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Empirical AI Transformation Research: A Systematic Mapping Study and Future Agenda

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Abstract

Background: Intelligent software is a significant societal change agent. Recent research indicates that organizations must change to reap the full benefits of AI. We refer to this change as AI transformation (AIT). The key challenge is to determine how to change and which are the consequences of increased AI use.
Aim: The aim of this study is to aggregate the body of knowledge on AIT research.
Method: We perform an systematic mapping study (SMS) and follow Kitchenham's procedure. We identify 52 studies from Scopus, IEEE, and Science Direct (2010–2020). We use the Mixed-Methods Appraisal Tool (MMAT) to critically assess empirical work.
Results: Work on AIT is mainly qualitative and originates from various disciplines. We are unable to identify any useful definition of AIT. To our knowledge, this is the first SMS that focuses on empirical AIT research. Only a few empirical studies were found in the sample we identified.
Conclusions: We define AIT and propose a research agenda. Despite the popularity and attention related to AI and its effects on organizations, our study reveals that a significant amount of publications on the topic lack proper methodology or empirical data.

Keywords: AI transformation, digital transformation, organizational change, systematic mapping study

1. Introduction

Artificial Intelligence (AI) technology can yield a competitive advantage and new business models for many types of organizations [1] provided that they have sufficient knowledge, skills, and a suitable infrastructure [2]. Technology adoption is one of the driving forces of economic growth [3]. In particular, this adoption can help in tackling global challenges such as health, education, environment, science and it has significant capability to address our regional, local, and organizational challenges [4]. However, technology adoption itself can be a challenge that leads to success or failure based on how it is tackled.

AI is intrinsically software-based and entails massive software engineering [5]. The increased use of AI is closely connected to recent hardware development (the computational resources are now sufficient) and developments in software engineering (it is now possible to

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design, implement, and test AI-based software systems) [6]. Most successful AI applications are data-driven and use machine learning as core technology [7]. Organizations today are either developers or users of data-driven products and services. An organization is deemed data-driven, or AI mature, if it possesses sufficient knowledge and skills to use AI internally (to improve the organization) and externally (to improve products or services) [8]. The main question for many organizations is how to successfully adopt AI (become data-driven and achieve AI maturity). Despite the expansion, availability, and value of AI technologies, organizations are still struggling to adopt AI [1]. Recent collaborative research made by researchers from MIT, University of Toronto, and the US Census Bureau point out that the adoption rate of AI technologies in organizations is low in general and concentrated to older and larger firms [9].

Organizations are difficult to change in the ways necessary for technology adoption. With rapid development and change of AI technologies, organizations must change continuously. Various factors that could potentially influence willingness or the ability to adopt AI include the availability of relevant resources (computational, economical, and human), legislation (governance and ethics), cost, limited computational capability and infrastructure, security, organization size and structure, traditions, and organizational culture [10]. We identify several studies that explore the phenomenon of digital transformation (DT). One existing definition of DT states that it is a “radical improvement in business performance and operations outcomes due to the use of technology” [11]. DT is thus a very broad umbrella term encompassing all transformations relating to digital technologies.

We argue that the type of transformation that organizations need to undergo to benefit from AI technology is sufficiently different from DT to deserve its own definition and exploration. Our main motivation for making this distinction is connected to the primary function of AI, which is to offload cognitive work from humans to computers. This functionality will potentially lead to more drastic organizational changes than DT in general. The key problem is that AIT is understudied as a distinct phenomenon. This means that it is typically defined indirectly through digital transformation research and explorations into which factors actually contribute to failure or successful AI adoption are scarce.

The aim of this study is to aggregate the body of knowledge concerning the relationship between AI and organizational transformation (OT), to map the field by performing a systematic mapping study (SMS) and, by doing so, identifying gaps in research that represent opportunities for future studies. Our work can help organizations to optimize AIT by finding approaches and models that have been successful in similar contexts.

This study is organized as follows: Section 2 discuss the concept of AI and organization. Section 3 present the aim and the scope, lists and motivates the research questions, and discusses the methodology and the threat and validity. Section 4 summarizes the results for each research question and describes the overall implications of the results. Section 5 includes an assessment of validity threats as well as a discussion and definition of AIT. Finally, Section 6 provides conclusions and pointers to future work.

2. Background

2.1. AI and organizations

AI changes the composition of human skills and tasks required in an organization [3]. Organizations need to develop new knowledge and competences to comprehend new technologies so that they will be aligned with the strategy, processes, and structure.

Organizational adaptation to AI can be viewed as an external catalyst for change, where organizations react on a strategic and tactical level. It also acts as an augmentation to an internal catalyst, where organizations change processes and their operation to meet the technological and societal challenges [12]. Adaptation of AI is inevitable and will affect the business models.

AI will eventually change the composition, business models, and the tasks required in an organization. New business models can be a result of strategy or a strategizing action [13]. AI vastly changes organizations' resources, operations and structure. It is argued that organizations that adjust to this change will become more efficient [14].

Rapid change requires organizations to be flexible and to quickly adapt and adopt new technologies while preparing the organization from a human, societal, and technological perspective to meet this dynamic change [15]. It is suggested that the social and technological changes that organizations are experiencing in the new millennium, will lead to changes in social values, practices, and in the structure and processes of organizations [16]. It has been pointed out that AI has immense influence on organizations, such as: reducing costs, improving human task solving efficiencies, and supporting business customer relationships [17]. However, there are also limitations of AI, and humans will still play an important role in the organization as well [17]. In addition, the importance of human skills that cannot be *learned* by intelligent technologies, will only increase [18]. A reference is made to Michael Polanyi's expression "we know more than we can tell" [19]. This is known as Polanyi's Paradox [18]; where many decisions and actions made by humans cannot be learned or described, which creates an implication for intelligent technologies to duplicate human behavior or improve upon *gut feelings* [20]. Decision making based on *gut feeling* cannot explain the reasons behind the decisions, which are often described as *feel-right decisions*. Moreover, it is hard to identify which decisions are based on this kind of intuition since many employees will find it hard to admit that a crucial decision they have made is based on gut feeling [20].

The discussion of the effect of new technologies on organizations and the changes they will lead to are not new, but rather a continuous discussion of previous industrial revolutions. Research shows two different approaches toward AI: the utopian, where machines will improve human life quality, and the dystopian, where machines will take over the human society [21]. AIT triggers scholarly interests in various disciplines. The scientific literature presents various models related to smart technology transformation, regardless of whether the future of AI will be utopian, dystopian, or something in between, research must be carried out to support the best possible use of AI.

We observe large organizations such as Apple, Amazon, Microsoft, Google, Facebook, and other corporations that have the resources (capital and human) and the market position to invest and develop their use of AI technologies to transform their organization. In addition, research shows that companies upgrade their workflows and the way they work based on AI technologies which lead to enhancement of their financial and market performance [22].

2.2. What is AI transformation (AIT)?

Artificial Intelligence (AI) is used as a genre name and it is becoming increasingly discussed, following the developments related to, for example: IBM Watson, Google DeepMind, Google AlphaGo, and IBM Deep Blue. To the best of our knowledge, this is the most well-known case dealing with AIT. However, AI transformation has also been observed in other studies, such as the impact of AI on business performance, business value, business capabilities etc. One example is an in-depth study on the impact of AI on firm performance that presents a framework for building on the business value of AI-based transformation projects based on 500 case studies from IBM, AWS, Cloudera, Nvidia, Conversica, and Universal Robots websites [23]. It becomes a dynamic tool that people and communities make use of to refer to various technologies. AI does not have a specific, universal definition but its overarching focus is intelligent systems that can think humanly, act humanly and learn as humans [24]. AI discussions often feature topics such as the possibility of machines to perform as humans in terms of thought processes, reasoning, and behavior. From a technological point of view, AI includes a number of subareas of importance [25]: machine learning deals with the intellectual ability to learn from experience and to improve in order to increase the performance at solving some task, natural language processing deals with the interpretation and production of natural (human) language, computer vision deals with the parsing of data from vision-based sensors to capture aspects of the physical world in the computer, agent-based systems deal with simulation and optimization of micro an macro world models [6].There are a number of additional subareas of AI and it is possible to view some of these different subareas as complementary or overlapping in terms of the overall mission to design intelligent computer-based systems. In this SMS, we view AI as an umbrella term for all such subareas.

The focus on AI as an interdisciplinary research area is relatively new, and the capacity of this technology is versatile and enormous [26]. The interest associated with AI involves economical, psychological, technological, political, and ethical aspects [27]. AIT receives scholarly interest from various domains as well as the attention of various industries in recent years (see the linked data sheet for more detailed information [28]). We also observe that there is a substantial scientific discussion around digital transformation [11, 29–31], but few studies focused only on AI transformation.

Out of the 52 papers we identify in this study, 23% discuss digital transformation of AI technologies (the technologies that are discussed in these papers are AI, Big Data Analytics (BDA), and Data Analytics (DA)). We observe that other concepts such as various smart industries, i.e., smart manufacturing, smart agriculture, and Industry 4.0 also discuss the concept of AIT (see subsection 4.2). This helps us to distinguish between the two concepts and to argue that this SMS mainly discusses AIT and focuses only on AI technologies, which is partly discussed in DT.

AIT should be discussed distinctly from any other DT. The reason for this is that, unlike other forms of DT, AIT will clearly shift cognitive work from human actors to computers. The consequence for many organizations is significant.

2.3. Organizational transformation

Organizational transformation can be described from various perspectives; on the one hand it denotes to be a radical change in the form or character of something or someone that completely changes the organization. Transformational change is discussed as a complex phenomenon, where the change requires a shifting of the current organization strategy, structure, process, culture, work behavior and mindset [32]. This change occurs by a breakthrough to pursue new opportunities. Furthermore, it is argued that organizations that will not identify these types of needs for a change will be disrupted [32].

On the other hand, the change can also be considered to be incremental; an ongoing, gradual, discontinuous process which leads to change [33]. It is argued that organizational change is a continuous process in organizations as a result of various activities that occur on a regular basis, such as hiring new employees, getting new facilities, renewing the organization strategy, implementing new technologies, and restructuring [34]. Continuous and confluent organizational change can be described as a slow and evolutionary change which is not episodic or a result of a crisis [35]. The organizational ambidexterity theory states that organizations as part of their growth, in a simultaneous way, need to pursue both an evolutionary change – a discontinuous incremental change where the organization is expanding the existing business – and a revolutionary innovative change where the organization is incubating novel opportunities [36].

3. Research methodology

The following section refers to present the aim and the scope, lists and motivates for the research questions, and discusses the methodology and the threat and validity techniques used to obtain and analyze data. This part outlines the approach used in order to fulfill the purpose of this paper.

3.1. Aim and scope

The focus of this article is on change that is led by a particular purpose; AI, we are interested in both incremental and radical change that will lead to a transformation in the organization. We will follow AIT as a change agent; an incremental or radical change that can happen in the organization. By using AI capabilities, the traditional organization transforms its structure, processes, organizational learning, work routine, knowledge management, products, and services [37]. We do not focus on the process of the change or in a particular model or theory that explains the change, but rather on the concept of AIT.

To explore AIT, it is important to understand the concept of AI and its implications, while understanding its relationship to the organizational structure, leadership, culture, vision, and mission and the human attributes within the organization. Organizations are frequently integrating various technologies, but technology transformation related to AI is considered to have a strong impact on organizations [12]. AIT is related to the integration and adaptation of AI into an organization's business, although it can also be considered as a disruptive process that creates new forms of organizations [38].

The scope of this study is AIT. The aim is to follow the SMS process to aggregate the body of knowledge on AIT research and to map the field and identify the research gaps that represent opportunities for future studies [39].

3.2. Research questions

The research questions and the motivation for each question are formulated based on the aim for the SMS. In this work, we seek to answer the following research questions:

RQ1. How is AI transformation conceptualized in the literature?

Motivation. To find existing definitions of AIT in the literature, to analyze these definitions to identify contradictions, similarities, or issues. This analysis can be used to establish a common and useful definition for AIT.

