrossRef]
121. Dwivedi, Y.K.; Ismagilova, E.; Hughes, D.L.; Carlson, J.; Filieri, R.; Jacobson, J.; Jain, V.; Karjaluoto, H.; Kefi, H.; Krishen, A.S.; et al. Setting the future of digital and social media marketing research: Perspectives and research propositions. *Int. J. Inf. Manag.* **2020**, *59*, 102168. [CrossRef]
122. Sartor, G. *The Impact of the General Data Protection Regulation (GDPR) on Artificial Intelligence (AI)*; A study comissioned by the Panel for the Future of Science and Technology (STOA) and managed by the Scientific Foresight Unit, within the Directorate-General for Parliamentary Research Services (EPRS) of the Secretariat of the European Parliament; STOA: Strasbourg, France, 2020.
123. Davenport, T.; Ronanki, R. *Artificial Intelligence for the Real World*; Harvard Business Review: Harvard, MA, USA, 2018.
124. Hrischev, R. ERP systems and data security. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *878*, 012009. [CrossRef]
125. Hrischev, R. Determining the Role of Information Security in Enterprise Resources Planning Systems. *Innov. Sci. Technol.* **2022**, *7*, 97–104. [CrossRef]
126. Hrischev, R. Planning and implementation of the ERP system in packaging production. *J. Fundam. Sci. Appl.* **2018**, *24*, 25–28.
127. Mihova, T.; Ivanova, I.; Nikolova-Alexieva, V. E-Learning—The practice in industrial enterprises. In Proceedings of the International Conference Automatics and Informatics, Varna, Bulgaria, 30 September–2 October 2021; pp. 129–134. [CrossRef]
128. Hrischev, R.N. ERP Systems in Corrugated Packaging Industry. In Proceedings of the 57th International Scientific Conference on Information, Communication and Energy Systems and Technologies (ICEST), Ohrid, North Macedonia, 16–18 June 2022; pp. 1–4. [CrossRef]
129. Song, B.D.; Park, K.; Kim, J. Persistent UAV delivery logistics: MILP formulation and efficient heuristic. *Comput. Ind. Eng.* **2018**, *120*, 418–428. [CrossRef]
130. Jennings, D.; Figliozzi, M. Study of Sidewalk Autonomous Delivery Robots and Their Potential Impacts on Freight Efficiency and Travel. *Transp. Res. Rec. J. Transp. Res. Board* **2019**, *2673*, 317–326. [CrossRef]
131. Srinivas, S.; Ramachandiran, S.; Rajendran, S. Autonomous robot-driven deliveries: A review of recent developments and future directions. *Transp. Res. Part E Logist. Transp. Rev.* **2022**, *165*, 102834. [CrossRef]
132. Bakach, I.; Campbell, A.M.; Ehmke, J.F. A two-tier urban delivery network with robot-based deliveries. *Networks* **2021**, *78*, 461–483. [CrossRef]
133. Sajid, M.; Mittal, M.; Pare, S.; Prasad, M. Routing and scheduling optimization for UAV assisted delivery system: A hybrid approach. *Appl. Soft Comput.* **2022**, *126*, 109225. [CrossRef]
134. Li, J.; Liu, H.; Lai, K.K.; Ram, B. Vehicle and UAV Collaborative Delivery Path Optimization Model. *Mathematics* **2022**, *10*, 3744. [CrossRef]
135. Malang, C.; Charoenkwan, P.; Wudhikarn, R. Implementation and Critical Factors of Unmanned Aerial Vehicle (UAV) in Warehouse Management: A Systematic Literature Review. *Drones* **2023**, *7*, 80. [CrossRef]
136. Liu, H.; Chen, Q.; Pan, N.; Sun, Y.; An, Y.; Pan, D. UAV Stocktaking Task-Planning for Industrial Warehouses Based on the Improved Hybrid Differential Evolution Algorithm. *IEEE Trans. Ind. Inform.* **2022**, *18*, 582–591. [CrossRef]
137. Kalinov, I.; Petrovsky, A.; Ilin, V.; Pristanskiy, E.; Kurenkov, M.; Ramzhaev, V.; Idrisov, I.; Tsetserukou, D. WareVision: CNN Barcode Detection-Based UAV Trajectory Optimization for Autonomous Warehouse Stocktaking. *IEEE Robot. Autom. Lett.* **2020**, *5*, 6647–6653. [CrossRef]
138. Jacob, F.; Grosse, E.H.; Morana, S.; König, C.J. Picking with a robot colleague: A systematic literature review and evaluation of technology acceptance in human–robot collaborative warehouses. *Comput. Ind. Eng.* **2023**, *180*, 109262. [CrossRef]
139. Alias, C.; Nikolaev, I.; Magallanes, E.G.C.; Noche, B. An Overview of Warehousing Applications based on Cable Robot Technology in Logistics. In Proceedings of the 2018 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 31 July–2 August 2018; pp. 232–239. [CrossRef]