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Review Article

Artificial intelligence in information systems research: A systematic literature review and research agenda

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ABSTRACT

AI has received increased attention from the information systems (IS) research community in recent years. There is, however, a growing concern that research on AI could experience a lack of cumulative building of knowledge, which has overshadowed IS research previously. This study addresses this concern, by conducting a systematic literature review of AI research in IS between 2005 and 2020. The search strategy resulted in 1877 studies, of which 98 were identified as primary studies and a synthesise of key themes that are pertinent to this study is presented. In doing so, this study makes important contributions, namely (i) an identification of the current reported business value and contributions of AI, (ii) research and practical implications on the use of AI and (iii) opportunities for future AI research in the form of a research agenda.

1. Introduction

AI has been claimed to offer transformational potential across sectors and industries, ranging from supply chain management (Chi, Huang, & George, 2020; Collins, Youngdahl, Jamison, Mobasher, & Gini, 1998; Nissen & Sengupta, 2006; Rodriguez-Aguilar, Martin, Noriega, Garcia, & Sierra, 1998) to medicine (Ali, Shrestha, Soar, & Wamba, 2018; Cepolina & Muscolo, 2014; Mettler, Sprenger, & Winter, 2017; Wang, Savkin, Clout, & Nguyen, 2015) to automobiles (Lugano, 2017). Studies have reported that AI provides opportunities to reinvent business models (Duan, Edwards, & Dwivedi, 2019), change the future of work (Schwartz et al., 2019), performance improvements (Wilson & Daugherty, 2018), and even enhance human capabilities (Dwivedi, et al., 2021).

The heightened interest in AI to transform economies (Majchrzak, Markus, & Wareham, 2016; Ransbotham, Fichman, Gopal, & Gupta, 2016; Watson, 2017) is reflected in the scale of global spending, which the International Data Corporation (IDC) predicts that global spending on AI will reach nearly $98 billion in 2023, more than twice the $37.5 billion that was spent in 2019. Yet, there is no consensus on what defines AI or what distinguishes it from other digital technologies (Bhatnagar et al., 2018; Monett & Lewis, 2018; Nilsson, 2009).

There are a few reasons attributed to this upswing in AI interest in recent years (von Krogh, 2018). The past few decades have seen tremendous advancements in some of the underlying AI methods such as current and convential neural networks, many of which have been made open-source and thus available to everyone. AI requires extensive and sophisticated computation, so the decreasing cost in computer hardware and dedicated AI chip designs is making it much more feasible and thus attractive to organisations. The expansion of cloud-based services related to AI has also made it much more attainable for organisations would otherwise be hesitant. Additionally, while research is still in the early stages, preliminary studies may be showing that the advent of COVID has also increased interest in AI, as people get used to the reduced human element in all levels of society and the increased use of automation (Coombs, 2020; Sipior, 2020).

The aim of this research is to understand the various characteristics of AI studied within the context of IS. A systematic literature review is important as it can be used to provide a valuable baseline to aid in further research efforts (Kitchenham, Budgen, & Brereton, 2011; Petersen, Vakkalanka, & Kuzniarz, 2015). The aims of this systematic review are to:

1. identify the reported business value and contributions of AI
2. examine the practical implications on the use of AI
3. identify the opportunities for future AI research in IS.

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The structure of the paper is as follows. First, an introduction to related work on AI in the IS field is presented. Then the methodology of the systematic literature review is explained, and limitations of the study are acknowledged. Next, state-of-the-art of AI research is presented, includes the reported business value and contributions of AI, and analysis on how AI is defined. Followed by a discussion, implications, and a research agenda for the future. The paper ends with a conclusion and directions for future research.

2. Background and related work

This section commences with an overview of extant information systems literature on AI. The lack of clarity concerning the concept and classification of AI are discussed.

2.1. Evolution of AI definition

AI has a history much longer than is commonly understood, in fields from science and philosophy ranging all the way back to ancient Greece (Dennehy, 2020), but its modern iteration owes much to Alan Turing (Turing, 1950) and conference in Dartmouth College in 1956 (McCorduck, 2004), where the term "Artificial Intelligence" was officially coined and defined by John McCarthy at the time as "the science and engineering of making intelligent machines". Russel and Norvig (2020) referred to it as the "the birth of artificial intelligence." One of the initial paradigms of AI was that it revolved around high-level cognition. Not the ability to recognise concepts, perceive objects, or execute complex motor skills shared by most animals, but the potential to engage in multi-step reasoning, to understand the meaning of natural language, to design innovative artefacts, to generate novel plans that achieve goals, and even to reason about their own reasoning (Langley, 2011). This general human like intelligence was referred to as strong AI (Kurzweil, 2005). For strong AI, the primary approach has centred on symbolic reasoning, that computers are not simply numeric calculators but rather general symbol manipulators. As noted by Newell and Simon (1976) in their physical symbol system hypothesis, intelligent behaviour appears to require the ability to interpret and manipulate symbolic structures. While this approach showed promise initially (Newell & Simon, 1963), many branches of AI have retreated from this approach due its difficulty and the lack of progress coming in to the 21st century. It remains yet uncertain on when and if strong AI will be made a reality.

The distinction between weak AI and strong AI is also concerned with rule adherence, i.e., the way machines interact with rules. Wolfe (1991) distinguishes rule-based decision making in which machines strictly respect the rules set by developers from rule following decision making which machines follow rules that have not been strictly specified to them. Rule-based decision-making matches weak AI, while rule-following decision making is an attempt that tends towards strong AI. An example of rule-following decision making is neural networks (NN), which allow algorithms to learn from themselves. Strong AI would be machines making their own rules and then follow them, which is not possible at the stage of right now (Wolfe, 1991).

AI has gone through many peaks and troughs since its early inception in the 1950s, usually referred to as AI "summers and winters" (Russel and Norvig, 2020). Since 2010, however, AI can be said to have once again entered a summer period, mainly due to considerable improvements in the computing power of computers and the access to massive amounts of data (PWC, 2019).This resurgence in AI research is the result of three breakthroughs: (1) the introduction of a much more sophisticated class of algorithms; (2) the arrival on the market of low-cost graphics processors capable of performing large amounts of calculations in a few milliseconds; and (3) the availability of very large, correctly annotated databases allowing for more sophisticated learning of intelligent systems (Jain, Ross, & Prabhakar, 2004; Khashman, 2009; PWC, 2019).

Despite the length of time the field has existed, there is still no commonly accepted definition (Allen, 1998; Bhatnagar et al., 2018; Brachman, 2006; Hearst & Hirsh, 2000; Nilsson, 2009). This is not considered a problem yet, as many scientific concepts only get true definitions after they have matured enough, rather than at their conception, and given the complexity and breadth of AI, it may not be feasible to expect AI to have a set definition yet. Still, this doesn't mean that the topic should be ignored, especially with the recent advancements and advancements relating to the field (LeCun, Bengio, & Hinton, 2015; Silver et al., 2016). However, without a clear definition of the term, "*it is difficult for policymakers to assess what AI systems will be able to do in the near future, and how the field may get there. There is no common framework to determine which kinds of AI systems are even desirable*" (Bhatnagar et al., 2018). A similar concern has been echoed by Monett and Lewis (2018), that "*theories of intelligence and the goal of Artificial Intelligence (A.I.) have been the source of much confusion both within the field and among the general public*".