RQ2. What are the research methods used in AI transformation research?

Motivation. An understanding of which research methods are applied, and how, allows us to assess the maturity of the research, and to characterize the existing body of knowledge generated in the field.

RQ2.1. What are the main theories and frameworks adopted in AI transformation research?
Motivation. AIT is inherently interdisciplinary. Due to this, theories and frameworks come from multiple disciplines, which makes it difficult for a specific discipline to make sense of results and conclusions. An understanding of the underlying theories and frameworks of AIT enables the establishment of a unified framework, in which results, and conclusions could be reinterpreted by any discipline, and by stakeholders from the private and public sector.

RQ2.2. What real-world scenarios and contexts are studied in AI transformation research?
Motivation. To identify the maturity of AIT in different domains, and to explore unique characteristics related to AI transformation in these domains.

RQ3. What are the emerging questions for future research and the important research gaps in the area?
Motivation. It is important to identify the major trends of AIT research and to identify research gaps, as they seed new research opportunities. In addition, an ever-increasing number of organizations are looking into how to transform due to AI. The identified research gaps may allow new research that helps these organizations reap the benefits and mitigate the risks involved in AIT.

By addressing these research questions, we aim to provide an insight concerning AIT definitions existing in literature. Secondly, we propose categories, based on the theories used in the literature, which may increase the clarity about existing research relating to AIT. Thirdly, we strive to offer a foundation for future research by finding research gaps in this research field.

3.3. Literature review procedure

Systematic mapping study (SMS) can be described as identifying, evaluating, and interpreting the available knowledge within a particular phenomenon of interest [39]. We follow the Kitchenham procedure [39] for performing the SMS. SMS is a form of literature review where one can gain a transparent and rigorous assessment of the literature. Furthermore, they aim to provide a foundation and empirical answer for one or more research question [39, 40] and to discover research trends [41].

Three databases (Science Direct, Scopus, and IEEE Xplore) are used as main literature sources. The motivation for this selection is that the first two databases are common in management and organization studies, while the third is linked to the profile of this study, which is interdisciplinary and can offer a technological perspective. Hence, our aim was to find a good sample, rather than finding all articles [41]. The papers are first selected based on title, keywords, and abstracts. The second screening is performed by two external reviewers. The third screening is performed based on the Mixed Methods Appraisal Tool (MMAT), and the two external reviewers independently involved in the appraisal process review 15% of the articles (the selection is performed based on a random sampling). We have selected two reviewers from two different fields (Computer Science and Business Administration). The reason was to make sure that we are catching both approaches, and not missing relevant articles. Having two different reviewers in the review process is useful, so one researcher extract the data and the two others reviewing the extraction [39]. In this

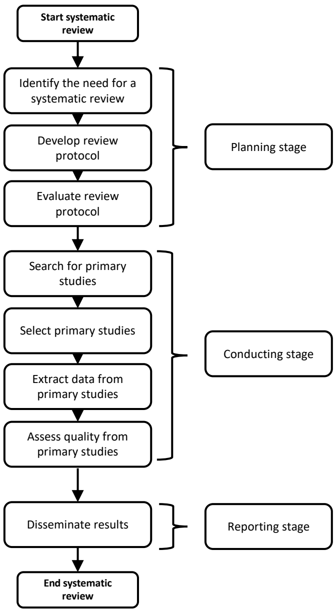

Figure 1. SMS process [39]

way we also reduce the bias, though, given that this step involves human judgment, the threat cannot be eliminated [39]. Based on the screening, a full text reading is conducted to ensure that the right articles are selected. The search strategy and the selection criteria are thoroughly described in Sections 3.3.3 and 3.3.4.

An SMS provides information about the effect of some phenomenon "across a wide range of settings and empirical methods" [39] and gives a robust and thorough view of the current status of research in a particular discipline, by collecting and summarizing the empirical work that exist [42]. Worth mentioning in this context is that the purpose of an SMS is not necessarily to be complete or exhaustive (something we can never assure) but rather to be systematic and transparent. Concerning the former it will allow other researchers to reproduce the results (now or in the future), and concerning the latter an SMS provides a clear view of different sources of evidence and how said evidence is weighted.

An SMS is conducted in three phases: planning the review, conducting the review, and reporting the review. Each phase is divided into a step-by-step process, where an evolution from phase-to-phase must occur. Once the last step is achieved one can progress to the next phase (see Figure 1).

3.3.1. Define and evaluate review protocol

We develop a review protocol to specify the methods we use, and to reduce the possibility for bias. The components of the review protocol are the research questions, the search strategy for collecting primary studies, the exclusion and inclusion criteria, assessment of quality, and data extraction strategy. The external reviewers evaluate and validate the review protocol and, as per their suggestions, changes are incorporated to refine the protocol.

3.3.2. Source selection

We select as sources the following main literature databases:
1. Science Direct;
2. Scopus;
3. IEEE Xplore.

We have also carried out an additional pilot search in the proceedings of top-tier software engineering conferences (ICSE, ESEC/FSE and ASE) and ACM digital library to ensure the validity of the search results. We have followed the same search patterns employed for the three already included databases, and we found 104 conference articles and 378 articles at ACM digital library. We reviewed the title and the abstract but did not encounter any additional papers that discussed AIT (the article's focus was more on the technology than the organization). Our mapping will provide a basis for more in-depth follow-up studies on specific subtopics for which additional databases would be more appropriate. This work can serve as a foundation for future research investigating AIT.

3.3.3. Search strategy

We divide the search into two stages: pilot search and primary search. For each search, we perform the following:
1. Keywords: Keywords are identified based on the research questions,
2. Variants: Synonyms and alternate spellings of search keywords are identified,
3. Search keyword connectors: Combinations of **OR** and **NOT** are used to define sub searches.

Following the SMS methodology and the research questions, in order to identify the most relevant keywords, we perform a pilot search where we evaluate various combinations of relevant keywords. Additionally, we check which word combinations provide the greatest number of hits.

Based on this pilot, we identify the following keyword search terms:

transformation* **OR** organizational change* **OR** learning organization* **OR** change management* **OR** organization restructuring* **OR** organization redesign* **OR** organization design* **OR** technology adoption* **AND** Artificial Intelligence* **OR** AI* **OR** Machine learning* **OR** ML* **OR** Data mining* **OR** Data analytics* **OR** Decision support system* **OR** Expert system* **OR** Knowledge-based system* **OR** Intelligence system* **OR/AND** Human machine*

In addition, we consult with key stakeholders within the field of business administration, economics, and AI, to review the keywords to make sure that we remain within the scope of AIT.

3.3.4. Inclusion/exclusion criteria

To select the most relevant studies and exclude irrelevant studies, we establish inclusion and exclusion criteria (see Table 1). We limit the study to existing management and organization studies (MOS) during the period January 2010 to September 2020, since there is a significant growth of publications on these issues within this time frame. We include only studies that relate to AIT. For publications that are within the frame of our inclusion criteria, the following filters are applied as exclusion criteria:
- **Filter 1:** remove publication types other than journal articles;

– **Filter 2:** remove non-English language studies;
– **Filter 3:** remove duplicate studies.

For quality purposes, we limit the selection criteria to journal articles that are published in the English language [43]. The reasoning behind this filtering is that, in most mature areas journals are identified as a more influential and reliable source than other publication channels.

Table 1. Exclusion/Inclusion Criteria

Inclusion criteria
Studies involving AIT
Studies published between 2010–2020
AI and organizational change
AI and organizational restructuring
Business, Management and Accounting
Decision Sciences, Psychology
Exclusion Criteria
Publication types other than journal articles
Duplicate studies
Non-English language studies

After the search, six stages of selection are used to reduce the initial 571 papers (Scopus), 252 papers (IEEE, only two duplicates), and 143 papers (Science Direct, 24 duplicates). The search and selection processes are described below and summarized in Figure 2.

1. Screening the articles based on the title and abstract, and articles that we can identify from the title and the abstracts that are relevant to the SMS, are categorized as *include*, while articles that are irrelevant are categorized as *exclude* (see Table 2 – initial include).
2. A second screening of the included articles is conducted by two external reviewers who evaluate and validate the screening incorporated changes to refine *include* articles (see Table 2 – final include).
3. Krippendorff's α (K_α) (inter-rater reliability statistic) is used to estimate the reliability of the evaluation [45]. The Krippendorff's α results for each database are presented in Table 2. A $K_\alpha > 0.8$ implies a strong inter-rater reliability, i.e., the reviewers were in strong agreement.
4. A third screening is conducted based on the MMAT, which is a tool used to appraise the quality of empirical studies and designed to support systematic reviews that have various methods, i.e., qualitative, quantitative, and mixed methods [46]. The screening questions are used as an indication of the level of quality of the empirical investigation. The screening questions are: (1) Are there clear research questions? (2) Do the collected data allow to address the research questions? Responding 'No' or 'Can't tell' = 0 (the paper is not an empirical study), 'Yes' = 1 [46] (see Tables 3–5). Two external reviewers are independently involved in the appraisal process. We randomly select: Scopus: 14 articles (15% of 95 articles), IEEE: 2 articles (14% of 14 articles), Science direct: 3 articles (18% of 17 articles).
5. The remaining 47 papers are used as the basis for the full-text review. The basic structure of the search and selection process can be seen in Figure 1.
6. The last assessment is based on a full-text reading and leads to the further exclusion of 7 studies.

Table 2. Overview of Inclusion/Exclusion

Source	Number of articles	Initial include	Final include	K_α^1
Scopus	571	129	95	0.91
IEEE	252	16	14	0.85
Science Direct	143	19	17	0.93

[1]Krippendorff's Alpha (K_α) test score

Table 3. MMAT (Scopus)

Scopus	MMAT	Screening question	
		0	1
Qualitative	73	47	26
Quantitative	18	6	12
Mixed methods	4	2	2
Total	95	55	40

Table 4. MMAT (IEEE)

IEEE	MMAT	Screening question	
		0	1
Qualitative	11	9	2
Quantitative	3	1	2
Total	14	10	4

Table 5. MMAT (Science Direct)

Science Direct	MMAT	Screening question	
		0	1
Qualitative	15	11	4
Quantitative	2	1	1
Total	17	12	5[1]

[1]Two articles have been excluded since it was out of the frame of management and organization

