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Artificial intelligence and internet of things adoption in operations management: Barriers and benefits

Barreiras e benefícios na adoção de inteligência artificial e IoT na gestão de operação

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Abstract

Purpose: Based on the context of digital transformation and the evolution of digital technologies, this research sought to understand how artificial intelligence (AI) and internet of things (IoT) collaborate to improve the efficiency of operations management (OM).

Originality/value: Digital transformation and the use of new technologies, such as AI and IoT, have impacted the management of the companies' operation. A preliminary survey carried out in the Web of Science (WoS) database, analyzing data through the VOSviewer bibliometric software, identified an important relationship between AI, IoT, and OM through industry 4.0 (i4.0), which has as one of its main objectives the improvement in OM. The results of this research bring a practical contribution to business managers, such as the identification of the main barriers and expected benefits when adopting AI and IoT in their operations. For researchers, this study differs from studies already published by conducting a systematic review of the literature that investigates the relationship of OM with technological tools, such as AI and IoT.

Design/methodology/approach: A systematic review of the literature was carried out with the objective of analyzing all articles that brought some contribution to a better understanding of how AI and IoT collaborate to improve the efficiency of operations.

Findings: The results demonstrated how AI and IoT were being incorporated into OM, identifying the main barriers of its use, as well as indications of research gaps that may lead to further investigations to advance on this topic.

Keywords: digital technologies, digital transformation, operations management, artificial intelligence, internet of things

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Resumo

Objetivo: Tomando como base o contexto de transformação digital e a evolução das tecnologias digitais, esta pesquisa buscou compreender como a inteligência artificial (IA) e a internet das coisas (*internet of things* – IoT) colaboram para melhorar a eficiência da gestão da operação (GO).

Originalidade/valor: A transformação digital e o uso de novas tecnologias, como a IA e a IoT, têm impactado a gestão da operação das empresas. Um levantamento feito na base de dados Web of Science (WoS) e a análise deles, realizadas pelo *software* bibiliométrico VOSViewer, identificaram uma importante relação entre IA, IoT e GO por meio da indústria 4.0 (i4.0), que tem como um de seus principais objetivos a melhora na gestão da operação. Os resultados da presente pesquisa trazem uma contribuição prática aos gestores de negócios, como a identificação das principais barreiras e benefícios esperados ao adotarem a IA e a IoT em suas operações. Para os pesquisadores, este estudo difere de pesquisas já publicadas ao realizar uma revisão sistemática da literatura que investiga a relação da GO com as ferramentas tecnológicas IA e IoT.

Design/metodologia/abordagem: Foi realizada uma revisão sistemática da literatura com o objetivo de analisar todos os artigos que trouxessem alguma contribuição no sentido de fornecer uma melhor compreensão de como a IA e a IoT colaboram para melhorar a eficiência das operações.

Resultados: Os resultados demonstraram de que forma a IA e a IoT foram sendo incorporadas na gestão da operação, com destaque às barreiras e aos benefícios de seu uso. Verificaram-se ainda as indicações de lacunas de pesquisa que podem levar a novas investigações para avançar no tema.

Palavras-chave: tecnologias digitais, transformação digital, gestão da operação, inteligência artificial, internet das coisas

INTRODUCTION

In the current period when many of the operations are being digitized, there is a greater demand for shorter response times and greater attention to the current competitive scenario (Venkatraman, 2017). To improve their competitiveness, companies have been seeking new digital technologies (Afuah, 2002; Ross et al., 2016; Ross et al., 2019a, 2019b) demanding attention from executives on how to use them to improve their organizational strategies (Heavin & Power, 2018; Mithas et al., 2013; Razavi et al., 2016).

Among so-called digital technologies, artificial intelligence (AI) and the internet of things (IoT) have excelled (Brock & Wangenheimz, 2019; Özdemir & Hekim, 2018; Saarikko et al., 2020; Sestino et al., 2020). However, although many studies mention the benefits of these digital technologies (Balakrishnan & Das, 2020; Ross et al., 2019b), they still lack a demonstration of how the benefits of AI and IoT can be obtained in operations management (OM). In March 2021, a preliminary survey was conducted on the Web of Science (WoS) database using the keywords "artificial intelligence" and "IoT". The results of this search showed that of the 627 publications extracted, only 1% referred to the OM's area (Dhamija & Bag, 2020). Analyzing the results through VOSviewer software, it was noticed that the connection between AI and IoT and the OM's area was through industry 4.0 (i4.0) (Ahuett-Garza & Kurfess, 2018; Fettermann et al., 2018). The strengthening of i4.0 and the rapid technologies' development in the management sectors as a way of generating new values (Albertin & Moura Albertin, 2021) highlight the importance of digital transformation, in which the use of new technologies is important (Lohmer & Lasch, 2020; Schiavone & Sprenger, 2017).

The IoT in this context has emerged as a new paradigm that allows the integration between the cyber world and the physical world (Čolaković & Hadžialić, 2018), and AI, as an important ally in decision making due to its machine learning ability that enables the emergence of new business models (Li et al., 2017; Yang et al., 2017). Among the different motivations for the adoption of new technologies, there are the current competitive scenario, immense volume of data generated through different devices, scarcity of resources, and a need for speed in decision making (Borges et al., 2020; Venkatraman, 2017).