In the years immediately preceding and after the 1956 Dartmouth conference where the term was coined, when the concept for AI was first brewing in academic consciousness, many researchers (would later become famous for their contributions to AI) formulated many theories and proposals that focused on the common features of mind and (McCulloch & Pitts, 1943; Turing, 1950; von Neumann, 1958; Wiener, 1948). While these thought leaders were influential, the field of AI as we know it owes more to McCarthy, Minsky, Newell, and Simon. While this is partly due to their own attendance of the famous 1951 Dartmouth conference, it is likely more since they went on to establish three leading research centres which shaped the stream of though regarding AI for years. Their own opinion on AI was as follows;

> *"By 'general intelligent action' we wish to indicate the same scope of intelligence as we see in human action: that in any real situation behaviour appropriate to the ends of the system and adaptive to the demands of the environment can occur, within some limits of speed and complexity" (Newell & Simon, Computer science as empirical enquiry: Symbols and search, 1976).*

Intelligence usually means "*the ability to solve hard problems*" (Minsky, 1958).

> *"AI is concerned with methods of achieving goals in situations in which the information available has a certain complex character. The methods that have to be used are related to the problem presented by the situation and are similar whether the problem solver is human, a Martian, or a computer program"* (McCarthy, 1988).

With the variety of separate opinions on what AI is, lacking agreement on a standard evaluation (i.e., criteria, benchmark tests, milestones) makes it extremely challenging for the field to maintain healthy growth (Hernández-Orallo, 2017).

2.2. Previous systematic literature reviews of AI in IS research

Despite the heightened interest in AI (Watson, 2017), it is claimed that there is a noticeable absence of theoretically-grounded research on how organisations should develop their digital business strategies incorporating AI to create business (Mikalef, Bourab, Lekakosb, & Krogstiea, 2019). We investigate this claim and identify gaps in AI research conducted by IS scholars. We acknowledge four previous Systematic Literature Reviews (SLRs) have been conducted (Hofmann, Oesterle, Rust, & Urbach, 2019; Rzpeka & Berger, 2018; Borges, Laurindo, Spínola, Gonçalves, & Mattos, 2021; Karger, 2020) but highlight limitations of these studies (see Table 1).

The literature review conducted by Rzpeka and Berger (2018) cited 91 studies total as their primary studies, taken from a combination of conferences and journals. However, it is focused on the context of individual user interaction with AI systems in IS, while this study studies how it is being defined and gives value. The literature review conducted

Table 1
Comparison of previous SLRs in IS.

Comparison Element	Purpose	Years Included	Number of primary studies
Rzpeka and Berger (2018)	Provides insight into individual user interaction with AI systems in IS.	1987–2017	91
Hofmann et al. (2019)	Identifies opportunities and challenges of ML across the radiology value chain.	2012–2018	29
Borges et al. (2021)	Studies the integration of AI and organisational strategy	2009–2020	41
Karger (2020)	Studies the interactions between Blockchain and AI	Not specified (primary studies ranged from 2014 to 2020)	32
This Study	AI, as a subject and as a use in the field of IS	2005–2020	98

by Hofmann et al. (2019) was primarily concerned with the effects of AI and ML in the context of the radiology value chain, and so had a time span reflecting that, focusing on 2012 to 2018. The review conducted by Borges et al. (2021) focused more on specific AI interactions with organisational strategy and so misses some of the context in how it is being defined and how it creates value. The literature review conducted by Karger (2020) is focused narrowly on the relations between AI and blockchain and excludes everything else. This study includes all the relevant studies in a fifteen year period in a number of high quality journals and conferences, and includes studies that use AI in more oblique ways than these SLRs, such as studies that use machine learning approaches when researching their focus.

2.3. AI Functions

The current difficulty to settle on an agreed definition of AI has been discussed above, but for the purposes of this systematic literature review, we focus on functions of AI as described by Dejoux and Léon (2018). The broad range of functions is shown in Table 2 below.

Table 2
AI functions.

Title (Dejoux & Léon, 2018, p. 188)	Description (Brynjolfsson & McAfee, 2014; Jarrahi, 2018a, 2018b)	Example (Dejoux & Léon, 2018, p. 188)
Expert Systems (ES)	Designed to simulate the problem-solving behaviour of a human.	DENDRAL: Expert system used for chemical analysis to predict molecular structure.
Machine learning	Automatically refines its methods and improve its results as it gets more data.	Many of the more advanced recommendation systems i.e., Google, YouTube etc.
Robotics	Concerned with the generation of computer-controlled motions of physical objects in a wide variety of settings	Service robots
Natural Language Processing (NLP)	Designed to understand and analyse language as used by humans. NLP is the base for the AI-powered Speech Recognition.	Intelligent agents i.e., Apples Siri, Amazons Alexa
Machine vision	The analysis of images using algorithmic inspection.	The computer vision used to help drive autonomous vehicles
Speech recognition	Can be understood as an approach that deals with the translation of spoken words into the text.	Google Dictate uses speech recognition to convert spoken words into text

Already, studies are showing the potential opportunities of adopting AI in a wide range of fields, with manufacturing, digital marketing and healthcare generating considerable academic interest (Juniper Research, 2018). For manufacturing, factories are likely to extensively use AI as product automation increases and industry uses more AI and cyber physical systems (Wang & Wang, 2016). Healthcare researchers propose using AI systems linked to sensors placed on humans to monitor and record their health (Rubik & Jabs, 2018). For digital marketing, Juniper Research (2018) predicts that demand forecasting using AI will more than treble between 2019 and 2023 and that chatbot interactions will reach 22 billion in the same year from current levels of 2.6 billion. However, these opportunities are only available if one can undertsand what AI is.

3. Research methodology

This section outlines the systematic review process adopted for this study. A Systematic Literature Review is defined as "means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest" (Kitchenham, 2004). This systematic approach was chosen for its ability to offer reviews of high quality (Dingsøyr & Dybå, 2008) and transparent and replicable review (Leidner & Kayworth, 2006). Additionally, it is useful for studies with a clearly formulated research question (Petticrew & Roberts, 2006) and summarising large quantities of research studies (Fink, 2005). Thus, the SLR was chosen for the following reasons: (i) the study will generate large amounts of literature; (ii) this study aims to answer a specific research question; (iii) we intend to systematically extract relevant AI references from the studies transparently; and (iv) the rigour and replicability it offers leads to an unbiased scientific study. The foundation of our guide was taken from the guideline developed by Okoli (2015).

3.1. A systematic guide to literature review development

Okoli (2015) propose a systematic review process that consists of 8 steps, namely planning (2 steps), selection (2 steps), extraction (2 steps) and execution (2 steps) that are completed across 4 phases (see Fig. 1.). Each of these four phases and eight steps are discussed in detail in the remainder of the section.

The objective of the systematic literature review is to answer the research questions shown in Table 3. RQ2 is a comprehensive research question. Five questions (RQ2.1 – RQ2.5) are used to answer RQ2. RQ1

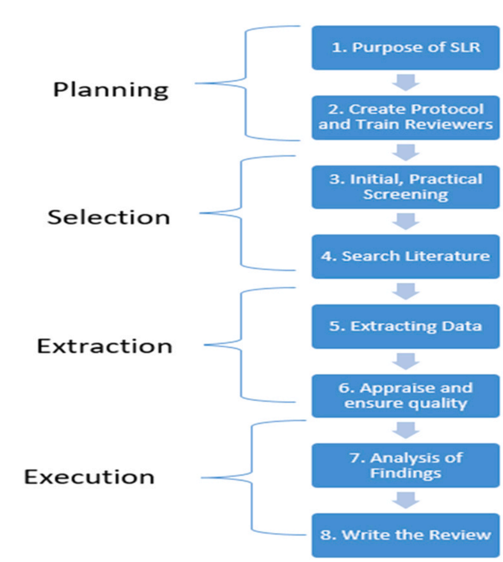

Fig. 1. A systematic guide to literature review development (Okoli, 2015).

Table 3
Research questions.