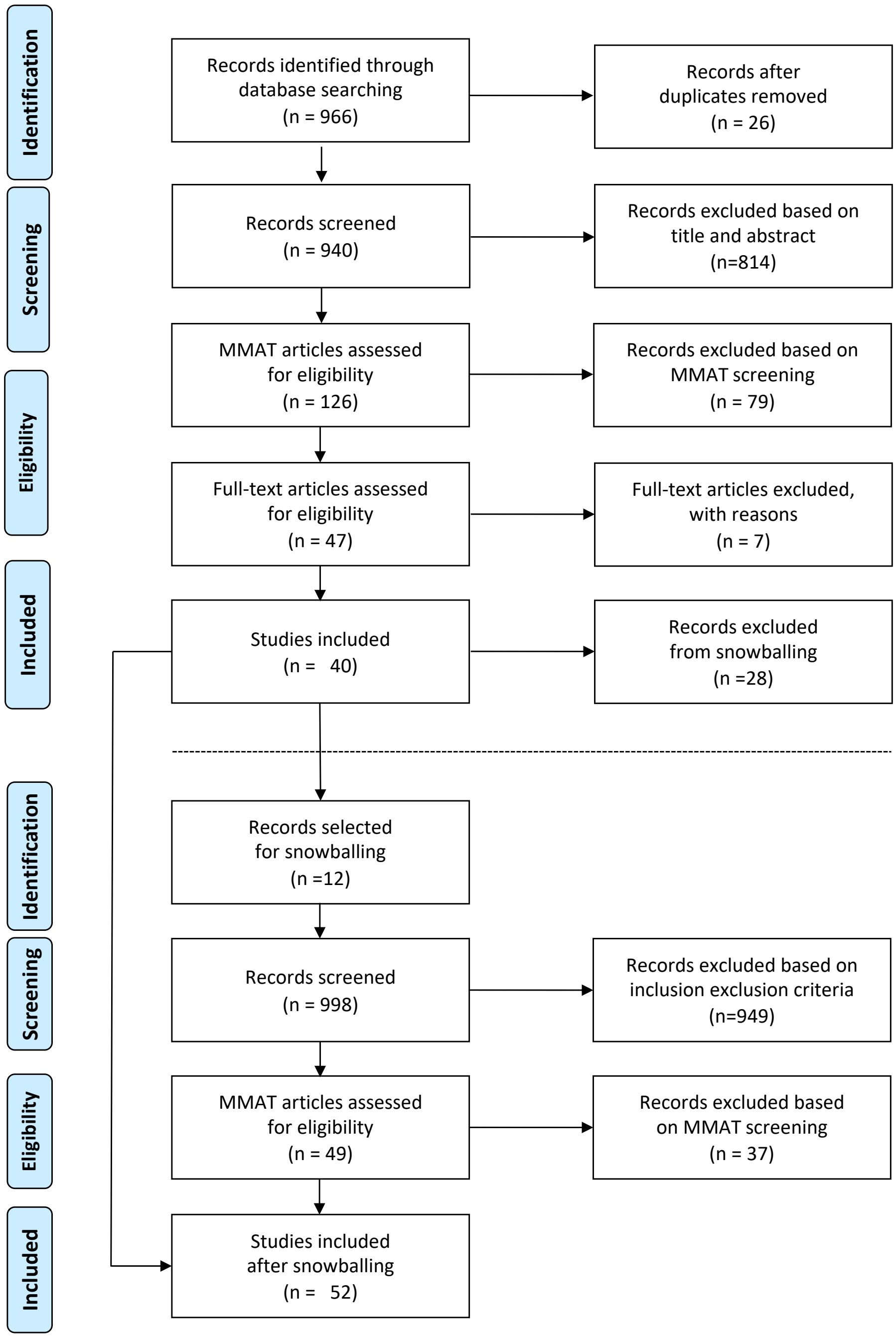

Figure 2. The phases of the SMS through PRISMA [44]

The remaining 40 papers are classified as primary studies and incorporated in the analysis for this study. The basic structure of the search and selection process can be seen in Figure 2.

As a final step, to control for bias, we conduct snowball sampling on the primary studies according to suggested guidelines for secondary search procedures [47]. We identify 12 studies, from the selection of primary studies, to increase the numbers of articles which discuss topics related to AIT. The motivation for selecting the 12 studies as the starting

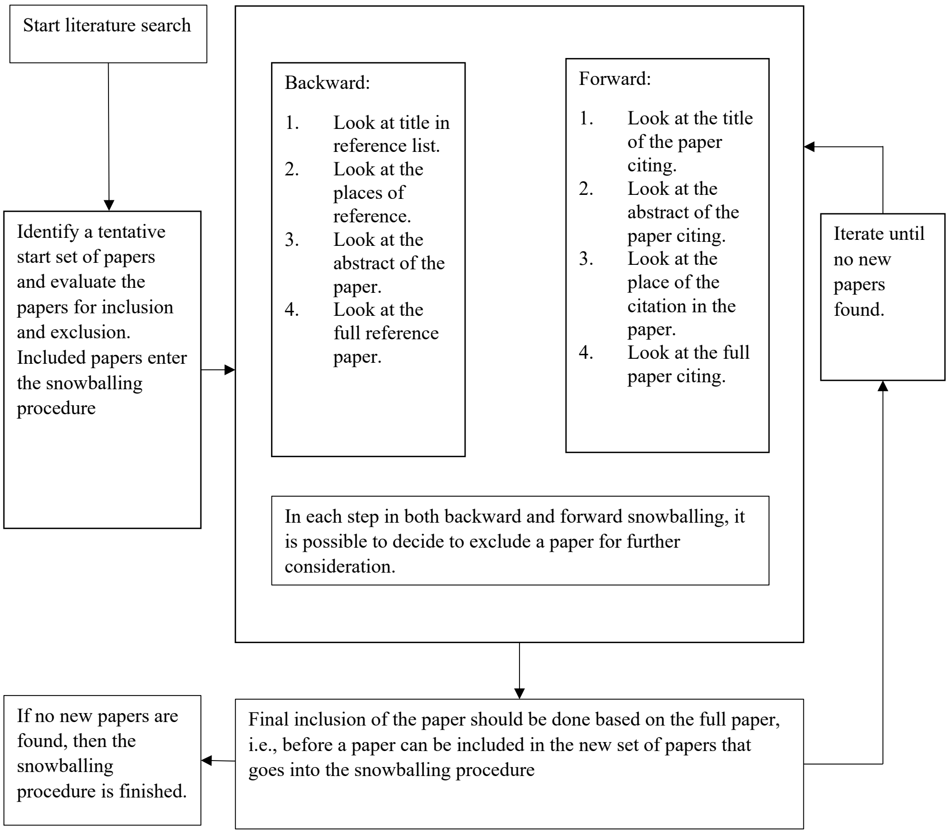

Figure 3. Snowballing procedure [47]

set is based on: the variety in disciplines and publishers, the number of Google Scholar[1] citations in relation to all 40 articles (we have decided to include), and the rank of the journal. We also include articles that thoroughly discuss topics closely related to AIT.

Snowballing is a complementary tool that increases the likelihood of finding all relevant papers on a subject [47]. We perform one-step backward snowballing, which means that we review the reference list of each selected article and follow the same inclusion and exclusion criteria as mentioned in Section 3.3.4.

The studies we review are published between January 2010 to September 2020 and for this reason we cannot perform forward snowballing. However, to complement the snowball sampling, we contact the authors of the primary studies to potentially identify some additional papers. We evaluate the papers retrieved as a consequence of this contact and determine, using our inclusion and exclusion criteria, that none of the papers are to be included as primary studies. Figure 3 describes the snowball procedure we follow, and Figure 2 shows the phases of the snowballing through PRISMA.

We screen the reference list of the 12 studies (in total 998 references) and based on our exclusion and inclusion criteria, we exclude 949 articles. The remaining 49 articles are scrutinized according to MMAT, and 37 articles are excluded. In total 12 papers are included in the full-text review. Hence, after the snowballing procedure, a total of 52 papers are selected as primary studies.

[1]Google Scholar, http://scholar.google.com

3.4. Validity threats

There can be different threats to the validity of study results. There exist additional databases which we are not including in this study. In addition, there are likely other keywords, or combinations of keywords, that would result in different sets of found, included, and excluded papers. We use a particular research design, but there are other ways to perform SMS. One validity threat is human judgment in data extraction and analysis. Additionally, the focus of this SMS is on articles published within the interval 2010–2020. Since AIT is gaining traction in the research community, later SMS will most likely include a significantly higher number of well-performed empirical studies.

To overcome the SMS limitations and to validate its results, several actions were taken. By following the suggested SMS guidelines [39] and by performing our analyses in the prescribed way, we reduce the risk of biased assumptions and conclusions. The analysis of our SMS threats to validity, considering construct validity, reliability, internal and external validity.

Construct validity refers to establishing the correct operational measures for the concepts under study. It describes how closely the phenomenon under study represents what the researchers had in mind and what is investigated according to the research questions [48]. The main constructs in our study are the concepts of "AI Transformation" and "systematic mapping study". Regarding the first, we identified some field roots and discussed related work. We could have used keywords for specific AI-related technologies (NLP, ML, machine vision, neural networks, deep learning, etc.), but our focus was on the broader concept of AI and the related transformation of the organization to support or adopt AI technologies. It is important to perform follow-up studies that focus exclusively on specific areas of AI (such as Deep Learning, Neural networks, and Natural Language Processing) but in the present study, we have chosen to focus on empirical work that considers the general toolbox of AI, without specifying particular areas.

As for the second construct, we followed the guidelines [39] to design our research questions, search criteria, and review protocol. We also did a pilot study and documented all steps to address possible threats to construct validity. We used additional databases (such as ACM) and different keywords (such as deep learning) in our pilot study, and based on the results, we decided which databases and keywords to use. We used keywords that we argue are sufficiently stable to be used as search strings. A broad search of general publication databases, which index the majority of well-regarded publications, was conducted so that all papers on the selected topic could be found. Moreover, we have also carried out an additional search in the proceedings of top-tier software engineering conferences (ICSE, ESEC/FSE and ASE) to ensure the validity of the search results. Hence, our work could be complemented with a systematic literature review that covers a larger number of databases and keywords in order to give a broader overview of this topic.

Reliability focuses on whether the data are collected, and the analysis is conducted in a way that it can be repeated by other researchers with the same results. All steps and processes have been well documented, so replications of our study should yield similar results. The selection of databases was based on providing coverage for management and organizational studies (the first two databases), while the last one was linked to the profile of this study, which is interdisciplinary and can offer a technological perspective. Hence, we have relatively good coverage of the topic of AIT. We established a rigorous search strategy (see Section 3.3.3) and addressed relevant questions related to AIT. The search strategy was tested and reviewed by two external reviewers, and Krippendorff's α statistic was calculated to ensure that a high inter-rater agreement had been reached. The MMAT tool was used to evaluate the quality of empirical studies and was designed to support the systematic review. The design of this SMS followed a rigorous structure to ensure reproducibility and control for bias.

Internal validity concerns the analysis of the data [48]. Selecting primary studies and assessing them individually pose the greatest threats. Our major source of data was a journal on AIT. In order to increase the reliability of our conclusions, we extended our literature review to several rounds in order to integrate the most complete primary studies possible. We recognize that a much broader search string could have been beneficial. Furthermore, we could include data from a wide range of sources, include keywords strongly associated with AI technology, and include all types of articles. Based on our pilot study, we defined the scope of our study, which was not to obtain an exhaustive sample but rather a representative sample. Since the topic we are interested in is multi-disciplinary, we opted for breadth (disparate databases in terms of venues covered) instead of depth (e.g., exclusive focus on classical computer science or software engineering venues). The second threat stems from the bias of individual researchers in assessing the primary studies they have been assigned. In the analysis, we use various methods to increase the trustworthiness of the results. By following this structure (i.e., by following a predetermined protocol and determining the differences collaboratively), we decrease the risk of assumptions biases.

External validity refers to the domain in which a study's findings are generalizable [48]. The scope of our systematic mapping study was on AIT within the interval 2010–2020. There may be limitations in generalizing our findings to broader time periods, or broader choices of primary research, for example, books and white papers. The results of our current study were drawn from qualitative analysis. To enable analytical and statistical generalizations, quantitative analysis can be considered to complement our findings.

4. Results

This section presents the results for each of the research questions as stated in Section 3.2. The grounds for the results are the papers found in the SMS. The number of papers that have been kept in each step described in Figure 2. It can be seen, that in the end 52 papers have been kept to fulfil the aim and the scope of this SMS and to answer the research questions. A complete list of papers included in the SMS can be found in Appendix A and on the online link [28].

4.1. Evaluation of methodological quality

The primary use of the MMAT tool in this SMS is to support the identification of empirical studies based on the screening questions. The 52 papers included in this review have been re-evaluated based on the MMAT quality criteria for these empirical studies. MMAT categorizes papers into: qualitative studies, quantitative randomized controlled trails, quantitative non-randomized studies, quantitative descriptive studies, and mixed-methods studies). We perform this categorization of the 52 included papers and assess their quality based on the MMAT methodological quality criteria.

We rate the papers into two groups: low methodological quality studies and high methodological quality studies. Studies which score 0 in one or more of the MMAT methodological quality criteria questions, are categorized as studies with a low methodological quality.

Studies which score 1 in all of the MMAT methodological quality criteria, are categorized as studies with a high methodological quality.