In this context, this research has as its general objective to analyze how companies are using IoT and AI to improve the flexibility and reliability of their operations while improving their competitiveness in the market (Castagna et al., 2020; Matt et al., 2015; Renzi et al., 2014). The research

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questions were elaborated to provide answers to the gaps in the literature and to assist in the analysis and consolidation of the research results. They are:

- Q1: What are the main barriers found in the literature to the adoption of new technologies, such as AI and IoT, in OM?
- Q2: What operational capabilities could or have been impacted and improved by the adoption of new technologies, such as AI and IoT?

To meet the objective and answer the research questions, this work adopts the method of systematic literature review once it is a method that provides, through the analysis of past publications, a better understanding of contemporary phenomena and makes inferences for the future. In the end, it is expected to have a better understanding of the integration of these tools in the OM and present a discussion about future research directions by bringing to the discussion 1. the general impacts on OM; 2. the potential barriers to the adoption of new technologies; and 3. what benefits are generated to OM.

THEORETICAL FOUNDATION

Digital transformation

One of the first concepts about digital transformation was mentioned in the book written by Patel et al. (2000), which introduced the term but without a consolidated definition. Since then, different definitions of the term have emerged in the literature. To Albertin and Moura Albertin (2021), digital transformation is the creation of value for both society and companies through the application of digital innovations. Lankshear and Knobel (2008) mention that digital technologies foster innovation and creativity and encourage significant changes in the professional and knowledge field. Bharadwaj et al. (2013) and Westerman et al. (2019) mention that digital transformation reflects the need for organizations to rethink the role that information technology (IT) plays in organizational strategies. Zheng et al. (2019) affirm that digital transformation is related to the digitization of processes and Balakrishnan and Das (2020) state that digital transformation represents a profound change in business models, value creation, and all aspects related to it, from production to the distribution of products and services. González-Varona et al. (2021) mention that digital transformation brings extreme changes in business models and allows the development of

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new skills to adapt and promote the necessary changes in the organization's operations. This study adopts the definition given by Vial (2019), who states that digital transformation is a process of change that aims to promote improvements in organizations and societies by combining information, computer systems, communication infrastructure, and technologies that promote the connectivity of all these resources.

By adopting new technologies, regardless of the size or level of the adoption, companies have their businesses transformed somehow (Fitzgerald et al., 2014; Morakanyane et al., 2017). However, for many companies, it is still unclear how they can benefit from adopting these technologies. Among the challenges mentioned, there are the difficulty of coordinating culture, skills, and technology (Ross et al., 2019b); how to effectively align business and technology strategies, taking into account cultural, organizational, and technological aspects (Heavin & Power, 2018); how to develop the dynamic capabilities needed to transform the organization and processes in such a way that they can detect, model and capture opportunities in the new digital environment (Katkalo et al., 2010); and how to understand and effectively adopt new technologies while seeking to understand which aspects of their culture and processes should be kept or modified (Westerman et al., 2019).

Artificial intelligence

The term artificial intelligence (AI) was first cited and introduced by McCarthy (1960), and it was much more related to algorithms, generated by intelligent machines, which helped in decision making (Buchanan & O'Connell, 2006). Brynjolfsson and McAffee (2017) refer to AI as a technological tool introduced to compete with human performance and with the potential to draw conclusions through learning, having the potential to replace humans in tasks that require knowledge. For Russell and Norvig (2016), AI is an area of science that aims to develop software and hardware that are capable of simulating human behavior. In the present work, AI is considered a field of theory that aims at the development of software and hardware capable of performing actions that require some level of cognition (Russell & Norvig, 2016).

The AI's evolution has two dimensions: a human-centered approach – focused on empirical approaches involving the validation of hypotheses and experiments – and a rationalist approach, which combines mathematical and engineering aspects (Borges et al., 2020). Initial research on AI was based on learning capacity and indicated promising advances in tasks involving

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decision-making and problem-solving. However, the rise of AI was slower than expected, but from the 1990s on, governments and companies made efforts, investments, and research for the development of AI. Some of the reasons for the recent broad adoption of AI in organizations are the development of methods and technologies, the increase in IT efficiency in capturing and storing task-related data across organizations, the increasing ease of acquiring technology tools, and the increasing cloud service offerings (Russell & Norvig, 2016; Von Krogh, 2018).

In manufacturing industries, AI advances are related to the strengthening of industry 4.0. Through the adoption of different technologies, such as IoT, big data, cloud computing, and cyber-physical systems (CPS), these industries gain the ability to make decisions within a highly volatile and dynamic environment in a more effective way (Ahuett-Garza & Kurfess, 2018), going beyond the simple automation of processes. With the machine learning capabilities, these technologies become important allies in the decision making (Yang et al., 2017) and emergence of new manufacturing models, including networking (Li et al., 2017). The adoption of AI in the business areas has primarily focused on the management of IT (Pandl et al., 2020; Zhu et al., 2019), decision-making (Ding et al., 2020)2020, evaluation of sustainable performance (Souza et al., 2019), and the future of work (Wang & Siau, 2019).