ID	Research question
RQ 1	How is AI being defined in the field of IS?
RQ 2	What is the current state of AI in IS?
RQ 2.1	What number of IS academic studies on AI has been published between 2005 and 2020?
RQ 2.2	What were the Publication channels used?
RQ 2.3	What were the research methods and data collection techniques used?
RQ 2.4	What kind of contributions are provided by studies on AI in IS?
RQ 2.5	What AI functions are used by IS researchers?
RQ 3	What is the business value of AI?

and RQ3 were used to create rich data for the synthesis and discussion stages. Additionally, this review also aims to contribute to conducting an IS SLR. A further contribution will be that of a study which conducts a SLR: (i) where the complexity and type of AI is incorporated into a search strategy; (ii) to find relevant AI studies; (iii) which are then systematically analysed.

A literature review's quality is dependent on the rigor of the search process (Vom Brocke et al., 2009). Therefore, the search strategy is best developed in concert with the research question. The goal is to find as many studies as possible capable of answering the research question (Kitchenham & Charters, 2007). The starting point when searching literature is electronic sources and literature databases, followed by a keyword string search to locate the appropriate studies (Levy & Ellis, 2006).

A generally accepted approach to search string strategy is to base the search string on the research questions and include a list of synonyms, abbreviations, and alternative spellings (Kitchenham & Charters, 2007). Due to the nature of Artificial Intelligence and the variety of different types, subtypes, and methods in use, in addition to the different ways it is referred to by researchers, a thorough strategy was needed. The search string was used following the Boolean practice. A simple "OR" operator was used between keywords. The use of "*" after some word was implemented so the search would include multiple variations of the word. The use of quotation marks ("") over some terms was to exclusively search for that specific term.

The selected databases are pertinent to this study as these return the most studies (Dingsøyr & Dybå, 2008).

For each of the three selected databases (AIS eLibrary, Scopus, ISI Web of Science), using the specified search string retrieves an initial list of studies. One or many of these databases had been used by multiple researchers in the literature (Agarwal, Kumar, & Goel, 2019; Busalim & Hussin, 2016; Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018; Rekik, Kallel, Casillas, & Alimi, 2018) The records are first imported into Endnote for sorting and categorisation, and then further imported into Microsoft Excel sheet format. The basic input includes meta-data such as (i) title, (ii) author, (iii) year, (iv) publication type, and (v) abstract. The keyword strategy was applied to nine IS journals and the top two IS conferences. The search string used across the three databases retrieved 1877 studies (shown in Table 4).

Once the literature searches in leading journals have commenced, the leading conferences of a field should follow (Webster & Watson, 2002). Due to the multidisciplinary nature of IS literature is heavily dispersed across different data sources (Levy & Ellis, 2006). To ensure all relevant studies were retrieved, three databases were used, these being (i) AIS eLibrary; (ii) Scopus, and (iii) the ISI Web of Science. *AIS eLibrary* was used as of the databases used it was unique in being able to provide studies from the leading IS conferences. *Scopus* was used as it claims to be largest database for abstracts and citations (Ballew, 2009; Kitchenham & Charters, 2007). *ISI Web of Science* was used as it is the largest citation database which stores over 800 million references (Manikandan & Amsaveni, 2016).

Table 4
Search string.

Source	String
Science Direct-IJIM AIS eLibrary Web of Science	("AI" OR "artificial intelligence" OR "machine learning" OR "neural networks" OR cognitive* OR automation* OR robot* OR augment*)
SCOPUS	TITLE-ABS-KEY ("AI" OR "artificial intelligence" OR "machine learning" OR "neural networks" OR cognitive* OR automation* OR robot* OR augment*) AND SRCTITLE ("MIS Quarterly: Management Information Systems" OR "INFORMATION SYSTEMS RESEARCH" OR "JOURNAL OF MANAGEMENT INFORMATION SYSTEMS" OR "JOURNAL OF STRATEGIC INFORMATION SYSTEMS" OR "EUROPEAN JOURNAL OF INFORMATION SYSTEMS" OR "INFORMATION SYSTEMS JOURNAL" OR "JOURNAL OF INFORMATION TECHNOLOGY" OR "JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS") AND PUBYEAR = 2020

These databases were used to retrieve studies from relevant IS journals, which were chosen as we belief these nine journals focus on the social-technological aspects of AI, which is the scope of this SLR.

i. International Journal of Information Management
ii. Management Information Systems Quarterly
iii. Journal of the Association of Information Systems
iv. Information Systems Journal
v. Information Systems Research
vi. Journal of Information Technology
vii. Journal of Management Information Systems
viii. Journal of Strategic Information Systems
ix. European Journal of Information Systems

Conference papers from two of the leading IS conferences, namely, *International Conference on Information Systems* (ICIS) and the *European Conference on Information Systems* (ECIS) were also retrieved and analysed. The number of papers retrieved from each selected database is shown in Table 5.

Screening of the retrieved studies was achieved by following the best practices proposed by Kitchenham (2004) and Dingsøyr and Dybå (2008). The study selection process used in this study is illustrated in Fig. 1. Two authors independently analysed the 1877 studies to remove (i) duplicate studies, (ii) non-English studies, (iii) non-IS studies, and (iv) non-peer reviewed scientific studies (books, book chapters, experience reports). As searching through literature can result in many studies, using an inclusion and exclusion criteria can serve to eliminate unnecessary studies (Okoli, 2015).

Studies were eligible for inclusion in the systematic review if they presented empirical data on AI or ML in IS, or of AI and ML being used in the IS literature, or if a non-empirical study shows clear evidence of academic rigour. The inclusion criteria applied was;

- The studies should be written in English.

Table 5
Selected databases and retrieved papers.

Database	Filter	No. of retrieved studies
AIS eLibrary	Only conference papers	468
Scopus	Only conference papers and journal articles	399
ISI Web of Science	Only conference papers and journal articles	210
International Journal of Information Management	Only conference papers and journal articles	800

- The studies should be published between 2005 and 2020.
- The studies directly answer one or more of the research questions of this study.
- The studies should clearly state its focus on AI/ML or use AI/ML as a large part of their methodology. For example, publications that explicitly use a machine learning approach as a fundamental part of their methodology/research.
- If the studies have been published in more than one journal or conference, the most recent version of studies is included.
- Opinion/perspective studies were included as we believe that if they were published in the relevant journals than they could be used to gain insight into the state of AI in IS.

The exclusion criteria applied was;

- Not written in English.
- Duplicate articles.
- Simulation studies.
- Editorials.
- Studies with no focus on AI.
- Non-peer-reviewed scientific publications (editorials books, book chapters, articles).

Fig. 2 shows the study selection process. After the initial step of identifying a search string was complete, pilot steps were carried out on the databases used. This entailed refining the search string for each database. However, the terms used to search the databases were used the same throughout. The lead author analysed the 1877 studies retrieved in the initial search. A second reviewer was invited to analyse these studies as well, to pre-emptively combat potential bias. The two reviewers had to agree for a study to stay a primary study. Based on the removal of duplicates, non-scientific and non-English studies, 91 were removed, leaving 1786. These 1786 studies were then analysed based on title. The title gave a clear indication on whether they were outside the focus of the study, and thus excluded. If a title did not clearly reveal application domain of the study it was included for review in the subsequent steps, where title, keywords and abstract were examined. Based on title, abstract and keyword, the 1786 studies were further narrowed down to 187. There were still cases where the abstract was unclear, so these studies carried onto the next stage, where the contents of the full study were examined. An in-depth examination of the 187 remaining studies was undertook by the reviewers, which resulted in a further 90 studies being excluded. This resulted in a total of 98 primary studies used as the basis of this SLR.