The MMAT-based quality assessment reveals that, for a subgroup of the qualitative studies (11 out of 33), the methodological quality is considered low. These studies are lacking adequate explanation of how the findings are derived from the data and an evaluation of whether the results are sufficiently substantiated by data. This implies that the credibility of the reported findings can be put into question. However, 22 out of the 33 qualitative studies are considered as studies with high methodological quality. In the quantitative group of papers, 7 studies out of 18 are considered to be of low methodological quality. These studies are lacking discussion about the risk of non-response bias, which can indicate that there are potential validity and reliability issues. The mixed-methods study is considered to be of high methodological quality. We conclude that a majority of the studies (63%) are of high methodological quality.

4.2. AI transformation conceptualization (RQ1)

Research question 1 (RQ1) concerns in which ways AIT is conceptualized in the literature. The motivation behind RQ1 is to find existing definitions of AIT in the literature, and to analyze these definitions to identify contradictions, similarities, or issues. This analysis can potentially be used to establish a common and useful definition for AIT.

Method description and motivation

This research question is explored using content analysis, which helps to reduce and organize large data to concrete concepts that describe a particular phenomenon [49]. It can be employed using both quantitative and qualitative approaches. It can be used inductively or deductively. Quantitative content analysis relies on the measurement instrument and its reliability, while qualitative content analysis relies on the knowledge and experience of the scholar [50].

Quantitative content analysis is defined as “the systematic, objective, quantitative analysis of message characteristics” [51], in this view content analysis is a quantitative method that includes human coding and computer text analysis. In addition, the quantitative content analysis approach does not rely on the researcher. Moreover, the empirical results can be reproduced if sufficient care has been taken during the design, execution, and reporting of the research. On the other hand, qualitative content analysis follows a similar coding process of a phenomenon, but mainly relies on the researcher’s comprehension of the text/context.

In this study, we apply both methods: first we perform an inductive content analysis (ICA) to improve our understanding of the existing definitions. Inductive content analysis is used when there is insufficient or fragmented knowledge about a particular phenomenon [52]. It is used as a tool to identify repetition or commonality of use of a word, phrase, or text which appears in a document. The concept of content analysis is to identify commonalities in the text, gather it into groups, and evolve understanding of it [53].

The process of ICA comprises three steps: preparation, organization, and reporting of results. In the preparation step, the focus is on collecting the data. In this study, the collection of data for the analysis is performed based on the guidelines by Kitchenham [39]. In total, 52 primary studies were included in the analysis. This process and the systematic procedure of the literature review strengthens the trustworthiness of the data collection [49].

We argue that the methods for selecting the data for the SMS ensure an acceptable level of trustworthiness for answering the research questions of our interest. In the organization step, we review the conceptualization of AIT in the literature. This is a crucial step in understanding the work that has been done within the field [54], and will help us to find common understanding, definitions, and keywords used.

Results and analysis

When reviewing the articles in the final selection, we find that only 21% ($n = 11$) include a clear definition of transformation related to technology. The remaining 79% ($n = 41$) articles discuss AI transformation without providing a definition.

We follow the abstraction process [52] and identify five general themes. The purpose of these themes is that they help us gain a better understanding of the different perspectives discussed related to AIT, which is the main topic of our investigation.

The first theme is focused on *transformation*, where emphasis is put on the process of change, and transition from the current state to a new state. This type of transition seems to usually happen in the form of evolution or revolution. The second theme, *fourth industrial revolution*, includes common phrases related to digital technologies that provide intelligent and innovative solutions, such as smart city, smart manufacturing, and smart agriculture. The third theme, *the organization and its environment*, consists of the forces that influence the organization's current status, such as adoption, adaptation, and integration of smart technologies. The fourth theme, *enterprise architecture* is focused on the way the organization strategizes and organizes, as well as its capabilities and structure. The last theme, *idea transformation*, concerns how organizations transform through ideation as a form of innovation. It can be radical, incremental, or a consequence of the ambidexterity of the organization.

The overview of AIT literature by means of categories indicates that prior studies lack an integrated approach to AIT and the associated challenges due to this transformation. The literature uses digital transformation as a common denominator for any kind of technological transformation. In all reviewed articles that discuss ideas related to AIT, the authors use digital transformation as a concept. However, digital transformation *per se* does not always involve AI. Hence, AI, in our view, is focused on smart technologies, intelligent machines which can work, act and have human-like abilities [55]. We follow the overarching definition of Russell and Norvig [24], which discusses the possibility of machine to perform as humans in terms of thought processes, reasoning, and behavior, i.e., intelligent systems that can think humanly, act humanly, and learn as humans.

We are unable to find any definition for AIT in the literature. One likely reason for this is the lack of a universal definition of AI. For example, depending on the context, AI is sometimes described as including areas such as machine learning, big data analytics, and even Internet of things. In other contexts, machine learning, natural language processing, and computer vision are described as sub areas of AI. Some definitions of AI assume the narrow, data-driven applied AI that is pervasive in many sectors today. Other definitions assume the general, human-like AI. There are definitions of AI that benchmark the level of intelligence by comparing with human performance. Other definitions assume objective measures of intelligence. These multiple views of intelligence and of AI are captured well in what could arguably be considered as the standard textbook on AI [24].

It is important to define and clarify the meaning of AI before defining AIT. Once a suitable definition of AI is adopted, it can serve as a starting point to define and describe AIT. We propose a definition of AIT in Section 5.

Evaluation of validity

We performed an additional quantitative content analysis of the abstracts and titles of the articles included in the study. We counted the frequencies of words (excluding punctuation and stop words) to explored the patterns and clusters of terms used. This quantitative content analysis is fully reproducible in that a researcher can perform the same analysis on the same abstract and title corpus and achieve identical results[2].

The top-20 most frequent words in the abstracts and titles of the articles included in this study are listed in Table 6 [28]. It is clear that the most frequent words correspond well together with the five manually identified themes. In Table 7, we report on an analysis of bigrams (consecutive written words) in the abstracts of the papers included in this study. When reviewing the list of most frequent bigrams, we identify a clear mapping to the five identified themes and, in addition, some key phrases related to academic research.

Table 6. The top-20 most frequent words in the abstracts and titles of the articles included in this study. For a full list of words, including common English language construct words (refer to the linked data sheet for more detailed information [28])

Word	Frequency	Word	Frequency
data	84	analytics	30
study	77	transformation	29
business	61	value	28
research	60	adoption	27
digital	52	paper	26
big	43	case	25
smart	40	technologies	24
technology	40	process	23
organizational	33	model	22
new	32	impact	21

Table 7. The top-20 most frequent bigrams (consecutive written words) in the abstracts of the articles included in this study

No.	Bigram	Frequency	No.	Bigram	Frequency
1	big data	45	11	originality value	11
2	artificial intelligence	20	12	publishing limited	11
3	data analytics	19	13	change management	10
4	digital transformation	19	14	data driven	10
5	dynamic capabilities	13	15	digital technologies	10
6	case study	12	16	firm performance	10
7	decision making	11	17	case studies	9
8	design methodology	11	18	industry 4.0	9
9	emerald publishing	11	19	smart manufacturing	8
10	methodology approach	11	20	business value	7

[2]The R scripts used to perform the content analysis are provided in the linked data sheet [28].

AI receives significant attention and the discussions on AI and its consequences are becoming more and more frequent. The question is what is actually known about such consequences. We argue that there is a need for a useful definition of AIT. The reason for this is that, unlike other forms of digital transformation, AI shifts cognitive work from human actors to computers. The consequences for many organizations are therefore likely be more significant. We also suggest more focused research related to specific AI technologies and their respective impact on organizations.

4.3. The main research methods used in AI transformation research (RQ2)

Research question 2 (RQ2) concerns which research methods are used in research related to AIT. The motivation behind RQ2 is that we want to acquire an understanding of *which* research methods are commonly used, as well as gaining more knowledge concerning *how* the methods are used and reported in published work. This allows us to assess the maturity of the research, and to characterize the existing body of knowledge generated in the field.

We review the 52 primary studies included in this study. The analysis reveals that there is a multitude of research designs employed in AIT research. The majority of research tends to be qualitative ($n = 33$) in nature. Also, 18 articles employ a quantitative approach, and one article uses a mixed-methods approach [28].

The quantitative studies are primarily based on surveys or questionnaires. Common analysis approaches include structural equation modeling and partial least squares, descriptive statistic, correlation analysis, and basic regression analysis.

The qualitative studies primarily use case studies and interviews as the method of data collection ($n = 21$). In some cases, secondary data are used for additional data collection. This document analysis involves, for example: white papers, archive documents, and other forms of documentation. Analysis is mainly performed through content analysis using various coding techniques. The use of data triangulation increases the credibility of the results. In these studies, the authors overcome a common bias that would occur when only one research method is used. However, it does not imply that the results can be generalized. In 33% of the qualitative studies ($n = 11$), the primary analysis method is not presented. For the purpose of scientific clarity and reproducibility, the full disclosure and motivation of the primary data analysis approach is paramount [56]. The lack of such descriptions and motivations significantly reduces the credibility of the findings, and the conclusions that have been drawn.

We identify one article which uses a mixed-methods approach to gather empirical data from a real-world setting (Stantec in Edmonton, Canada) [57]. In this article, a case study is performed. In the case study, interviews are combined with regular check-ins, document analysis with data mining, social network analysis, surveys, and a snowball sampling strategy. The use of mixed-methods to answer a specific research question provides both breadth and depth evidence [46]

In many cases, it is difficult to classify published empirical research articles in a simple, unambiguous way, according to which data collection and analysis method are used. One reason is that many published research articles do not provide clear descriptions of how the data collection and analysis are performed. Another reason is that some research articles use multiple methods for data collection and analysis. We identify which of the selected articles do not describe their analysis approaches ($n = 11$). We then study the remaining articles ($n = 41$) to extract any listed data collection or analysis method. We argue that our categorization is sufficiently correct to allow us to summarize the nature and maturity of the selected articles.

4.4. The theoretical perspectives and frameworks in the field (RQ2.1)

Research question 2.1 (RQ2.1) concerns which theories and frameworks are adopted in AIT research. The motivation behind RQ2.1 is that we identify AIT as inherently interdisciplinary. Due to this, theories and frameworks may come from multiple disciplines, which could make it difficult for a specific discipline to make sense of results and conclusions. An understanding of the underlying theories and frameworks of AIT enables the establishment of a unified framework, in which results, and conclusions could be reinterpreted by any discipline, and by stakeholders from the private and public sector.

The linked data sheet [28] describes the main theories and frameworks adopted in AIT research (see Figure 4 for a stacked bar graph of the 52 included papers). Out of 52 articles, 14 (26%) of the studies clearly mentioned the use of a theory, model, or framework. These 14 studies are found to use 19 different theories that can be grouped into three major categories. The first category uses theories/frameworks within the domain of business and economics: socio-technical systems, the contingency theory, network theory, the theory of the growth of the firm, the resource-based view, the organizational evolutionary theory, and the dynamic capabilities view theory.

The second category uses theories/frameworks within the domain of psychology: the stimulus-organism-response, the psychological reactance theory, decision making and mental models, and the information processing theory. Additionally, one can find theory that is

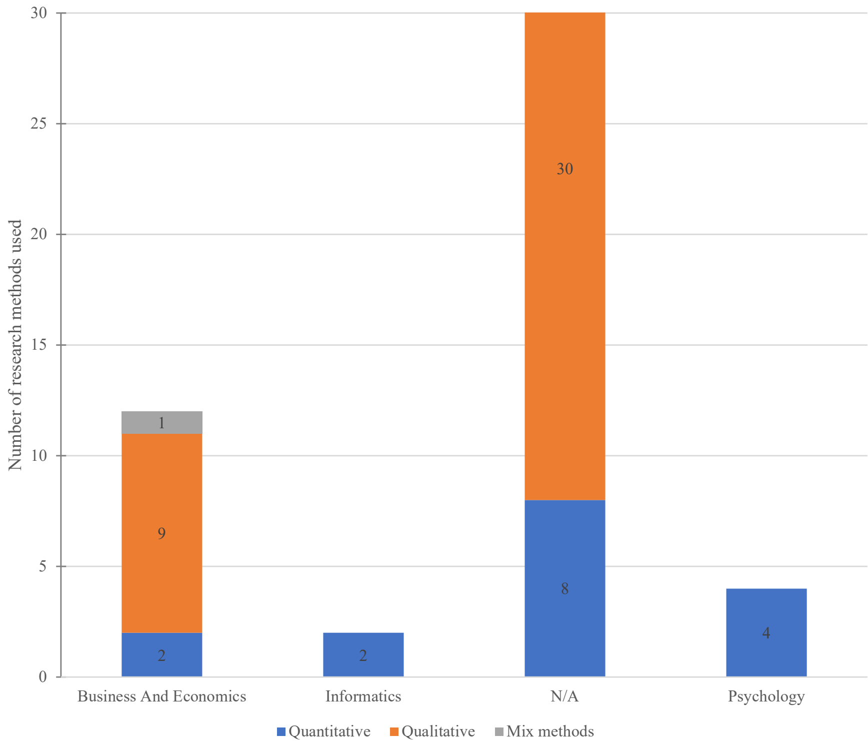

Figure 4. Stacked bar graph of the types of research methods used versus the theories used with respect to the 52 included papers

used within the domain of computer science and information technology, i.e., technology--organization-environment. In this category, we also decide to include the diffusion of innovations theory even though it can be related to various domains (e.g., business and economics, psychology, and so on).