According to Brynjolfsson and McAffee (2017), two factors are among the main drivers for the adoption of new technologies: 1. the learning capacity that machines have today; and 2. the possibility of achieving a superior performance than the ones achieved by humans nowadays. However, according to Davenport (2018), since the adoption of AI can represent a disruption of current models and processes, managers need to reorganize their strategic plans and decide both for the type of technology and the speed of deployment of these technologies.

Internet of things

The term internet of things (IoT) was first mentioned by Ashton (2009), who states that IoT is not due to unique new technology, but from several technologies that complement each other by reducing the distance between the physical and virtual worlds. This is a result of technological progress in parallel and often in overlapping fields. IoT integrates different things for different people and has the potential to change aspects of the economy, society, politics, and the environment.

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Different definitions of IoT have emerged in the literature. Among them, we can mention Atzori et al. (2010) and Chen et al. (2013), who define IoT as the existence of different objects and technologies that, through a common architecture, can interact and collaborate to achieve similar goals. For Miorandi et al. (2012), IoT can be understood as a means by which physical and digital devices can be interconnected through an adequate communication infrastructure that enables a whole set of new applications and services. Kortuem et al. (2009) and Miorandi et al. (2012) refer to IoT as the development of technologies and solutions that allow the identification, communication, and interaction of any device with each other. To Mishra et al. (2016), IoT is a network that connects numerous smart devices, which constantly produce and consume information. Lopes and Moori (2021) define IoT as the combination of sensor, connectivity, and mobility to enable digitization in industrial operations. In this study, IoT is considered a system of technological networks with the main objective of simplifying processes in several areas, to ensure better efficiency of the systems, allowing the identification, communication, and interaction of any device with each other (Miorandi et al., 2012).

The application of IoT can be perceived in different areas, such as 1. smart buildings/houses; 2. smart cities controlling traffic, parking lots, infrastructure, among others; 3. patient's health-improving care by providing better information to both them and the physician; and 4. production and control of stocks (Miorandi et al., 2012).

RESEARCH METHODOLOGY

The reasons for conducting a systematic analysis may be to summarize empirical evidence of the benefits and limitations of a given field, identify any gaps in current research to suggest areas for future research, and provide a framework to properly establish new research activities (Kitchenham, 2004; Tranfield et al., 2003). The systematic review of the literature in the present study aims to summarize the empirical evidence of the benefits and limitations of a given field of research.

The important points in a systematic review of the literature are to define how the data will be extracted; the selection of databases; to define the criteria for data selection and exclusion; to elaborate the guidelines for data analysis, as well as to establish qualitative and quantitative analysis procedures to report the results (Rethlefsen et al., 2021). There are different recommendations to conduct a systematic review of the literature, such

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as Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), which is composed of a 27-item checklist and a flowchart with the three main strategic blocks, namely: 1. identification; 2. selection; and 3. inclusion. Each of these steps must be properly documented and identified to enable further replication. Similarly, Tranfield et al. (2003) recommend dividing the review into three blocks: 1. revision planning; 2. conducting the review; and 3. reporting and disseminating. Each of these blocks has stages – ten in total, three for the planning block, five for the driving block, and two for the reporting and disseminating block. Kitchenham et al. (2007) also use the same three blocks as Tranfield et al. (2003), however, detail the blocks in 13 steps.

The present research structured its methodological procedure following the flowchart model of the blocks recommended in PRISMA and similar works, such as Borges et al. (2020) and Kitchenham et al. (2007), which detailed the review steps following the recommendations suggested by Kitchenham et al. (2007). The main parts of the methodology are described below in the "Revision planning" and "Conducting the review" subsections. The next section, "Description of analyses", presents the stage of reporting and disseminating the results of the review.

Review planning

Tranfield et al. (2003) and Kitchenham et al. (2007) state that the planning phase should define the search and analysis guidelines, both oriented to the research's objective. The main points of this protocol will be presented below.

Search process

The bases used for this research were Institute for Scientific Information (ISI) WoS and Scopus, because they are widely covered and validated by the academic community (Chadegani et al., 2013). There are other possible sources of databases, such as the Google Scholar database. However, in the comparative study developed by Harzing and Alakangas (2016), some restrictions related to this database are presented, being the most relevant the lack of the publications' quality control, which leads to include some non-academic publications, such as blogs or articles from secular journals in search results. Other limitations mentioned are operational, such as duplication of records or the difficulty in performing filters, which, in the case of

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WoS and Scopus, is easy to solve, reasons that justify the use only of WoS and Scopus bases.