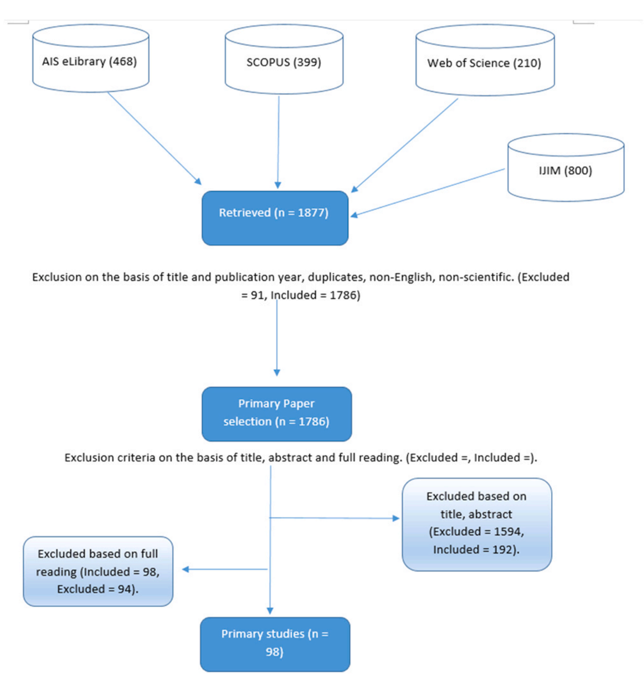

Fig. 2. Study selection process.

The findings and analysis of these 98 primary studies is presented in the next section.

3.2. Threats to validity and limitations of study

There are always several common threats to validity concerning SLRs (Petersen, Vakkalanka, & Kuzniarz, 2015; Wohlin et al., 2012). This section considers those threats and outlines the strategies used to combat and mitigate them, as well as explores the limitations of this study. The validity framework by Wohlin et al. (2012) examines validity threats in terms of (i) construct validity, (ii) external validity, (iii) internal validity, and (iv) conclusion validity. *Construct validity* states that the author must attain the right measures for the concept under study (Petersen, Vakkalanka, & Kuzniarz, 2015; Wohlin, et al., 2012). To minimise this threat, this SLR followed a structured eight-step guideline required to conduct a scientifically rigorous SLR, as seen in Fig. 1. Within those guidelines was the paper selection process (see Fig. 2.) which documents the process of filtering studies from the original 1877 to the 98 primary studies. To further mitigate this threat, authors three and four were experienced in reviewing studies and acted as external reviewers to validate the research protocol. This, this threat has been significantly neutralised.

External validity is focused on the generalisability of the study. That is, the extent to which the study can be generalised to other areas outside of the context of this study (Petersen et al., 2015; Wohlin et al., 2012). To know to what degree the results of a study can be generalised it is essential that the research process is described (Petersen & Wohlin, 2009). As this systematic study followed the eight-step guideline laid out by (Okoli, 2015), it is attributed to mitigating the threats to validity. *Internal validity* relates to causal relationships and ensuring that it is not a result of a factor that was not measured, or the researcher had no control over. As the aims of this study were not to establish a statistical causal relationship on AI in IS, other mitigations were used to combat it, such as regular meetings with all authors to explore any potential of bias. *Conclusion validity* relates to bias of the researchers in the interpretation of that data. While this risk cannot be eliminated, several measures were taken to combat it; (i) three authors were involved in data extraction of the primary studies, (ii) a full 'audit trail' from the initial 1877 studies to the identification of 98 primary studies was provided, and (iii) conclusions drawn from analysis of the 98 primary studies involved all authors.

Although this paper concentrated on mitigating threats to validity using well-established strategies, we acknowledge that publication bias is a limitation of this study, as we focused on a select number of IS journals, meaning that other studies from IS conferences and non-IS outlets were excluded.

4. Findings and analysis

This section presents the results from the analysis of the 98 primary studies, based on the research questions listed previously. The results represent the state of AI research in IS and is based on the following (i) how AI is being defined, (ii) study by year, (iii) publication channel, (iv) research methods adopted, (v) type of contribution, (vi) types of AI and (vii) the reported business value of AI.

4.1. RQ1: how is AI being defined in the field of IS?

The aim of this research question is to identify and analyse the different definitions of AI used in the field of IS. It was noted in Section 2.1 the difficulties the field of AI had with definitions, and this research questions aims to look at how IS has handled those difficulties. However, despite AI and Machine Learning being a large part of the primary studies, many did not provide a definition, or used definitions that were not cited (see Fig. 3).

Of the 98 primary studies, 54 of them gave no clear definition of the AI relevant to the study. And of the 44 studies that did give a definition, 7 of them cited no reference for the definition given. The definitions of AI used in the primary studies varied in both term of definition and source cited. Disregarding the seven studies that defined AI without citing a source, Russel & Norvig's book *Artificial Intelligence: A Modern Approach* was the most frequently cited source for defining AI, though the actual edition of the book varied, with each studies using the latest edition at the time. The definitions and cited sources of the primary studies can be seen in Table 6.

4.2. RQ2: what is the current state of AI in IS?

This aim of this research question is to examine the current state of AI in the field of IS through a series of sub-related research questions.

4.2.1. RQ 2.1. What number of IS academic studies on AI has been published between 2005 and 2020?

The aim of this research question is to identify the number of academic studies involving Artificial Intelligence and Machine Learning in the field of Information Systems, specifically those between the years 2005 and 2020 (see Fig. 4.). Fig. 4. reveals that studies on AI remained relatively low for most of this period, with a total of 11 studies between the years 2005 and 2015. 2019 and 2020 show an immense surge in AI related studies in IS, signifying a much greater interest in the field. Due to the inclusion and exclusion criteria of this study, there were no studies on AI in Information Systems in the years 2007, 2008, 2010, and 2012.

4.2.2. RQ 2.2 What were the publication channels used?

The aim of this research question is to identify the main channels where AI studies are disseminated. Table 7 shows that 32 of the primary studies were published in journals and 65 were published in the top two IS conferences. The highest number of studies were published in ICIS, a total of 41 studies over the 15-year period. The journal with the most studies was IJIM with 14 studies, especially notable as the scope for IJIM was five years in comparison to the 15 years of the other journals.

4.2.3. RQ 2.3 research methods and data collection techniques used

The aim of this research question is to identify the research methods and data collection techniques which were used to study AI and Machine Learning in the IS field. Each study was either empirical, theoretical, conceptual, or experimental. Analysis was conducted to determine the

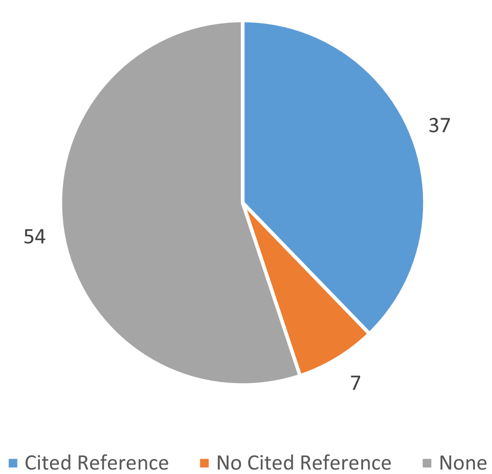

Fig. 3. AI definition cited.

Table 6
AI definitions in primary studies.