We observe that 32 of the qualitative studies lack theoretical grounding, while only five of the quantitative and the mixed-methods studies do not discuss theoretical grounds (11 quantitative and 3 studies use theory a a foundation). Since qualitative studies tend to be more descriptive and generally not aim for statistical generalizability, the use of theory helps to clarify the logic behind the selected methods. Also, it allows the researcher to reveal existing biases about a study and support the researcher with the primary analysis and interpretation [58]. In quantitative studies, the theory is the foundation for testing and answering the research question, and the research design is built on identifying the theoretical framework that will support the research structure [59].

Based on the results of this SMS, we emphasize the need for more theory research focused on the impact of AIT on organization.

4.5. The real-world scenarios and contexts in AI transformation research (RQ2.2)

Research question 2.2 (RQ2.2) concerns which real-world scenarios and contexts are studied in AIT research. The motivation behind RQ2.2 is that we want to identify the extent or maturity of AIT in different domains, and to explore potentially unique characteristics related to AIT in these domains.

The analysis reveals that AIT research is conducted related to a number of industrial or societal domains. See Figure 5 for a horizontal bar chart of the 52 included papers. We categorize the domains into general segments and describe sectors. The categorization leads to four sectors: the industrial sector, the service sector, the knowledge sector, and the extraction sector. In the industrial sector, manufacturing is the most common industry discussed in the literature. In the service sector, the finance industry (banking, finance, accounting and auditing, and insurance) is the most frequently studied, followed by healthcare. The last two sectors are less represented. In the knowledge sector, high-tech and information technologies are the main industries discussed in the literature. In the

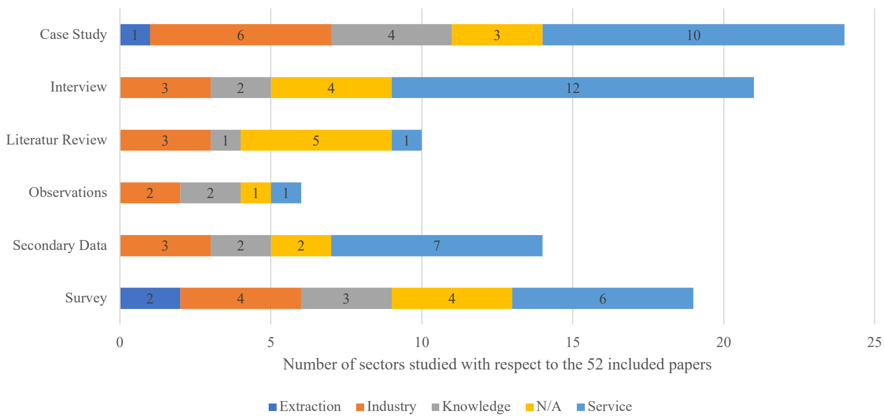

Figure 5. Horizontal bar chart of the types of data collection methods used versus the sector studied with respect to the 52 included papers

extraction sector the studied domains include agriculture, oil, and gas (refer to the linked data sheet for more detailed information [28]).

To identify the maturity of AIT research in different domains, we also review the distribution of papers in terms of publication venue. The 52 primary studies included in the review are published in 44 different journals that belong to 15 different focus areas. Of these 44 journals, 33 are ABS[3]-listed journals, and three are CORE[4]-listed journals. In addition, we present the three-citation indices based on Web of Science, which covers the articles in this study in Appendix B the linked data sheet [28]. In total, 21 articles are included in SSCI[5], 6 articles are listed SCIE[6], six articles are included in both, 7 articles are included in ESCI[7], and 4 articles are not listed in any index.

It is clear that AI is increasingly influential as technology area, and the results of this SMS shows the attention AIT has within various domains. We observe for the results that the most discussed sectors are the industrial sector (manufacturing), and the service sector, while big data analytics is the most researched AI technology when discussing AIT.

4.6. Future research (RQ3)

Research question 3 (RQ3) concerns the emerging questions for future research and the important research gaps in the area. It is important to identify the major trends of AIT research and to identify research gaps, as they seed new research opportunities. In addition, an ever-increasing number of organizations are looking into how to transform due to AI. The identified research gaps may allow new research that helps these organizations reap the benefits and mitigate the risks involved in AIT. The review of the 52 articles included in this study identifies potential opportunities for future research and outline future research directions related to AIT. This can be beneficial both to academics and professionals.We summarize the "future research" section from primary study, and we discuss the gaps appearing when mapping studies. We identify at least six avenues for future research.

Research methods

From a theoretical point of view, there is still a lot of potential for research in the field of AIT. The use of multiple measurement methods, or the use of various approaches to investigate AIT is suggested [60]. The use of mixed-methods approaches, increased sample sizes and in different industries would be of significant value [57]. In addition, future research could take alternative approaches, such as field experiments [61]. Moreover, the need to use various primary data collections to validate research findings and uncover

[3]ABS ranking list is a guide to the range and quality of journals in which business and management academics publish their research. Its purpose is to give both emerging and established scholars greater clarity as to which journals to aim for, and where the best work in their field tends to be clustered.

[4]CORE provides assessments of major journals in the computing disciplines (https://www.core.edu.au/home).

[5]SSCI, stands for Social Science Citation Index, which covers over 3,400 journals across 58 social sciences disciplines, as well as selected items from 3,500 of the world's leading scientific and technical journals (https://clarivate.com/webofsciencegroup/solutions/webofscience-ssci/).

[6]SCIE, stand for Science Citation Index Expanded which covers over 9,200 of the world's most impactful journals across 178 scientific disciplines (https://clarivate.com/webofsciencegroup/solutions/webofscience-scie/).

[7]ESCI, stands for Emerging Sources Citation Index which cover all disciplines and range from international and broad scope publications to those that provide deeper regional or specialty area coverage (https://clarivate.com/webofsciencegroup/solutions/webofscience-esci/).

the impact of AI is emphasized [62]. Furthermore, the importance of the use of various databases and sources is stressed [63]. More research is needed to strengthen the validity of smart technology transformation research [64].

Theoretical foundations

Future research should consider potential links to existing theories, which help to explain, predict, and understand AIT. The articles included in this study discuss potential opportunities for theoretical assumptions, which should be reviewed as a basis for investigation of organizational change fueled by smart technologies. Further research can be accomplished by the use of various theories related to the interaction, assessment and comparison of organizations ordinary capabilities vs. dynamic capabilities [65].

Societal aspects

Legal, ethical, societal, and economic changes which are the result of AIT are relevant for future investigation [66]. Legal and ethical considerations in relations to societal anticipation is an important aspect from an organizational perspective and it provides a broader perspective of the consequences concerning AI [11]. When studying AIT, researchers should consider the development of organizational and societal expectations, the outcomes related to opportunities, and the challenges involving AI. These factors and their implications from an organizational perspective, we argue, are highly relevant for future research.

The importance of ethical challenges related to smart technologies, new data sets, algorithms, and various AI solutions and machine learning is stressed [67]. Additional research, along those lines can be taken from different organizational perspectives (operation, strategy, structure, process, human labor, and so on). This may lead to an increase of the level of usage and understanding of the concept of AI. It is argued that an increased understanding of the factors that shape experiences on the transition age, not only of technological changes, but also of any social and economic changes, may lead to a better adaptation of smart technologies. It is further argued that there is a high value in the collaboration between academia and industry, which can help to identify business, technical, and societal challenges in the implementation of smart technologies [68].

The impact of adoption and adaption

The value of exploring the impact of investing in big data analytics to create higher-order capabilities or dynamic capabilities is discussed [62]. The impact of AI capabilities on firm performance should be studied from an organizational perspective, in a way which makes it possible to comprehend the importance AI personal expertise and AI infrastructure. In this way, organizations will be able to improve their business value and to gain a better understanding of AI. It is claimed that organizations, while adopting AI, should consider the impact on the firms [57]. A comparison of various findings and trends related to smart technologies can be beneficial to gain an understanding of the capabilities of smart technologies and its effect on the organization. Further research could explore the advantages and disadvantages of AI and its impact on organizational structures [57]. To extend the concept of technological transformation one should examine the adoption of one specific digital innovation in a particular organizational context, as well as verifying and elaborating on this particular context, and examine how boundary relations are reconfigured in other contexts and with other digital innovations [69].

The effect on human capital

The discussion on the effect of new technologies on human capital and organizations is not new, but rather a continuous discussion of previous industrial revolutions and changes in the labor market. It is stated that "any worker who now perform his task by following specific instructions can, in principle, be replaced by a machine" [70]. The authors further claim that physical jobs that disappear from the market as a result of the industrial revolution increase the need for the mental capacity of human labor and the importance of training and retraining of the labor to better anticipate future structural changes. The importance of creative imagination, entrepreneurship, and leadership are emphasized and viewed to be irreplaceable by a machine: "without creative imagination, neither art nor science could possibly advance" [70].

Furthermore, it is emphasized that an organization's future, based on new technologies, will cause some jobs to disappear [3]. But from the nature of capitalism (or humans) it will create other jobs which we cannot easily predict [3].

The user perspective plays a vital role in the way AI transforms. Future research that focus on potential moderators to the impacts of users' psychological reactance is suggested [71]. Moreover, it is pointed out that the most important factor in organizational transformation is not the technological but rather the managerial factor, along with employee attitudes [72]. A holistic view for future research is discussed, which should emphasize the need for collaboration between researchers and practitioners to contribute for clarifying the relevance of human resources in the firms' transformation and processes [73].

A focus is suggested on the reciprocal and symbiotic relationship between intelligent technologies and human capital, which will have a complementary role in the future organization [74]. The investment made in organizations to develop new technologies, or implementing new technologies such as AI, leads to investments in human capital in a way that can complement and support the decision-making. However, this type of human capital, that is complementary to AI decision support, is not adequately researched or identified. It is emphasized that future research should emphasize and compare the behavior of employees and managers in the context of delegation of strategic decision to a human being or an algorithm [75].

Complementary contexts

Smart technologies and their effects on the organization are investigated in various contexts. To enable a thorough understanding of AIT further research can be taken in various contextual basis. Published studies could be repeated in developing countries and different industries and sectors, or to compare between organizations of similar size [22]. Similar ideas are suggested that urge to also test conceptual models and theories in various service industries [71]. The research around AIT should extend the target research areas and cover more regions such as specific European and American countries to compare findings in emerging and developed economies and to increase generalizability [76].

5. Discussion

5.1. Understanding and defining AI transformation

In the last sections, we elaborate on our impetus for conducting an SMS on AIT, as a key concept for incremental and radical change that will lead to a transformation in the organization. AI and its technologies (for example: computer vision, machine learning, natural language processing, and robotics) are reshaping organizational structure, processes, organizational learning, work routines, knowledge management, products, and services [37]. AI involves both challenges and immense opportunities, its capability to manage information and knowledge required change in organizations culture, mindset and skills and organization that will understand and act on it will probably get a competitive advantage. AI counter business, and the reciprocity relations, and influence it has on each other is discussed [77]. AI changes organizations, but organizations influence the way AI develops. Understanding this link between the two is highly relevant from a research perspective.