The definition of search terms went through two stages. The first stage aimed to evaluate and validate the relationship and relevance between the terms IA, IoT, and OM. To this end, a preliminary search was performed only in the WoS database using the term "digital transformation", resulting in 3,084 articles. To analyze these articles, VOSviewer bibliometric software 1.6.16 was used (Van Eck & Waltman, 2010, 2011). The identification of the theories areas was based on the keywords' co-occurrence, filtered for at least five repetitions. To improve the visualization, terms outside the scope of the search were deleted from the retrieved data, such as: "health", "government", "Covid-19" etc.); and, also, methods or terms out of scope, for example: "methods", "case study", "survey", "culture" etc.). As a result, the terms "industry4.0", "internet of things", "big data", "digitalization", and "artificial intelligence" showed to be the most evident and close to "digital transformation" (Figure 1). The relationship between OM and AI/IoT can be observed in Figure 2, which shows OM as a more consolidated research area – before 2017 –, but which has been evolving and forming an important grouping around "industry 4.0", which, in turn, has been supported by technologies that use IoT, attracting newer areas, such as "artificial intelligence", "digital technologies", "smart manufacturing", "digital innovation", and "digital twin".

Figure 1a

Density (importance) of themes around "digital transformation"

Source: Extracted from VOSviewer in March 2021.

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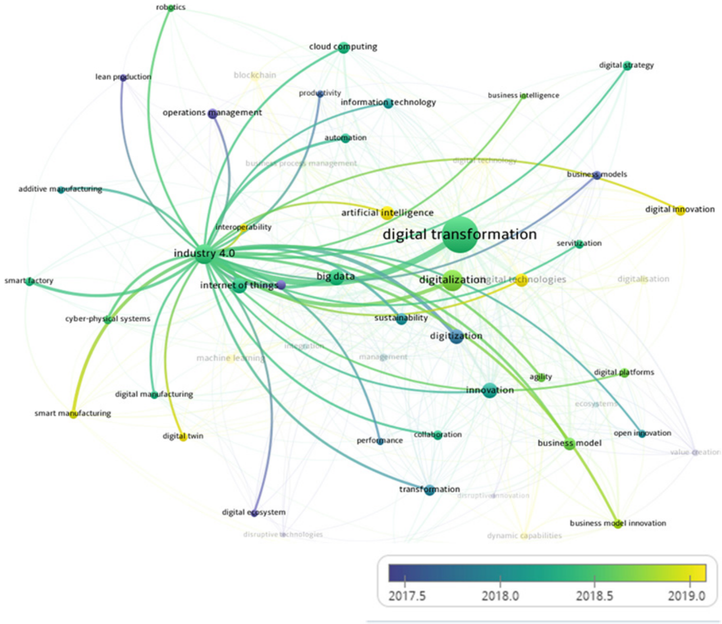
Figure 1b

Evolution of the theme over the years



Source: Extracted from VOSviewer in March 2021.

The second stage aimed to define the search's final keywords. For this definition, a cluster analysis was performed (Figure 2) around the three central terms – "digital transformation", "internet of things", and "artificial intelligence". From this analysis, the terms "industry 4.0", "digital technology", "operations management", "digitalization", and similar terms were chosen as keywords for extracting the databases by their relevance.

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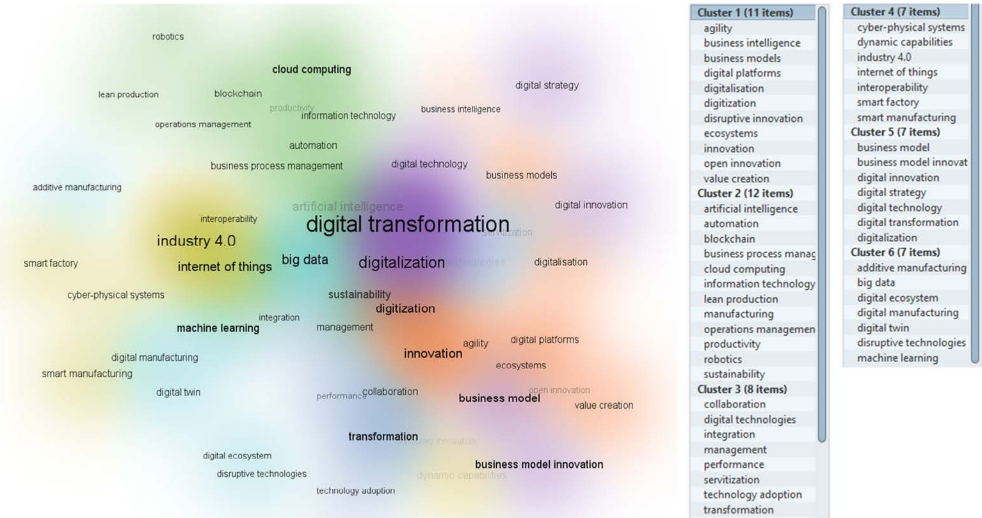
Figure 2

Clusters formed by the keyword set



Source: Extracted from VOSviewer in March 2021.

The definition of the inclusion and exclusion criteria of the data is a point highlighted both in the PRISMA methodology and by Kitchenham (2004) and Tranfield et al. (2003). In the present study, the inclusion criteria were:

- Articles published in reference journals that address the theme of digital transformation within the context of OM, IoT, and AI.
- Articles that remain within the area of management research or OM.
- Articles are written in English.