Source Cited	Definition	Primary studies source
N/a		P6, P21, P38, P39, P59, P61, P63
Bush (1945)	A kind of deep learning machine that has the ability to create intelligent agents based on the concepts, positions and patterns of argument.	P7
McCarthy (1958)	Referred to as "the science and engineering of making intelligent machines"	P68
Carbonell et al. (1983)	ML is based on inductive learning and infer general concepts from example data, ranging from simple memorising of facts that doesn't requires any inference at all (rote learning) over learning performed by instruction, by analogy, and by examples to learning by observation with increasing need of inference	P36
Trappl (1986)	Artificial intelligence (AI) was defined as: 1) making computers smart, 2) making models of human intelligence, and 3) building machines that simulate human intelligent behaviour	P24
Russel and Norvig (1995)	activities that we associate with human thinking, activities such as decision-making, problem solving, learning"	P47
Jennings et al. (1998)	A computer system, situated in some environment that is capable of flexible autonomous action in order to meet its design objectives.	P12
Cross (2003)	Defined as an Information Technology (IT) programs that perform tasks on the user's behalf independently of direct control of the users themselves.	P35
Russel and Norvig (2010)	Artificial intelligence (AI) enables the machine to exhibit human intelligence, including the ability to perceive, reason, learn, and interact, etc.	P31, P44, P50
Min (2010)	AI concerns understanding and learning the phenomena of human intelligence and to design computer systems that can imitate human behavioural patterns and create knowledge relevant to problem-solving	P56
Austin et al. (2013)	ML is an exploratory process where the accuracy and performance of models vary, based on the characteristics of variables and observations in a study	P92
Deng and Yu (2014)	The main idea of deep learning consists of multiple layers of features representations at increasing levels of abstraction	P48
LeCun et al. (2015)	A set of multiple interconnected layers of neurons, inspired by the human brain, which can be trained to represent data at high levels of abstraction	P53, P55
International Federation of Robotics (2016)	Under the label service robots, these types of devices are designed to "[…] operate semi- or fully autonomously to perform services useful to the well-being of humans […]"	P11
Goodfellow et al. (2016)	Deep learning is the state-of-the-art machine learning method that builds upon large-scale neural networks and unsupervised representation learning	P19, P94
DeCanio (2016)	AI is the broad suite of technologies that can match or surpass human	P69, P97

(continued on next page)

Table 6 (*continued*)

Source Cited	Definition	Primary studies source
	capabilities, particularly those involving cognition such as learning and problem solving	
Hengstler et al. (2016)	Intelligent automation is reaching a level, where it is capable of performing complex tasks that normally involve human experience and intuition	P82
Russel and Norvig (2016)	defined the term AI to describe systems that mimic cognitive functions generally associated with human attributes such as learning, speech and problem solving.	P58, P76, P77, P79
Günther et al. (2017)	The term algorithmic intelligence refers to business analytics applications and to artificial intelligence (AI) in domains such as robotics, machine vision, natural language processing, expert decision-making, and classification	P10
Li et al. (2017)	AI is the general concept for computer systems able to perform tasks that usually need natural human intelligence, whether rule-based or not, while ML is that subset of AI that is capable of "learning from data and making predictions and/or decisions" without human dictated rules.	P14
Kolbjørnsrud et al. (2017)	Artificial intelligence is defined as a subset of IT that can sense their environment, comprehend the collected information, learn, and derive actions based on interpreted information and their implemented objectives.	P70
Nichols (2018)	Robot can be defined as a programmable machine which is capable of sensing and manipulating its surroundings while performing complex tasks semi/fully autonomously	P66
Plastino and Purdy (2018)	Artificial Intelligence is a special form of an IT resource with hybrid features of an IT artefact and human capital	P78
Sutton and Barto (2018)	AI agents learn by themselves to achieve the optimal strategies by sequentially interacting with environments in a trial-and-error way only with the supervision of rewards or punishments	P81
von Krogh (2018)	AI can broadly be described as a collection of computer-assisted systems able to perform non-trivial tasks traditionally confined to humans	P88
Rai et al. (2019)	Artificial Intelligence (A.I.) is defined as the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity.	P16, P87
Duan et al. (2019)	Artificial intelligence (AI), in which machines can "learn from experience, adjust to new inputs, and perform human-like tasks"	P60
Berente et al. (2019)	Define AI as machines performing the cognitive functions typically associated with humans, including perceiving, reasoning, learning, interacting, etc	P75
Longoni et al. (2019)	We define artificial intelligence (AI) as algorithms that perform perceptual, cognitive, and conversational functions typical of the human mind	P84

research methods and data collection techniques of the 98 primary studies. Of the 98 primary studies, eight adopted a mixed method approach, thirteen took the form of a literature review, forty-four used a quantitative method and thirty-one used the qualitative method. The method and technique adopted for each of the primary studies is listed in Table 8.

A deeper analysis of the research methods was conducted to establish the data gathering techniques used in the primary studies. These are listed in Table 9. Many of the studies used multiple techniques to gather data in their studies, so some references in the table below are repeated. 22 studies used data mining and 21 reported the use of experiments. 10 studies adopted observation techniques and four collected data through documentation. Surveys were incorporated by 8 primary publications to collect data, with interviews being adopted by 20. Literary analysis was used by 22 of the studies, and questionnaires incorporated by two. Four studies adopted focus groups to collect data, with three using workshops. Sample analysis was used by two studies. Theory-as-discourse, Machine Learning subset selection, causal mapping and prediction markets were all used by a single study each.

Experiments were the most popular choice for collecting data. This usually took the form of the studies putting their relevant use of AI or Machine Learning into practise as an experiment and collecting data from the result. As AI is still a broad and relatively nebulous field in IS, performing experiments can provide rich data on AI usage in a variety of complex, contextual environments.

4.2.4. RQ 2.4. What kinds of contributions are provided by studies on AI in IS?

The aim of this research question is to identify and categorise the contributions of the primary studies. These contributions (see Table 10), adapted from Shaw (2003) and Paternoster, Giardino, Unterkalmsteiner, Gorschek, and Abrahamsson (2014) include six types of contributions, namely (i) framework, method, technique, (ii) guidelines, (iii) lessons learned, (iv) model, (v) tool, and (vi) advice/implication.

The contributions of the 98 primary studies and the data collection techniques that led to these contributions are listed in Table 11. This would provide significant practical contributions, as well as widening the academic discourse on AI in IS. Analysis of the 98 primary studies also shows that contributions were largely made as 'lessons learned' (39 studies), 'methods' (26 studies), 'advice or implication' (15 studies), guidelines (6 studies), tools (5 studies) and models (6 studies). Table 11 highlights the need for research to contribute to the categories of (i) models and (ii) tools.

Although several primary studies could potentially contribute to more than type one contribution type, the categorisation used in this systematic literature review is based on the primary contribution as stated by the authors of each of the 98 primary studies. A visual representation of the contribution types of the primary studies is shown in Fig. 5.

Fig. 5. shows that 'lessons learned' (40 studies) and 'methods' (26 studies) are the most popular contribution of AI studies in IS research. A limitation to these contributions is that they can often be context specific, especially for the methods contributions. This is compounded upon by AI encompassing such a broad array of uses and designs. This means there is less repetition of contributions and lessons learned, and that cumulative building of knowledge in this context may take time to accumulate. For example, a study that proposes a new framework for improving the radiology supply chain may not be aligned with a study that examines how AI can improve drug innovation.

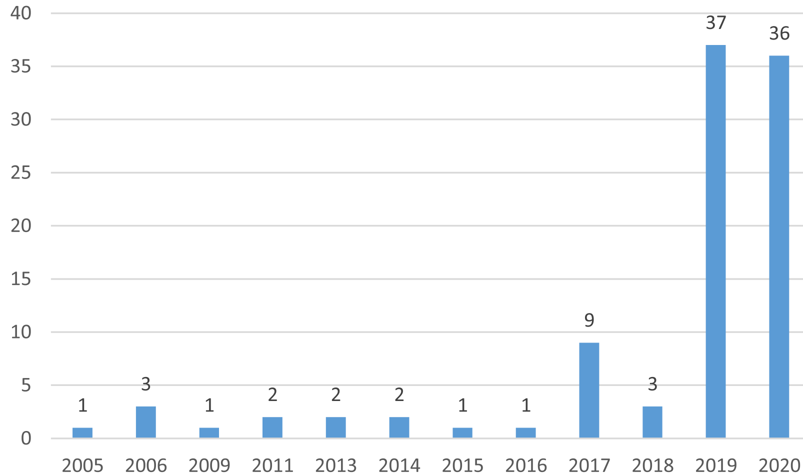

Fig. 4. Number of studies by year.