Researchers from various disciplines should collaborate to understand and improve the connection between the technology and the organization. AI and its effects on the organization is unavoidable [23], however, it is important to understand the concept of AI and its implications, while understanding its relationship to the organizational structure, leadership, culture, vision, and mission and the human attributes within the organization.

In this SMS, we aggregate the body of knowledge on the relationship between AI and organizational transformation, map the field, and identify the research gaps that represent opportunities for future studies. Our SMS follows Kitchenham's suggestions on conducting an SMS [39] and identifies 52 articles published in various journals. We present three main research questions and adopt both qualitative and quantitative approaches based on the analysis of the 52 articles to increase the trustworthiness of this study, and to give a thorough understanding of the phenomenon from different perspectives. In addition, the use of both methods was complementary; the strengths of one approach supplemented the weaknesses of another [78].

In general, from the review, we observe that MMAT reveals that very little empirical research is conducted on the topic of the SMS. We find that the topic is discussed in various academic disciplines and uses various methods, and theories, however only a few use established theories. We identify a number of themes as discussed in Section 4: The organization and its environment, enterprise architectures, idea transformation, and the fourth industrial revolution. Four sectors were identified: The industrial sector, the service sector, the knowledge sector, and the extraction sector (agriculture, oil, and gas). However, the most discussed sectors were the industrial sector and the service sector, while big data analytics is the most reviewed AI technology when discussing AIT.

However, we were unable to find a concise and useful definition of AIT. The available research that brings up this phenomenon is often focusing on digital transformation, and there is a substantial scientific discussion around digital transformation but few studies focused only on AI. However, we emphasize the need for a definition of AIT. The reason for this is that, unlike other forms of digital transformation, AI will clearly shift cognitive work from human actors to computers. The consequences for many organizations is significant.

We view AIT as an interdisciplinary phenomenon. In this context, we thus define AIT as:

Definition 1. *the ongoing change in organizational dimensions (strategy, structure, people, technology and processes), subject to constraints and interests of external forces (customers, suppliers, partners, competitors, regulators), and manifested in AI readiness.*

This division into organizational dimensions and external forces is suggested in an existing work on e-business transformation [79]. In this definition, **organizational dimensions** refer to strategy as the way organizations determine their goals, their actions, the implementation, and the resource allocation required for achieving these goals [80]. The *structure* is the way an organization is designed and the way it administrates, which is linked to the effectiveness, the coordination, and the communication of the organization [80]. The organizational *processes* are linked with the *strategy* and *structure*. The processes are essentially sequences of tasks, distributed in time and space. They are required to assign tasks to people and to accomplish these tasks [81]. The external forces are uncontrollable factors that can influence an organization. AI *technology* can refer to either the actual hardware and software systems which are based on AI, or to the knowledge, skills, and processes required to apply AI in the real world. These definitions of AI technology are based on typical definitions of technology (see for example [82]). Most researchers discuss the internal dimensions and the external forces as two separate agents of change. In our view, AIT occurs when one or more of the organizational dimensions or the external forces change due to the use of AI technologies. Transformation, on the one hand, can be of a revolutionary nature, where the organization changes radically and quickly along one or more of the organizational dimensions. On the other hand, transformation can also be of a gradual or incremental nature, where the organization, in a discontinuous way, respond to basic changes in its environment [83]. An organization that has a clear sense of its position along the organizational dimensions is able to align itself properly to external factors.

The AIT Playbook[8] discusses the journey of a successful organization's transformation, and the leveraging of AI capabilities to significantly advance, due to the use of AI technologies. Our definition of AIT is concretely connected to the knowledge and insights about successful AIT provided in the playbook. The AI transformation playbook describes various relevant organizational aspects (for example: resources, AI expertise, up-skilling people, adjustment of processes and strategy).

Our definition categorizes these aspects into organizational dimensions. It also adds the perspective of external forces (interests and constraints originating from outside the organization), and introduces AI readiness to quantify the level of fulfilment of the transformation. We argue that our definition provides the research community with a clear description, which can be criticised, elaborated upon, and used to frame future work. It also provides organizations with a foundation for their AI journey and a basis for evaluation of the progress.

6. Conclusions

In this study, we systematically review the field of AI and organizational transformation, and provide a thorough understanding of the field. By doing so, we identify gaps in research that represent potential opportunities for future study. Despite the popularity and attention related to AI and its effects on organizations, this Systematic mapping study (SMS) shows

[8]AI Transformation Playbook, https://landing.ai/ai-transformation-playbook/

that the number of studies discussing this topic are opinion papers rather than scientific research papers.

The results reveal that there is no existing useful definition of AIT and that in the sample we identify there are few empirical research papers. Existing work on AIT originates from various academic disciplines and domains. This shows that AI is interdisciplinary in its nature and that it has impacts on various domains and industries. AIT researchers are mainly using qualitative methods. We provide a new definition for AIT and attempt to consolidate and relate existing work from the various disciplines and domains. We also observe a clear need for research using mixed methods approaches.

This Systematic mapping study enriches the current state-of-the-art knowledge regarding AIT research. We propose several directions for future research, including: a Systematic mapping study to determine, for each specific AI technology, how it transforms organizations. Another proposed direction for future work is to explore how one particular dimension of the organization (i.e., strategy, structure, people, technology, processes) transform based on the implementation of AI technology. It could be interesting to look into AIT in various contexts, such as: private sector vs. public sector, different industries, different size of organization and the context of various countries (developing countries vs. industrialized countries and so on). The use of mixed-methods research approaches to investigate AIT will give a more broad view about this phenomenon.

This SMS reveal that there is a substantial scientific discussion around digital transformation, but only few works discuss the concept of AIT. In this SMS we develop a definition for AIT. This definition can be used as a foundation for future work involving the impact of AI on organizations.

The selected 52 papers in this SMS should be interesting for industry, academia and public sector since it may contain relevant information for practitioners. We believe that the results of this SMS can be a foundation for improvements of the collaboration between these three actors. The university responsibility should be knowledge production, the industry is responsible for market and economic production and exchange, and the government stands for policy making.

The results introduced in these papers can provide valuable insight for organizations which are adopting AI.

References

[1] J. Holmstrom, "From AI to digital transformation: The AI readiness framework," *Business Horizons*, 2021.

[2] U. Lichtenthaler, "Beyond artificial intelligence: Why companies need to go the extra step," *Journal of Business Strategy*, 2018.

[3] E. Brynjolfsson, *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* Norton and Company, 2014.

[4] J. Maclure and S. Russell, *AI for Humanity: The Global Challenges.* Springer International Publishing, 2021, pp. 116–126.

[5] R.C. Schank, "Where's the AI?" *AI Magazine*, Vol. 12, No. 4, 1991.

[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, Vol. 521, No. 7553, 2015, pp. 436–444.

[7] E. Ntoutsi, "Bias in data-driven artificial intelligence systems – An introductory survey," *WIREs Data Mining and Knowledge Discovery*, 2020.

[8] C. Anderson, *Creating a data-driven organization: Practical advice from the trenches.* O'Reilly Media, Inc., 2015.

[9] N. Zolas, Z. Kroff, E. Brynjolfsson, K. McElheran, D. Beede et al., "Advanced technologies adoption and use by u.s. firms: Evidence from the annual business survey," National Bureau of Economic Research, Working Paper 28290, 2020.
[10] M. Cubric, "Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study," *Technology in Society*, Vol. 62, 2020, pp. 101–257.
[11] S. Akter, K. Michael, M. Uddin, G. McCarthy, and M. Rahman, "Transforming business using digital innovations: The application of AI, blockchain, cloud, and data analytics," *Annals of Operations Research*, 2020, pp. 1–33.
[12] F. Khanboubi and A. Boulmakoul, "Digital transformation in the banking sector: Surveys exploration and analytics," *International Journal of Information Systems and Change Management*, Vol. 11, No. 2, 2019, pp. 93–127.
[13] L. Achtenhagen, L. Melin, and L. Naldi, "Dynamics of business models – Strategizing, critical capabilities and activities for sustained value creation," *Long Range Planning*, Vol. 46, No. 6, 2013, pp. 427–442.
[14] S. Makridakis, "The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms," *Futures*, Vol. 90, 2017, pp. 46–60.
[15] A. Schumacher, S. Erol, and W. Sihn, "A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises," *Procedia Cirp*, Vol. 52, 2016, pp. 161–166.
[16] H.A. Simon, *Administrative Behavior: A Study of Decision-making Processes in Administrative Organization*, 3rd ed. Free Press, 1976.
[17] A. Ebbage, "Banking on artificial intelligence," *Engineering and Technology*, Vol. 13, No. 10, 2018, pp. 66–69.
[18] H. David, "Why are there still so many jobs? The history and future of workplace automation," *Journal of Economic Perspectives*, Vol. 29, No. 3, 2015, pp. 3–30.
[19] M. Polanyi, *The Tacit Dimension*. University of Chicago Press, 2009.
[20] E. Sadler-Smith and E. Shefy, "The intuitive executive: Understanding and applying 'gut feel' in decision-making," *Academy of Management Perspectives*, Vol. 18, No. 4, 2004, pp. 76–91.
[21] M. Tegmark, *Life 3.0: Being Human in the Age of Artificial Intelligence*, 1st ed. Alfred A. Knopf, 2017.
[22] P. Maroufkhani, W.K.W. Ismail, and M. Ghobakhloo, "Big data analytics adoption model for small and medium enterprises," *Journal of Science and Technology Policy Management*, Vol. 11, No. 4, 2020, pp. 483–513.
[23] S.L. Wamba-Taguimdje, S.F. Wamba, J.R.K. Kamdjoug, and C.T. Wanko, "Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects," *Business Process Management Journal*, Vol. 26, No. 7, 2020.
[24] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Pearson Education, 2016.
[25] L. Deng, "Artificial intelligence in the rising wave of deep learning: The historical path and future outlook [perspectives]," *IEEE Signal Processing Magazine*, Vol. 35, No. 1, 2018, pp. 180–177.
[26] J. Lee, H. Davari, J. Singh, and V. Pandhare, "Industrial artificial intelligence for industry 4.0-based manufacturing systems," *Manufacturing Letters*, Vol. 18, 2018, pp. 20–23.
[27] E.P.R. Service, "The ethics of artificial intelligence: Issues and initiatives," European Parliament, Tech. Rep., 2020.
[28] E. Peretz-Andersson, "AI transformation: A systematic literature review (linked data sheet)," https://osf.io/3afw6/?view_only=fd36e2c55f044f1abe55e6e9d1d0f852, 2021, [Online; accessed 2021-05-21].
[29] F. Li, "The digital transformation of business models in the creative industries: A holistic framework and emerging trends," *Technovation*, Vol. 92, 2020, p. 102012.
[30] L. Heilig, E. Lalla-Ruiz, and V. Stefan, "Digital transformation in maritime ports: Analysis and a game theoretic framework," *Netnomics: Economic research and electronic networking*, Vol. 18, No. 2, 2017, pp. 227–254.
[31] A. Nadeem, B. Abedin, N. Cerpa, and E. Chew, "Digital transformation and digital business strategy in electronic commerce-the role of organizational capabilities," 2018, pp. 1–8.