Exclusion criteria were:

- Articles on research areas outside the scope of management or OM.
- Articles that contain search keywords only in titles or abstracts and that discuss very particular aspects, not providing only a broader view of the topic.
- Articles published before 2007.
- Articles whose full texts have not been identified.
- Duplicated articles in the same or different databases.

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Data extraction and analysis strategy

For the data extraction strategy, an Excel spreadsheet was used to organize the collected data and allow a cross-analysis between the selected articles. The data were organized according to the following identifications: title, authors, journal or conference, year of publication, methodology, relationship with research questions, intersection of themes identified in the articles, and main definitions.

Data analysis was guided both by stratifying data in Excel and through the research questions. Since the analysis was qualitative, to avoid the risk of research bias, this phase of the analysis was developed in two stages: 1. the first step of reading and tabulating the data according to the established identifications, relating each article to the research questions and highlighting the main points of each research; and 2. the second step of in-depth analysis of the definitions and relationship with the research questions to identify possible consolidations of topics or similar definitions among authors.

Conducting the review

Table 1 shows the final search strings used in each of the selected databases, as well as the amount of initial data extracted from each database.

Table 1

Sequences used for data extraction

Database	Search strings	Articles
WoS	TS = (*"Operation management" OR "operations management" OR "production management" OR "Operation* manager" OR "Production manager") AND TS = ("digital transformation" OR "IoT" OR "AI" OR "Internet of Things" OR "Artificial Intelligence" OR "Industry 4.0" OR "I4.0" OR "Technolog* Trends" OR "Digital Trends" OR "Digital Technolog*" OR "Digitali*"*)	401
Scopus	TITLE-ABS-KEY (*"Operation management" OR "operations management" OR "production management" OR "Operation* manager" OR "Production manager"*) AND TITLE-ABS-KEY (*"digital transformation" OR "IoT" OR "AI" OR "Internet of Things" OR "Artificial Intelligence" OR "Industry 4.0" OR "I4.0" OR "Technolog* Trends" OR "Digital Trends" OR "Digital Technolog*" OR "Digitali*"*).	1,005

Source: Extracted from WoS and Scopus in March 2021.

[1] The number of articles before applying filters to delete the data.

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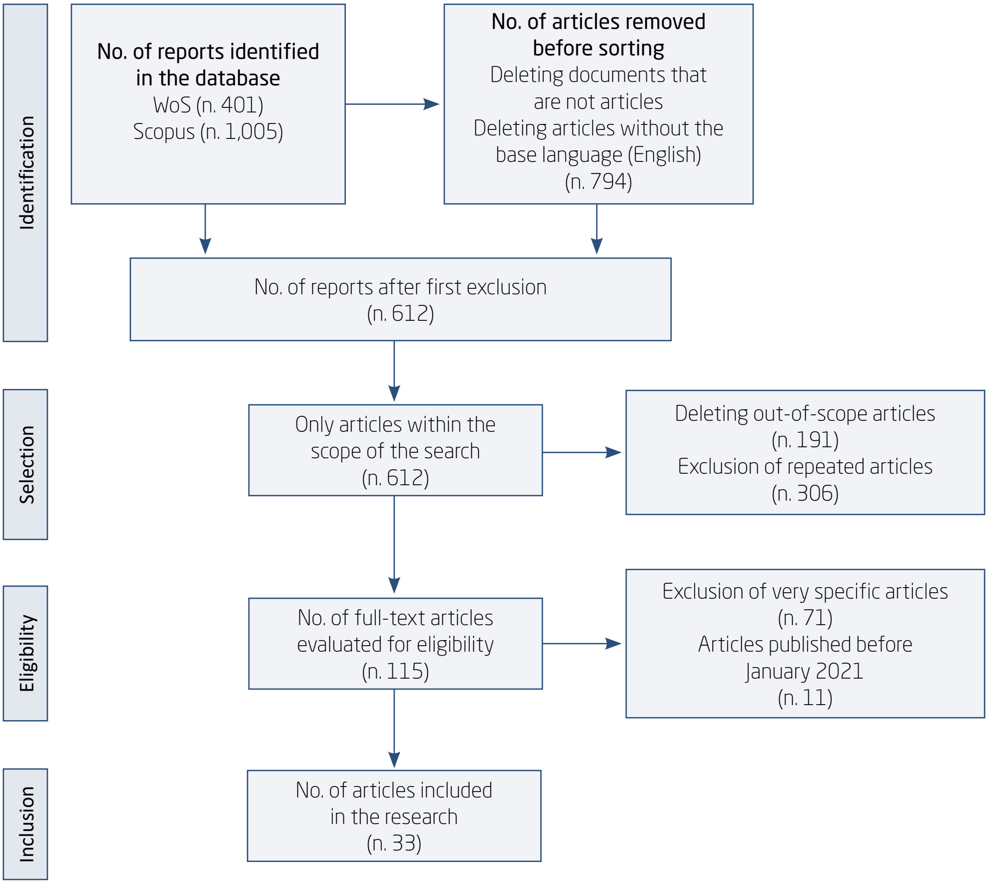
The selection of articles for final inclusion to the study followed the exclusion criteria defined previously, leaving 72 articles from WoS and 43 from Scopus. Finally, an in-depth reading was made of 115 articles, remaining, in the end, 27 from WoS and six from Scopus, to be included in the review analysis. Figure 4 illustrates this process, based on the PRISMA flow diagram.