Table 7
Primary studies by journal and conference.

Channel	Title	Number of studies	Primary studies
Journal (n=9)	MIS Quarterly Management Information Systems	3	P3, P4, P12
	Information Systems Research	1	P1
	Journal of Management Information Systems	3	P2, P13, P94
	European Journal of Information Systems	2	P7, P11
	Journal of Strategic Information Systems	3	P10, P93, P97
	Journal of Information Technology	3	P6, P8, P95
	Journal of The Association of Information Systems	3	P5, P9, P96
	Information systems journal	0	
	International Journal of Information Management	14	P56, P57, P58, P59, P60, P61, P62, P63, P64, P65, P66, 67, P68, P69, P98
Conference (n=2)	International Conference of Information Systems	41	P14, P16, P17, P18, P19, P21, P22, P23, P24, P26, P27, P30, P33, P38, P39, P40, P42, P43, P44, P46, P47, P49, P50, P51, P52, P54, P55, P80, P81, P82, P83, P84, P85, P86, P87, P88, P89, P90, P91, P92
	European Journal of Information Systems	24	P15, P20, P25, P28, P29, P31, P32, P34, P35, P36, P37, P41, P45, P53, P70, P71, P72, P73, P74, P75, P76, P77, P78, P79
Total		98	98

Table 8
Research method and technique adopted.

Method	Technique	Primary studies	Total
Quantitative	• Survey • Descriptive • Case Study • Deep Learning	P1, P3, P4, P9, P13, P16, P18, P19, P21, P23, P27, P29, P33, P34, P35, P38, P39, P40, P42, P46, P48, P51, P52, P53, P55, P57, P59, P62, P63, P64, P66, P70, P71, P81, P82, P84, P86, P87, P89, P90, P91, P94, P95, P98	44
Qualitative	• Interview • Case Study • Design Science	P2, P7, P8, P12, P14, P17, P20, P22, P26, P28, P32, P41, P43, P47, P49, P50, P56, P61, P67, P69, P73, P74, P75, P76, P77, P79, P80, P85, P88, P93, P96	31
Literature Review	• Systematic • Monographic	P5, P6, P10, P15, P25, P36, P37, P44, P45, P60, P68, P83, P97	13
Mixed Method	• Survey • Focus group • Q-Methodology	P11, P30, P31, P54, P58, P72, P78, P92	8
Action Research	• Canonical Action Research	P24	1

Table 9
Data collection techniques.

Data collection technique	Primary studies
Data Mining (n=22)	P1, P3, P13, P33, P40, P46, P48, P51, P52, P53, P59, P62, P66, P74, P78, P81, P85, P89, P92, P94, P95, P98
Experiment (n=21)	P2, P4, P7, P12, P17, P19, P21, P23, P27, P29, P38, P39, P54, P55, P63, P64, P65, P71, P80, P84, P90
Observation (n=10)	P7, P8, P11, P20, P30, P49, P50, P80, P81, P93
Causal Mapping(n=1)	P9
Documentation(n=4)	P7, P30, P42, P50
Survey(n=8)	P11, P34, P43, P57, P70, P72, P86, P91
Interview(n=20)	P11, P15, P22, P25, P26, P28, P30, P32, P41, P49,P50, P54, P56, P72, P76, P77, P79, P82, P88, P93
Sample Analysis(n=2)	P16, P87
ML subset selection (n=1)	P18
Lit Analysis(n=22)	P5, P6, P10, P14, P22, P24, P25, P28, P36, P37, P44, P45, P60, P61, P67, P68, P69, P73, P75, P78, P83, P96, P97
Workshop(n=3)	P22, P28, P47, P58,
Focus Groups(n=4)	P11, P22, P31, P47
Questionnaire(n=2)	P32, P35
Prediction Markets (n=1)	P39

4.2.5. RQ 2.5. What types of AI technologies are used by IS researchers?

The aim of this research question is to categorise studies on AI based on the type of AI used in the primary study. It is possible to combine a variety of these types together into a single AI system. For example, IBM's Watson combines NLP, ML and machine vision techniques (Jarrahi, 2018a, 2018b). However, for the purpose of this SLR, the study will be categorised solely based on the primary AI type of the study (see Fig. 6.).

Fig. 6 shows that ML is the most popular form of AI used in the

Table 10
Contribution type (adapted from Shaw (2003), Paternoster et al. (2014)).

Title	Description
Framework/Method/ Technique	The contribution of the study is a particular framework, method, or technique used to facilitate the construction and management of software and systems.
Guidelines	A list of advice or recommendations based on synthesis of the obtained research results.
Lessons Learned	The set of outcomes directly based on the research results obtained from the data analysis.
Model	The representation of an observed reality in concepts or related concepts after a conceptualisation process.
Tool	A technology, program, or application that is developed in order to support different aspects of information
Advice/Implication	A discursive and generic recommendation based on opinion.

Table 11
Contributions across studies.

Contribution	Primary papers
Framework/ Method	P1, P13, P18, P19, P20, P21, P22, P24, P28, P29, P37, P43, P46, P48, P53, P55, P63, P64, P73, P74, P75, P78, P85, P92, P94,
Guidelines	P4, P5, P8, P16, P35, P59
Lessons Learned	P3, P11, P12, P14, P15, P17, P25, P26, P30, P31, P32, P33, P34, P36, P39, P42, P44, P45, P49, P50, P56, P57, P58, P66, P67, P68, P70, P71, P72, P77, P80, P82, P84, P86, P89, P90, P91, P93, P98
Models	P23, P38, P40, P41, P62, P79, P97
Tool	P2, P9, P27, P65, P76, P81,
Advice/ Implication	P6, P7, P10, P47, P51, P52, P54, P60, P61, P69, P83, P87, P88, P95, P96

primary studies, with 69 studies categorised under it. There was less range between the other types, expert systems having 11, machine vision with five and NLP at 6. Robotics was the least common with 3 studies having it as the primary focus. The studies corresponding to each category can be seen on Table 12.

There were a few studies that couldn't be said to have focused on any one category specifically, instead looking at AI in the broader sense. These 14 studies that could not be sorted cleanly into the framework were simply categorised as "other".

4.2.6. RQ3: What is the business value of AI?

As noted by Davenport and Ronanki (2018), within IS, it may be more useful to look at AI through the lens of its business capabilities rather than its technologies. To that end. AI can be narrowed down to

Table 12
Primary publications mapped to AI type.

AI type	Primary studies
Machine Learning(n=68)	P1, P3, P4, P5, P9, P13, P14, P15, P17, P18, P19, P21, P22, P23, P27, P29, P33, P34, P36, P37, P38, P39, P40, P42, P45, P46, P47, P48, P49, P50, P51, P52, P53, P55, P56, P57, P62, P63, P64, P65, P67, P73, P74, P77, P78, P79, P80, P82, P83, P86, P87, P88, P90, P91, P92, P93, P94, P95
Machine Vision(n=5)	P2, P20, P25, P30, P43
Natural Learning Process (NLP) (n=6)	P7, P28, P32, P54, P84, P89
Expert Systems(n=11)	P8, P12, P16, P24, P31, P35, P44, P81, P85, P96, P97
Robotics(n=3)	P11, P66, P72
Other(n=14)	P6, P10, P26, P41, P58, P59, P60, P61, P68, P69, P70, P71, P75, P76

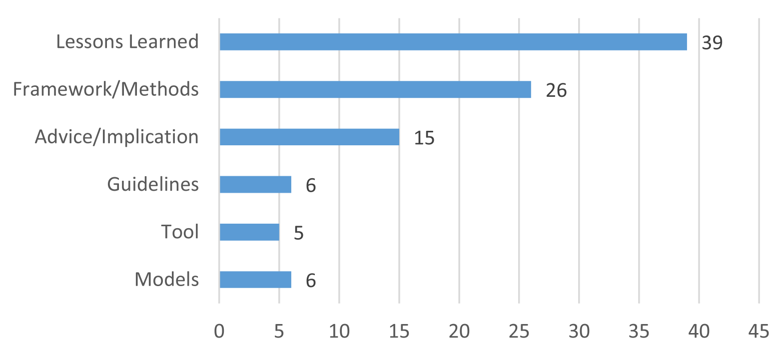

Fig. 5. Contribution types of primary studies.