[32] D. Anderson and L.A. Anderson, *Beyond Change Management: Advanced Strategies for Today's Transformational Leaders*. John Wiley and Sons, 2002.
[33] H. Tsoukas and R. Chia, "On organizational becoming: Rethinking organizational change," *Organization Science*, Vol. 13, No. 5, 2002, pp. 567–582.
[34] H. Mintzberg and F. Westley, "Cycles of organizational change," *Strategic Management Journal*, Vol. 13, No. S2, 1992, pp. 39–59.
[35] H. Arazmjoo and H. Rahmanseresht, "A multi-dimensional meta-heuristic model for managing organizational change," *Management Decision*, Vol. 58, No. 3, 2019, pp. 526–543.
[36] M.L. Tushman and C.A. O'Reilly III, "Ambidextrous organizations: Managing evolutionary and revolutionary change," *California Management Review*, Vol. 38, No. 4, 1996, pp. 8–29.
[37] P. Weill and S.L. Woerner, "Is your company ready for a digital future?" *MIT Sloan Management Review*, Vol. 59, No. 2, 2018, pp. 21–25.
[38] R. Ramilo and M.R.B. Embi, "Critical analysis of key determinants and barriers to digital innovation adoption among architectural organizations," *Frontiers of Architectural Research*, Vol. 3, No. 4, 2014, pp. 431–451.
[39] B. Kitchenham, "Procedures for performing systematic reviews," Keele University, UK, Tech. Rep., 2004.
[40] R. Mallett, J. Hagen-Zanker, R. Slater, and M. Duvendack, "The benefits and challenges of using systematic reviews in international development research," *Journal of Development Effectiveness*, Vol. 4, No. 3, 2012, pp. 445–455.
[41] K. Petersen, S. Vakkalanka, and L. Kuzniarz, "Guidelines for conducting systematic mapping studies in software engineering: An update," *Information and Software Technology*, Vol. 64, 2015, pp. 1–18.
[42] A. Bajaj and O.P. Sangwan, "A systematic literature review of test case prioritization using genetic algorithms," *IEEE Access*, Vol. 7, No. 126355–126375, 2019.
[43] I.M. Côté, P.S. Curtis, H.R. Rothstein, and G.B. Stewart, "Gathering data: searching literature and selection criteria," *Handbook of meta-analysis in ecology and evolution*, 2013, pp. 37–51.
[44] D. Moher, A. Liberati, J. Tetzlaff, D.G. Altman, and P. Group, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLoS Medicine*, Vol. 6, No. 7, 2009.
[45] A.F. Hayes and K. Krippendorff, "Answering the call for a standard reliability measure for coding data," *Communication Methods and Measures*, Vol. 1, No. 1, 2007, pp. 77–89.
[46] Q.N. Hong, P. Pluye, S. Fàbregues, G. Bartlett, F. Boardman et al., "Mixed methods appraisal tool (MMAT)," McGill University, Tech. Rep., 2018.
[47] C. Wohlin, "Guidelines for snowballing in systematic literature studies and a replication in software engineering," in *18th International Conference on Evaluation and Assessment in Software Engineering*. ACM Press, 2014, pp. 1–10.
[48] T.D.Cook, D. Campbell, and W.R.Shadish, *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin Boston, MA, 2002.
[49] S. Elo, M. Kääriäinen, O. Kanste, T. Pölkki, K. Utriainen et al., "Qualitative content analysis: A focus on trustworthiness," *SAGE Open*, 2014, pp. 1–10.
[50] U. Flick, *The SAGE Handbook of Qualitative Data Analysis*. Sage, 2013.
[51] K.A. Neuendorf, *The Content Analysis Guidebook*, 2nd ed. SAGE, 2017.
[52] S. Elo and H. Kyngäs, "The qualitative content analysis process," *Journal of Advanced Nursing*, Vol. 62, No. 1, 2008, pp. 107–115.
[53] M. Bengtsson, "How to plan and perform a qualitative study using content analysis," *NursingPlus Open*, Vol. 2, 2016, pp. 8–14.
[54] J. vom Brocke, A. Simons, B. Niehaves, B. Niehaves, K. Riemer et al., "Reconstructing the giant: On the importance of rigour in documenting the literature search process," in *17th European Conference on Information Systems*, 2009, pp. 2206–2217.
[55] A.C. Serban and M.D. Lytras, "Artificial intelligence for smart renewable energy sector in Europe – Smart energy infrastructures for next generation smart cities," *IEEE Access*, Vol. 8, 2020, pp. 77 364–77 377.

[56] M. Allen, *The SAGE encyclopedia of Communication Research Methods*. Sage Publications, 2017.
[57] M.M. Bonanomi, D.M. Hall, S. Staub-French, A. Tucker, and C.M.L. Talamo, "The impact of digital transformation on formal and informal organizational structures of large architecture and engineering firms," *Engineering, Construction, and Architectural Management*, Vol. 27, No. 4, 2019, pp. 872–892.
[58] C.S. Collins and C.M. Stockton, "The central role of theory in qualitative research," *International Journal of Qualitative Methods*, Vol. 17, 2018, pp. 1–10.
[59] J.W. Creswell and J.D. Creswell, *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage, 2018.
[60] M. Jocevski, N. Arvidsson, G. Miragliotta, A. Ghezzi, and R. Mangiaracina, "Transitions towards omni-channel retailing strategies: A business model perspective," *International Journal of Retail and Distribution Management*, Vol. 47, No. 2, 2019, pp. 78–93.
[61] X. Fan, N. Ning, and N. Deng, "The impact of the quality of intelligent experience on smart retail engagement," *Marketing Intelligence and Planning*, Vol. 38, No. 7, 2020, pp. 877–891.
[62] S.F. Wamba and S. Akter, "Understanding supply chain analytics capabilities and agility for data-rich environments," *International Journal of Operations and Production Management*, Vol. 39, No. 6–8, 2019, pp. 887–912.
[63] G. Elia, G. Polimeno, G. Solazzo, and G. Passiante, "A multi-dimension framework for value creation through big data," *Industrial Marketing Management*, Vol. 90, 2020, pp. 508–522.
[64] K. Tiwari and M.S. Khan, "Sustainability accounting and reporting in the industry 4.0," *Journal of Cleaner Production*, Vol. 258, 2020.
[65] Y. Gong and M. Janssen, "Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation," *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 16, No. 1, 2021, pp. 37–51.
[66] T. Nam, "Technology usage, expected job sustainability, and perceived job insecurity," *Technological Forecasting and Social Change*, Vol. 138, 2019, pp. 155–165.
[67] P. Dahlbom, N. Siikanen, P. Sajasalo, and M. Jarvenpää, "Big data and HR analytics in the digital era," *Baltic Journal of Management*, Vol. 15, No. 1, 2020.
[68] M. Gotthardt, D. Koivulaakso, O. Paksoy, C. Saramo, M. Martikainen et al., "Current state and challenges in the implementation of smart robotic process automation in accounting and auditing," *ACRN Journal of Finance and Risk Perspectives*, Vol. 9, 2020, pp. 90–102.
[69] M. Barrett, E. Oborn, W.J. Orlikowski, and J. Yates, "Reconfiguring boundary relations: Robotic innovations in pharmacy work," *Organization Science*, Vol. 23, No. 5, 2011, pp. 1448–1466.
[70] W. Leontief, *The Long-Term Impact of Technology on Employment and Unemployment*. The National Academies Press, 1983.
[71] W. Feng, R. Tu, and Z. Zhou, "Understanding forced adoption of self-service technology: The impacts of users' psychological reactance," *Behaviour and Information Technology*, Vol. 38, No. 8, 2019, pp. 820–832.
[72] D.J. Bowersox, D.J. Closs, and R. Drayer, "The digital transformation: Technology and beyond," *Supply Chain Management Review*, Vol. 9, No. 1, 2005, pp. 22–29.
[73] F. Caputo, V. Cillo, E. Candelo, and Y. Liu, "Innovating through digital revolution: The role of soft skills and big data in increasing firm performance," *Management Decision*, Vol. 57, No. 8, 2019, pp. 2032–2051.
[74] K. Conboy, P. Mikalef, D. Dennehy, and J. Krogstie, "Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda," *European Journal of Operational Research*, Vol. 281, No. 3, 2020, pp. 656–672.
[75] S. Schneider and M. Leyer, "Me or information technology? Adoption of artificial intelligence in the delegation of personal strategic decisions," *Managerial and Decision Economics*, Vol. 40, No. 3, 2019, pp. 223–231.
[76] W.E. Hilali, A.E. Manouar, and M.A. Idrissi, "Reaching sustainability during a digital transformation: A PLS approach," *International Journal of Innovation Science*, Vol. 12, No. 1, 2020, pp. 52–79.

[77] C.D. Francescomarino and F.M. Maggi, “Preface to the special issue on business process innovations with artificial intelligence,” *Journal on Data Semantics*, Vol. 8, 2019, pp. 77–77.
[78] A. Regnault, T.Willgoss, and S. Barbic, “Towards the use of mixed methods inquiry as best practice in health outcomes research,” *Journal of Patient-Reported Outcomes*, Vol. 2, No. 19, 2018.
[79] A. Farhoomand and R. Wigand, “Editorial: Special section on managing e-business transformation,” *European Journal of Information Systems*, Vol. 12, 2003, pp. 249–250.
[80] A.D. Chandler, *Strategy and Structure: Chapters in the History of the Industrial Enterprise*, 3rd ed. MIT Press, 2013.
[81] B.T. Pentland, C.S. Osborn, G. Wyner, and F. Luconi, *Useful Descriptions of Organizational Processes: Collecting Data for the Process Handbook.* Center for Coordination Science, Massachusetts Institute of Technology, USA, 1999.
[82] R. Bain, “Technology and state government,” *American Sociological Review*, Vol. 2, No. 6, 1937, pp. 860–874.
[83] E.Romanelli and M. Tushman, “Organizational transformation as punctuated equilibrium: An empirical test,” *Academy of Management Journal*, Vol. 37, No. 5, 1994, pp. 1141–1166.
[84] Y. Chen and Z. Lin, “Business intelligence capabilities and firm performance: A study in China,” *International Journal of Information Management*, Vol. 57, 2021, p. 102232.
[85] M. Aboelmaged and S. Mouakket, “Influencing models and determinants in big data analytics research: A bibliometric analysis,” *Information Processing and Management*, Vol. 57, No. 4, 2020, p. 102234.
[86] R. Balakrishnan and S. Das, “How do firms reorganize to implement digital transformation?” *Strategic Change*, Vol. 29, No. 5, 2020, pp. 531–541.
[87] F. Brunetti, D.T. Matt, A. Bonfanti, A.D. Longhi, G. Pedrini et al., “Digital transformation challenges: Strategies emerging from a multi-stakeholder approach,” *The TQM Journal*, Vol. 32, No. 4, 2020, pp. 697–724.
[88] C. Dremel, M.M. Herterich, J. Wulf, and J. vom Brocke, “Actualizing big data analytics affordances: A revelatory case study,” *Information and Management*, Vol. 57, No. 1, 2020, p. 103121.
[89] J. Lee and D. Kim, “Development of innovative business of telecommunication operator: Case of KT-MEG,” *International Journal of Asian Business and Information Management (IJABIM)*, Vol. 11, No. 3, 2020, pp. 1–14.
[90] P. Mikalef, J. Krogstie, I. Pappas, and P. Pavlou, “Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities,” *Information and Management*, Vol. 57, No. 2, 2020, p. 103169.
[91] K. Moore, “Smart connected sensors, cyber-physical networks, and big data analytics systems in internet of things-based real-time production logistics,” *Economics, Management, and Financial Markets*, Vol. 15, No. 2, 2020, pp. 16–22.
[92] N. Nguyen, R. Gosine, and P. Warrian, “A systematic review of big data analytics for oil and gas industry 4.0,” *IEEE Access*, Vol. 8, 2020, pp. 61 183–61 201.
[93] P. Osterrieder, L. Budde, and T. Friedli, “The smart factory as a key construct of industry 4.0: A systematic literature review,” *International Journal of Production Economics*, Vol. 221, 2020, p. 107476.
[94] R. Silva, C. Bernardo, C. Watanabe, R. Silva, and J. Neto, “Contributions of the internet of things in education as support tool in the educational management decision-making process,” *International Journal of Innovation and Learning*, Vol. 27, No. 2, 2020, pp. 175–196.
[95] M. Sott, L. Furstenau, L. Kipper, F. Giraldo, J. López-Robles et al., “Precision techniques and agriculture 4.0 technologies to promote sustainability in the coffee sector: State of the art, challenges and future trends,” *IEEE Access*, Vol. 8, 2020, pp. 149 854–149 867.
[96] A. Tuomi, I. Tussyadiah, E. Ling, G. Miller, and L. Geunhee, “x=(tourism_work) y=(sdg8) while y= true: automate (x),” *Annals of Tourism Research*, Vol. 84, 2020, p. 102978.
[97] Z. Zhang and T. Luo, “Knowledge structure, network structure, exploitative and exploratory innovations,” *Technology Analysis and Strategic Management*, Vol. 32, No. 6, 2020, pp. 666–682.