Figure 3

Scopus and WoS database data extraction flowchart



Source: Elaborated by the authors.

DESCRIPTION OF ANALYSES

Of the total of 33 studies analyzed, 100% refer to some topic related to OM. Among them, 93% (25 studies) mention i4.0, 81% (22 studies) mention

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IoT, and 70% (19 studies) relate OM to AI. Table 2 shows the distribution of the intersections between OM and each of the themes over the years.

Table 2

Distribution of publications according to intersections over the years

	2007	2011	2017	2018	2019	2020	2021
GO ∩ IA	1	1		2	3	9	3
GO ∩ IoT			1	7	2	12	
GO ∩ i4.0			1	6	4	12	2

Source: Elaborated by the authors.

In the sequence, the qualitative results are presented according to the research questions raised.

Q1: barriers to adopting AI and IoT tools

According to Ross et al. (2019b), there are challenges related to the adoption of technological tools. According to the authors, many companies report that they find it difficult to effectively adopt these new tools. Westerman et al. (2019) state that understanding and adopting new technologies while seeking to understand which aspects of the company's culture and processes should be kept or modified is another challenge faced by organizations. Table 3 presents the synthesis of the barriers encountered to adopting AI and IoT.

Table 3

Barriers to adoption of AI and IoT tools

Barriers to adopt AI and IoT	Authors
Incorrect, incomplete or non-existent data model	Venkatesh (2021)
Scenario changes	Venkatesh (2021)
It might cause uncertainity and lead to errors	Lee and Zhag (2016), Venkatesh (2021), and Wang et al. (2021)
Internal and external resistance	Lohmer and Lasch (2020)
Technological barriers	Lohmer and Lasch (2020)
High investments	Lee and Zhang (2016) and Tortorella et al. (2019)

Source: Elaborated by the authors.

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Incomplete data model and scenario changes

Venkatesh (2021) relates the use of AI in the context of OM and identifies some barriers to the adoption of this technology. One of these barriers is related to the complexity of dealing with data and information coming from different participants involved in the OM context. The complexity in managing these data and information is increased when there are the insertion and combination of other technologies, such as IoT and blockchain. As a consequence of this complexity, one of the most cited problems is the lack of data, which can be associated with incomplete, absent, incorrect data, and wrong assumptions generated by managers or IoT tools. These assumptions and incorrect data can cause problems in OM, such as production programming models generated based on wrong data causing errors in areas other than products, for example, material inventories and the distribution and delivery of products. Another point addressed by the author refers to the change of scenarios, a problem that can hinder the adoption of AI models. Some scenario changes that can affect current AI models or hinder decisions about how a model should be modified to adapt to these changes occur imperceptibly or even suddenly.

It causes uncertainty and may lead to errors

Another barrier identified is the uncertainty people have in the adoption of AI and IoT tools and the mistakes these technologies can cause (Lee & Zhang, 2016; Venkatesh, 2021; Wang et al., 2021). Adopting new technologies means that, besides the need to lead with the introduction of a new tool and a new way of collecting data, internal systems become highly dependent on these data. The use or failure to collect this data can generate uncertainties for managers who make their decisions based on this data, causing delays or even failure to deliver the expected results and in the planning of the company's operations. There is also resistance to the adoption of these new technologies by some employees who are used to other techniques.

Internal and external resistances

Lohmer and Lasch (2020) cite in their research about blockchain adoption in OM that one of the main barriers is the resistance, which can be internal to the organization itself or among the companies with whom they work collaboratively. These resistances are mostly related to the lack of

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transparency, knowledge, lack of trust between them, and lack of management, definitions of collaboration processes, among others. The difficulties in dealing with the risks of leakage and manipulation of data also arise as barriers in the adoption of blockchain, mainly due to the lack of knowledge and/or training for the users.

Technological barriers

The strengthening of i4.0 has increasingly demanded the adoption of new technologies, such as blockchain and IoT. However, according to Lohmer and Lasch (2020), there are still delays in the implementation of these technologies due to 1. technological insecurity and vulnerability; 2. lack of standardizations, which leads to insecurity as to which technology to adopt (Hackius & Petersen, 2020; Lohmer & Lasch, 2020); 3. lack of governance, since it is essential for chain decentralization and transparency; and 4. feeling of vulnerability both in terms of technological and security.

High investment

The adoption of new digital technologies requires a high investment (Lee & Zhang, 2016; Tortorella et al., 2019). The isolated adoption of technologies, such as IoT, before conducting a broad assessment of needs and practices can lead to errors in investments, generating losses and poorly planned processes. Organizations that want to invest in the adoption of new technologies should also invest in infrastructure improvements, which ends up making it more expensive and hindering investment by companies.