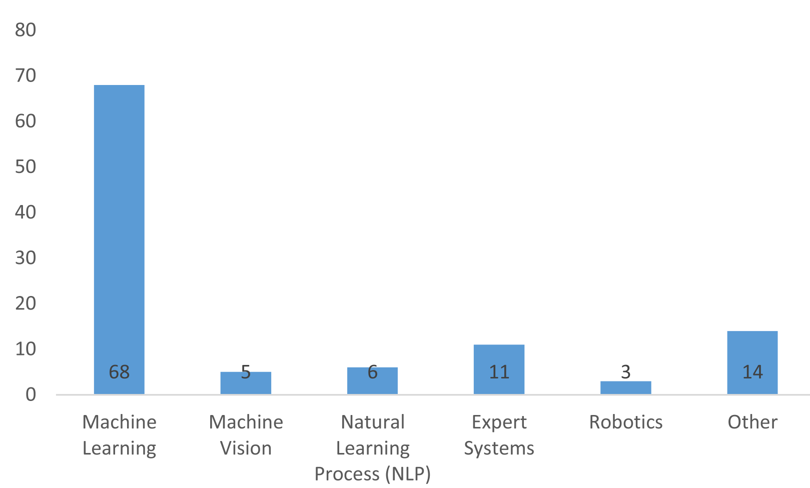

Fig. 6. Types of AI.

support three business needs: (i) Process Automation, automating business processes, (ii) Cognitive Insight, gaining insight through data analysis, and (iii) Cognitive Engagement, engaging with customers and employees (Davenport & Ronanki, 2018). In this study, we map the 98 primary studies to these three business needs (see Table 13). We acknowledge that it is possible that for some of these studies using AI could result in more than a single value type; however, to avoid complexity, they were mapped to the most relevant category.

Fig. 7. shows that the most common value type for AI was process automation (47 studies), followed by cognitive insight (32 studies). Cognitive engagement was reported with the lowest number of studies (17 studies).

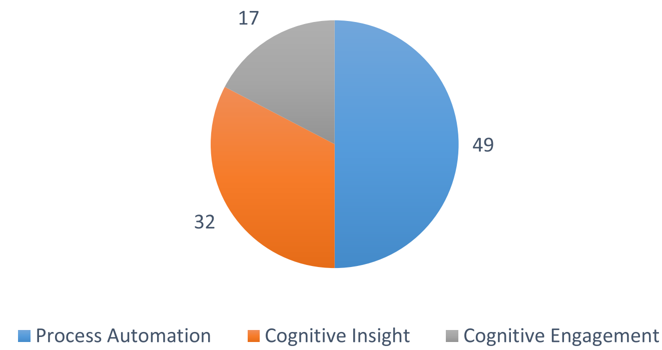

Fig. 7. Number of primary studies by value type.

5. Discussion

This section summarises the findings of the SLR and highlights some areas that research to date has focused and the key findings from these studies. It is then followed by a discussion on the theoretical contributions and implications for practice. The overall goal is to uncover themes that are relevant for research and practice and identify areas which warrant further research. This section will discuss relevant insights we found from the literature, starting with the lack of cohesion around the definition of AI, the resurgence of AI interest and research in recent years, the specific contribution types of AI literature, and the disproportionate focus on machine learning and process automation.

In this study we conducted a SLR that provides a comprehensive overview on AI in IS related studies. By using a systematic literature review, we identified, classified, and analysed 1877 studies on AI and ML in IS that were published between 2005 and 2020. Of these, 98 were identified as primary studies, after a rigorous filtering process. To understand the fundamentals of AI in IS we examined and studied the articles based on studies by year, publication channel, research methods used, and their contribution to IS contributions research. Prior to commencing this task however, we had to consider the problem that the definitions of artificial intelligence were largely varied and ambiguous.

5.1. Lack of cohesive definition of AI

This study identified a lack of cohesion when defining AI, with as many as 28 definitions being used is the respective studies. While the background research elaborated in section 2 shows this is not uncommon when concerning AI, it raises a concern that there is a high risk that IS studies on AI could experience a lack of cumulative building of knowledge (Fitzgerald & Adam, 2000). This resonates with the issue of 'fragmented adhocracy', which has previously overshadowed IS research (Banville & Landry, 1989; Hirschheim, Klein, & Lyytinen, 1996).

Table 13
Reported value types of AI studies.

Value type	Description (Davenport & Ronaki, 2018)	Primary studies
Process automation (n=49)	Automating business processes	P1, P5, P6, P9, P10, P11, P12, P13, P14, P15, P16, P17, P18, P25, P26, P28, P29, P30, P31, P33, P34, P36, P39, P40, P41, P43, P45, P47, P50, P52, P55, P56, P60, P61, P62, P64, P68, P69, P70, P76, P77, P78, P82, P83, P86, P88, P90, P93, P97
Cognitive insight (n=32)	Gaining insight through data analysis	P3, P4, P8, P19, P20, P21, P22, P23, P24, P27, P37, P42, P48, P51, P53, P57, P58, P59, P63, P65, P73, P74, P75, P79, P80, P81, P87, P91, P92, P95, P96, P98
Cognitive engagement (n=17)	Engaging with customers and employees	P2, P7, P32, P35, P38, P44, P46, P49, P54, P66, P67, P71, P72, P84, P85, P89, P94

The most common definition for AI seen was derived from Russel & Norvig, though the specific edition varied, followed by LeCun et al. (2015) and Rai et al. (2019) with two occurrences each. Looking at the definitions gathered from the primary studies, there seems to be a trend where AI is defined more in what its *capabilities* are rather than strictly defining what it *is.* Russel and Norvig (2020) defined it as something that "*enables the machine to exhibit human intelligence, including the ability to perceive, reason, learn, and interact, etc.*" for example, while Stone et al. (2016) refers to it as "*a science and a set of computational technologies that are inspired by—but typically operate quite differently from—the ways people [...] sense, learn, reason, and take action*". This means that the definitions of AI often end up being quite similar, even if they are taken from a separate source. While defining AI is outside the scope of this study, the most robust definition of AI in the context of IS research is provided by Rai et al. (2019) who define it as "*the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity*".

However, there may be issues with how IS research is approaching the defining of AI as there seems to be a believe that there is a true (i.e., real, natural) meaning of "intelligence" that AI research projects should abide by, at least among those that consider defining AI. Yet "intelligence" by its dictionary definition today was formed long before AI, and therefore strictly about human intelligence, where the various levels (conscious and subconscious) are unified, which is not the case for computer intelligence. For human intelligence, structure, behaviour, capability, and function are all relatively unified, while for AI these aspects are commonly pursued in different ways towards different goals. For example, an AI created by mimicking the *structure* of a human brain and one created by focusing on imitating human *behaviour* would be end up being very different both in its method and its result. Additionally, human intelligence is developed under certain evolutionary and biological restrictions, which are essential for human, but not really for intelligence in general. After all, "Artificial Intelligence" should not be taken to mean "Artificial Human Intelligence", since "Intelligence" should be a more general notion than "Human Intelligence".