[98] J. Brock and F.V. Wangenheim, “Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence,” *California Management Review*, Vol. 61, No. 4, 2019, pp. 110–134.
[99] D. Kalaivani and P. Sumathi, “Factor based prediction model for customer behavior analysis,” *International Journal of System Assurance Engineering and Management*, Vol. 10, No. 4, 2019, pp. 519–524.
[100] R. Leung, “Smart hospitality: Taiwan hotel stakeholder perspectives,” *Tourism Review*, 2019.
[101] S. Magistretti, C. Dell’Era, and A. Messeni Petruzzelli, “How intelligent is Watson? Enabling digital transformation through artificial intelligence,” *Business Horizons*, Vol. 62, No. 6, 2019, pp. 819–829.
[102] A. Mitra, S. Gaur, and E. Giacosa, “Combining organizational change management and organizational ambidexterity using data transformation,” *Management Decision*, 2019.
[103] L. Pee, S. Pan, and L. Cui, “Artificial intelligence in healthcare robots: A social informatics study of knowledge embodiment,” *Journal of the Association for Information Science and Technology*, Vol. 70, No. 4, 2019, pp. 351–369.
[104] A. Thomas, “Convergence and digital fusion lead to competitive differentiation,” *Business Process Management Journal*, 2019.
[105] K. Warner and M. Wäger, “Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal,” *Long Range Planning*, Vol. 52, No. 3, 2019, pp. 326–349.
[106] C. Lehrer, A. Wieneke, J.V. Brocke, R. Jung, and S. Seidel, “How big data analytics enables service innovation,” *Journal of Strategic Information Systems*, Vol. 35, No. 2, 2018.
[107] R. Torres, A. Sidorova, and M. Jones, “Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective,” *Information and Management*, Vol. 55, No. 7, 2018, pp. 822–839.
[108] H. Chen, R. Schütz, R. Kazman, and F. Matthes, “How Lufthansa capitalized on big data for business model renovation.” *MIS Quarterly Executive*, Vol. 16, No. 1, 2017.
[109] A. Gunasekaran, T. Papadopoulos, R. Dubey, S. Wamba, S. Childe et al., “Big data and predictive analytics for supply chain and organizational performance,” *Journal of Business Research*, Vol. 70, 2017, pp. 308–317.
[110] R. Basole, “Accelerating digital transformation: Visual insights from the API ecosystem,” *IT Professional*, Vol. 18, No. 6, 2016, pp. 20–25.
[111] M. Hengstler, E. Enkel, and S. Duelli, “Applied artificial intelligence and trust – The case of autonomous vehicles and medical assistance devices,” *Technological Forecasting and Social Change*, Vol. 105, 2016, pp. 105–120.
[112] M. Chalal, X. Boucher, and G. Marquès, “Decision support system for servitization of industrial SMEs: A modelling and simulation approach,” *Journal of Decision Systems*, Vol. 24, No. 4, 2015, pp. 355–382.
[113] P. O’Donovan, K. Leahy, K. Bruton, and D. O’Sullivan, “An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities,” *Journal of Big Data*, Vol. 2, No. 1, 2015, pp. 1–26.
[114] P. O’Donovan, K. Leahy, K. K. Bruton, and D. O’Sullivan, “Big data in manufacturing: A systematic mapping study,” *Journal of Big Data*, Vol. 2, No. 1, 2015, pp. 1–22.
[115] S. LaValle, E. Lesser, R. Shockley, M. Hopkins, and N. Kruschwitz, “Big data, analytics and the path from insights to value,” *MIT Sloan Management Review*, Vol. 52, No. 2, 2011, pp. 21–32.

Appendix A. List of selected articles

Author	Title	Year
Chen and Lin [84]	Business intelligence capabilities and firm performance: A study in China	2021
Gong and Janssen [65]	Roles and capabilities of enterprise architecture in big data analytics technology adoption and implementation	2021
Aboelmaged and Mouakket [85]	Influencing models and determinants in big data analytics research: A bibliometric analysis	2020
Akter et al. [11]	Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics	2020
Balakrishnan and Das [86]	How do firms reorganize to implement digital transformation?	2020
Brunetti et al. [87]	Digital transformation challenges: Strategies emerging from a multi-stakeholder approach	2020
Conboy et al. [74]	Using business analytics to enhance dynamic capabilities in operations research: A case analysis and research agenda	2020
Dremel et al. [88]	Actualizing big data analytics affordances: A revelatory case study	2020
Elia et al. [63]	A multi-dimension framework for value creation through big data	2020
Fan et al. [61]	The impact of the quality of intelligent experience on smart retail engagement	2020
Gotthardt et al. [68]	Current state and challenges in the implementation of smart robotic process automation in accounting and auditing	2020
Hilali et al. [76]	Reaching sustainability during a digital transformation: A PLS approach	2020
Lee and Kim [89]	Development of innovative business of telecommunication operator: Case of KT-MEG	2020
Maroufkhani et al. [22]	Big data analytics adoption model for small and medium enterprises	2020
Mikalef et al. [90]	Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities	2020
Moore [91]	Smart connected sensors, cyber-physical networks, and big data analytics systems in internet of things-based real-time production logistics	2020
Nguyen et al. [92]	A systematic review of big data analytics for oil and gas industry 4.0	2020
Osterrieder et al. [93]	The smart factory as a key construct of industry 4.0: A systematic literature review	2020
Serban and Lytras [55]	Artificial intelligence for smart renewable energy sector in Europe – Smart energy infrastructures for next generation smart cities	2020
Silva et al. [94]	Contributions of the internet of things in education as support tool in the educational management decision-making process	2020

Author	Title	Year
Sott et al. [95]	Precision techniques and agriculture 4.0 technologies to promote sustainability in the coffee sector: State of the art, challenges and future trends	2020
Tiwari and Khan [64]	Sustainability accounting and reporting in the industry 4.0	2020
Tuomi et al. [96]	x=(tourism_work) y=(sdg8) while y= true: automate (x)	2020
Wamba-Taguimdje et al. [23]	Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects	2020
Zhang and Luo [97]	Knowledge structure, network structure, exploitative and exploratory innovations	2020
Bonanomi et al. [57]	The impact of digital transformation on formal and informal organizational structures of large architecture and engineering firms	2019
Brock and von Wangenheim [98]	Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence	2019
Caputo et al. [73]	Innovating through digital revolution: The role of soft skills and big data in increasing firm performance	2019
Dahlbom et al. [67]	Big data and HR analytics in the digital era	2019
Feng et al. [71]	Understanding forced adoption of self-service technology: The impacts of users' psychological reactance	2019
Jocevski et al. [60]	Transitions towards omni-channel retailing strategies: A business model perspective	2019
Kalaivani and Sumathi [99]	Factor based prediction model for customer behavior analysis	2019
Leung [100]	Smart hospitality: Taiwan hotel stakeholder perspectives	2019
Magistretti et al. [101]	How intelligent is Watson? Enabling digital transformation through artificial intelligence	2019
Mitra et al. [102]	Combining organizational change management and organizational ambidexterity using data transformation	2019
Nam [66]	Technology usage, expected job sustainability, and perceived job insecurity	2019
Pee et al. [103]	Artificial intelligence in healthcare robots: A social informatics study of knowledge embodiment	2019
Schneider and Leyer [75]	Me or information technology? Adoption of artificial intelligence in the delegation of personal strategic decisions	2019
Thomas [104]	Convergence and digital fusion lead to competitive differentiation	2019
Wamba and Akter [62]	Understanding supply chain analytics capabilities and agility for data-rich environments	2019
Warner and Wäger [105]	Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal	2019
Lehrer et al. [106]	How big data analytics enables service innovation	2018
Torres et al. [107]	Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective	2018
Chen et al. [108]	How Lufthansa capitalized on big data for business model renovation	2017

Author	Title	Year
Gunasekaran et al. [109]	Big data and predictive analytics for supply chain and organizational performance	2017
Basole [110]	Accelerating digital transformation: Visual insights from the API ecosystem	2016
Hengstler et al. [111]	Applied artificial intelligence and trust – The case of autonomous vehicles and medical assistance devices	2016
Chalal et al. [112]	Decision support system for servitization of industrial SMEs: A modelling and simulation approach	2015
O'Donovan et al. [113]	An industrial big data pipeline for data-driven analytics maintenance applications in large-scale smart manufacturing facilities	2015
O'Donovan et al. [114]	Big data in manufacturing: A systematic mapping study	2015
Barrett et al. [69]	Reconfiguring boundary relations: Robotic innovations in pharmacy work	2012
LaValle et al. [115]	Big data, analytics and the path from insights to value	

Appendix B. Journal publication patterns

Source title	No. of studies	ABS rating	CORE rating	Citation index
Information Processing and Management	1	2	NA	SCIE, SSCI
International Journal of Asian Business and Information Management	1	NA	NA	ESCI
Journal of Cleaner Production	1	2	NA	SCIE
Technology Analysis and Strategic Management	1	2	NA	SSCI
Journal of Science and Technology Policy Management	1	1	NA	ESCI
International Journal of Production Economics	1	3	NA	SCIE
Annals of Operations Research	1	3	NA	SCIE
Journal of Theoretical and Applied Electronic Commerce Research	1	1	NA	SSCI
Information and Management	3	3	NA	SCIE, SSCI
International Journal of Innovation Science	1	NA	NA	ESCI
Business Process Management Journal	2	2	NA	SSCI
International Journal of Innovation and Learning	1	NA	NA	ESCI
Marketing Intelligence and Planning	1	1	NA	SSCI
TQM Journal	1	1	NA	NA
Baltic Journal of Management	1	1	NA	SSCI
Engineering, Construction and Architectural Management	1	1	NA	SCIE, SSCI
Business Horizons	1	2	NA	SSCI
Management Decision	2	2	NA	SSCI

Source title	No. of studies	ABS rating	CORE rating	Citation index
Behaviour and Information Technology	1	NA	B	SCIE, SSCI
California Management Review	1	3	NA	SSCI
International Journal of Systems Assurance Engineering and Management	1	NA	NA	ESCI
Long Range Planning	1	3	NA	SSCI
International Journal of Retail and Distribution Management	1	2	NA	SSCI
Journal of the Association for Information Science and Technology	1	NA	A*	SCIE, SSCI
Managerial and Decision Economics	1	2	NA	SSCI
Tourism Review	1	1	NA	SSCI
Technological Forecasting and Social Change	2	3	NA	SSCI
Journal of Decision Systems	1	1	NA	ESCI
Strategic Change	1	2	NA	NA
Economics, Management, and Financial Markets	1	NA	NA	NA
ACRN Journal of Finance and Risk Perspectives	1	NA	NA	NA
IEEE Access	3	NA	NA	SCIE
International Journal of Information Management	1	2	NA	SSCI
Industrial Marketing Management	1	3	NA	SSCI
Annals of Tourism Research	1	4	NA	SSCI
Journal of Big Data	2	NA	NA	ESCI
MIT Sloan Manag. Rev	1	3	NA	SSCI
Journal of Business Research	1	3	NA	SSCI
International Journal of Operations Production Management	1	4	NA	SSCI
IT Professional	1	NA	C	SCIE
MIS Quarterly Executive	1	2	NA	SSCI
Journal of Management Information Systems	1	4	NA	SCIE, SSCI
Organization Science	1	4*	NA	SSCI
European Journal of Operational Research	1	4	NA	SCIE