Q2: On operational capabilities that could or have been improved and impacted by the adoption of new technologies, such as AI and IoT

According to Lankshear and Knobel (2008) adopting new digital technologies trigger several improvements and encourages companies to transform themselves in a creative way, generating new knowledge. Borges et al. (2020) mention that adopting these new technologies makes it possible to extract data that a human beings could not and also has the potential to improve human decisions, create advantages, and deepen innovations in business. According to Lohmer and Lasch (2020) and Diwas (2020), access to information is essential to understand what the effective impacts are and to achieve greater accuracy in empirical analyses. Following, there is an analysis

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of whether these statements also occur within the OM. Table 3 presents the synthesis of this analysis and, then, some of the points are discussed.

Table 4

Improvements and impacts on operational capabilities with the adoption of AI and IoT tools

Improvements and impacts on operational capabilities	Authors
Automation	Chauhan et al. (2021), Lohmer and Lasch (2020), Olsen and Tomlin (2020), Wang et al. (2021), and Watanabe et al. (2019)
Improved decision-making	Diwas (2020), Olsen and Tomlin (2020), Thomas (2019), and Wang et al. (2021)
Real-time broad data collection	Guha and Kumar (2018), Hannola et al. (2018), Isaksson et al. (2018), and Li et al. (2020)
Centralization and sharing of information between the system and people	Erasmus et al. (2018), Fettermann et al. (2018), Kobbacy et al. (2007), Li, Dai et al. (2020), Lohmer and Lasch (2020), and Zhang et al. (2020)
More agile information on management	Diwas (2020), Fisch and Fleury (2020), Li et al. (2020), Thomas (2019), and Wang et al. (2021)
Increase in productivity	Felsberger et al. (2020), Hannola et al. (2018), Isaksson et al. (2018), Shou et al. (2019), and Yunus (2020)
Simplified monitoring	Chauhan et al. (2021), Kobbacy and Vadera (2011), Kumar et al. (2018), Lohmer and Lasch (2020), and Wamba and Queiroz (2020)
Reduction of unnecessary expenses and increase in employee satisfaction	Bienhaus and Haddud (2018) and Chonsawat and Sopadang (2020)

Source: Elaborated by the authors.

Automation

One of the great benefits that the introduction of I4.0 brought to OM is the automation of the operations and processes due to the adoption of digital tools, such as AI and IoT (Chauhan et al., 2021; Wang et al., 2021), that allow automating and monitoring processes. It brings a broad opportunity for growth for those who adopt them, increasing real-time communication and reducing costs and resources used (Lohmer & Lasch, 2020; Olsen & Tomlin, 2020; Watanabe et al., 2019).

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Improved decision-making

The potential to significantly change the design and organization of work is one of the main factors related to the implementation of the new technologies (Diwas, 2020; Lohmer & Lasch, 2020). Many AI technologies, such as neural networks or deep learning, are designed to detect human capability patterns that help monitor and present diverse decision options to assist in further decision-making (Diwas, 2020; Thomas, 2019; Wang et al., 2021).

IoT technologies, in turn, generate a lot of autonomy in the processes in which machines can interact autonomously, initiate steps in a process, or request maintenance measures based on the data collected from the distributed IoT sensors, thus helping in decision-making, facilitating the understanding of maintenance decision-making needs (Lohmer & Lasch; 2020).

Broad real-time data collection

The possibility of collecting data broadly and in real time by implementing AI and IoT tools in the area of operations allowed a better knowledge of factors that interfere with productivity. It enables improvements and the opening of new possibilities that greatly increased production efficiency and bring important advances in the area (Guha & Kumar, 2018). According to Li, Dai et al. (2020), in addition to real-time data collection, digital tools offer increased production capacity by providing data support for evaluation, planning, and decision-making in OM, all broadly, online, and quickly.

Centralization and sharing of information between the system and people

According to Zhang et al. (2020), AI and IoT technologies in OM help to build and connect platforms and to centralize data. These tools contribute to communication between systems and between people, improving processes, planning, and controls (Fettermann et al., 2018; Kobbacy et al., 2007), thus facilitating command and responses both for devices and teams to perform operations (Erasmus et al., 2018). High operational efficiency and more effective decision-making are observed when a complete sharing of data is present and there is an on-demand use of the generated information (Li, Dai et al., 2020; Lohmer & Lasch, 2020).

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More agile information management

AI and IoT perform tasks with greater agility and lower errors, which makes management easier and faster (Wang et al., 2021). In addition to analyzing large amounts of data to learn, simulate, and share, they can be useful in planning, operation, and decision-making (Diwas, 2020; Fisch & Fleury, 2020). Competitive differentiation in the market is obtained when this set of tools is configured to process information at high speed to allow a more effective and efficient alignment between functional groups, systems, and the different functions of OM (Li, Dai et al., 2020; Thomas, 2019).

Increase in productivity

One of the reasons why companies adopt digital technologies in several areas is the possibility of increasing productivity (Felsberger et al., 2020) by being able to reduce downtime, increase quality, minimize waste (Hannola et al., 2018), and make better use of data and productivity (Shou et al., 2019). In addition to investing in technologies, working on aspects such as training and the development of different competencies that are in line with digital transformation also helps to increase productivity in operations (Yunus, 2020).

Simplified monitoring

By using digital technologies in OM, one of the improvements that stand out is the more agile and facilitated monitoring, thus increasing trust between partners and managers (Kumar et al., 2018; Wamba & Queiroz, 2020). Monitoring can be simplified and centralized in OM by using AI in projects, scheduling, planning, quality, and fault diagnosis (Kobbacy & Vadera, 2011; Lohmer & Lasch, 2020; Isaksson et al., 2018).

Reduction of unnecessary expenses; increase employee satisfaction

By introducing technological trends in operations, it is possible to observe a reduction in costs, defect rates, heavy lifting, and incidents due to the more focused and fast planning that managers can do (Chonsawat & Sopadang, 2020). Other benefits perceived in the operation is the decrease in repetitive operations or certain cases, replacing some simple operations performed by employees, freeing them up for nobler tasks (Bienhaus & Haddud, 2018), which increases employee satisfaction.

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Summary of discussions and research proposals and opportunities

The objective of a systematic review of the literature is to improve the understanding of certain topics, based on what has been discussed previously; analyze what is currently happening; and start a discussion on future avenues for the theme studied (Webster & Watson, 2002). From the analyses performed, some questions are arising from gaps that still need to be investigated. Table 5 presents the consolidation of these questions and gaps related to OM.

Table 5

Summary of discussions highlighting the gaps identified

Gaps	Future reserach opportunities	Authors
Process automation and use of AI and other digital technologies	Among all the different processes in the OM context, which of them are done routinely and could be automated?	Lohmer and Lasch (2020)
Interaction of AI and IoT tools	How can the interaction between AI and IoT and other technologies, such as blockchain in operations, contribute to the creation of new values?	Wamba and Queiroz (2020)
Challenges of the implementation of AI, IoT, big data, and cloud computing technologies, from the perspective of managers.	How do people and companies perceive the issue of success and failure in implementing new technologies in operation?	Kumar et al. (2018)
Impact of socioeconomic context on the adoption of new technologies	Expand the research on I4.0 (and its tools, such as AI and IoT) and OM in a regional way, to understand whether the socioeconomic context can affect the adoption of new technologies.	Tortorella et al. (2019)
Analysis of the impacts of OM's digitalization processes	Global research to identify similarities, differences, problems, and consequences.	Bienhaus and Haddud (2018)

Source: Elaborated by the authors.

CONCLUSION

The present study had as general objective to analyze how companies are using IoT and AI to improve the flexibility and reliability of the operation,

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modify their way of acting, and improve their competitiveness by differentiating themselves in the market. To answer this question, a systematic review of the literature was conducted, analyzing articles published in the WoS and Scopus databases between 2007 and 2021. The research questions raised were:

- Q1: What are the main barriers found in the literature to the adoption of new technologies, such as AI and IoT, in OM?
- Q2: What operational capabilities could or have been impacted and improved by the adoption of new technologies, such as AI and IoT?

Answering Q1, among the barriers identified, some stand out, as the difficulty of working with data – generation, collection, and analysis –, which influences both the implementation and the use of IoT and the possibility of more elaborated analyses to improve decision-making. Another barrier identified is the adoption of new technologies by the users. This barrier can be seen in the expression of the insecurities and feelings of vulnerability when users start using these new technologies.

In response to Q2, concerning improvements made because of the use of new technologies, there is a group of studies that focus on operational improvements, such as automation of processes and procedures; ways to increase productivity; achieve improvements in the decision-making process; improvements related to the control and monitoring of information and operations; reduction of general costs; and improvements in employee satisfaction. As a consolidation of these analyses, this paper presents a summary table (Table 5) with some questions that arise from gaps that remain when analyzing the impact of both barriers and benefits of adopting AI and IoT in OM.

As a contribution to the practice, the results present an overview of the impact that AI and IoT have on OM. This understanding can help managers in the implementation of technologies such as AI and/or IoT, in order to identify which points of improvement should be sought and what care should be taken for a correct decision.

Regarding the theory, the contribution of this research begins with the analysis of the network of correlations formed by the keywords in which it was possible to observe how the area of OM was being incorporated by themes of digital transformation such as i4.0. The relationship between AI, IoT and OM, within the context of digital transformation, is presented in the present study, but there are other technologies that have been highlighted, such as big data and blockchain. Future research to assess how these tech-

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nologies impact OM can help advance knowledge of the field. Another line of future research is to evaluate whether the socioeconomic context could affect the adoption of new technologies in OM – an aspect that was not verified in the present study. This point and the fact that it has looked only at journal articles, leaving out those presented at congresses, represent the limitations of the present study. But the consolidation of both barriers and benefits, the presentation of the framework consolidating the still existing questions, and the suggestions made of future research are important contributions of this work to the advancement of the area.

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