Another major concern is the number of studies concerning or using some form of AI that do not define it at all. Of the 98 primary studies, 54 didn't define AI at all. These are primarily the studies that use AI as part of the methodology of their study, often in the case of using some type of machine learning in pursuit of that studies objective. While it is not feasible to ask every researcher, who uses a machine learning technique in their research to dedicate an entire section to AI, the lack of sufficient detail seen in many of the primary studies showcases a possible lack in the cumulative building of knowledge. A related concern is the 7 studies who defined AI by themselves, without sourcing any part it. This is something to be discouraged as much as possible, as it is important both for the individual researchers and for the field as whole to have knowledge built upon clearly and accurately.

5.2. The resurgence of AI in recent years

Our findings show that while there was a lack of studies in the first decade of the relevant time, there has been a resurgence in recent years. Over half of the primary studies were published in 2019 and 2020. Our findings also show that ICIS published the highest number of studies. ICIS published 41 studies to AI in Information Systems in comparison to the 24 studies published in ECIS. IJIM published 14 primary studies, making them the most published regarding AI in IS journals used in the systematic review.

As previously shown in Fig. 4., there was a resurgence in interest in AI in 2017, before it seemed to really expand in 2019 and 2020. It's already been noted that AI research tends to swing between its "winters" and "summers", and it seems clear that we have headed into one of its summer periods in recent years. In 2016, the Economist declared in its June Special Report (The Economist, 2016) that "After many false starts, artificial intelligence has taken off." This was followed by reports released by high level policy makers such as the US and UK governments on future directions and strategy for AI, noting its immense potential but also questions on accountability and use (Government Office for Science, 2016; U.S. National Science and Technology Council, 2016).

This surge of interest in the use of AI among businesses and policy makers naturally resulted in a matching surge in interest among researchers, who now have much more to study due to AIs ever increasing use. This resurgence in AI can be put down to a few reasons. One of the biggest is a convergence of advances in machine learning and big data and graphics processing units (GPUs) which made supervised learning from large datasets much more practical (Morris, Schlenoff, & Srinivasan, 2017). This surge in interest in AI seems to correlate with our own findings, as researchers now have much more access to empirical evidence and AI in use with the advent of this "summer". In the IS community specifically, the increased feasibility of building empirical models from experimental data and using these models to make predictions (the goal of predictive analytics using big data) is likely another reason for the resurgence of interest. However, despite the abundance of research related to machine learning, most of what we found in the literature was related to its technological use in specific domains, whether that domain be healthcare, manufacturing etc. There is a relative lack of research into societal or governmental implications of machine learning and its recent advancements.

5.3. Contribution mismatch

For identifying the contribution types that AI studies have made in IS in the past 15 years, the primary studies were categorised using a framework adapted from Shaw (2003) and Paternoster et al. (2014). The most prominent contribution type among the 98 studies was categorised as "lessons learned" with 40 studies, closely followed by "methods" at 26 and to a lesser extent "advice or implication" at 15. While these findings do show a steady gathering of cumulative knowledge in relating to AI in IS, it also showcases a lack of studies in relation to (i) tools and (ii) models. This is somewhat surprising, as this means there seems to be little interest in IS in researching new and innovative tools relating to AI. Instead, the bulk of the research seems to be focused on using types of AI, primariliy machine learning, to create a particular framework, method, or technique and use that to facilitate the construction and management of software and systems.

It seems likely that the reason for this lack of focus on tools or methods is related in some ways to the reasons for the AI resurgence itself noted in section 5.2. That is, the advancement of technology making supervised learning from datasets and machine learning much more feasible means that researchers are now focused on this new foray, and "tools" and "methods" are left to languish because it seems the resurgence doesn't lift up all aspects of AI equally.

5.4. Focus on machine learning

In terms of studying the categories of AI used, following the framework provided by Dejoux and Léon (2018), machine learning was found to be overwhelmingly prominent in the primary studies, with 69 of the 98 falling under it. Expert systems were the second most studies type of AI with 11 studies categorised as using it. Robotics saw the least use among the primary studies, with 3 studies concerned with it as its main focus. This machine learning dominance seems to be due to, at least in part, the wide variety of contexts in which machine learning is useful in comparison to the other types. For example, many of the primary studies differentiated themselves by using a "machine learning approach" (Meyer et al., 2014; Chatterjee, Saeedfar, Tofangchi, & Kolbe, 2018). In addition, the frequent appearance of machine learning as the AI application used in this paper can be attributed to the fact that it concerns a very broad spectrum of potential applications. Therefore, while the prominence of machine learning may be understandable, it is still a concern. It means there is a relative dearth in studies concerning the other categories under AI, especially robotics. Google Trends show that popularity of the search term for machine learning has surpassed the popularity of AI by almost twice as much (Google Trends, 2020). Additionally, the advances in hardware such as GPUs that has made AI much more feasible in recent years seems to disproportionally favour machine learning, which means more focus from industry and research. For example, text mining relatively inexpensive and can result in a wealth of information if done correctly (He, Zha, & Li, 2013) while there has been some research done on the critical success factors of data-mining that is lacking in other areas (Bole, Popovic, Zabkar, Papa, & Jaklic, 2015). This means that some of the other types of AI have received less research focus, though all of them can offer much both practically and academically. For researchers, this seems to have resulted in many more studies approaching research into their own domains using what is often simply called "a machine learning approach" with P1 (Meyers et al., 2014), P13 (Yin, Langenheldt, Harlev, Mukkamala, & Vatrapu, 2019) and P18 (Buettner et al., 2019) just being a few of the many examples.

From our own findings here, the papers focused on natural language processing (NLP) have chatbots and similar virtual assistants as a major focus. However, they seem focused on front facing interactions between these agents and customers, and less on actual employees working beside these agents. As chatbots and virtual agents rapidly advance in complexity, there needs to be more research into not just the effects on customers interacting with them, but the human-agent interaction of the people working *beside* and *with* them as well.

The studies we found that used expert systems (ES) seemed to favour using a hybrid knowledge base using a variety of AI systems, rather than the "classical" method of using just one or more human experts (Kunz, Stelzner, & Williams, 1989). However, it has been noted by other studies that this shift hasn't resulted in a greater impact than earlier systems, despite the advances in technology. This was noted by (Wagner, 2017), who also theorised that the reason for this lack of impact is that the earlier developers were able to capitalise on the 'low hanging fruit' that had bigger impact for organisations.

5.5. Focus on process automation

Regarding the business value of AI in the primary studies, the results aren't immensely surprising, and in fact align with the findings of Davenport and Ronanki (2018). Just as with (Davenport & Ronanki, 2018), process automation was the most reported business value found because of AI use. This is likely due to process automation being both the least expensive and the easiest to implement of the three value types discussed here (Davenport & Ronanki, 2018). Adopters of RPA have noted the automation can radically transform back offices, delivering much lower costs while improving service quality, and decreasing delivery times, as well as freeing up employees from tedious tasks so they can focus on more important, challenging, and varied work (Lacity, Willcocks, & Andrew, 2015). For the primary studies, this often took the form of the authors using some form of automated ML data mining. Another example would be P36, a paper which studied the application of machine learning in decision support systems and found that the primary value was in acquiring and refining the knowledge used as the basis of the decision, rather than it make decisions themselves, noted in the study for being much more difficult (Merkert, Mueller, & Hubl, 2015).

Cognitive insight was the second most common type of derived business value among the primary studies and was described by Davenport and Ronanki (2018) as "analytics on steroids". Organisations that used such applications of AI find their value in performing and enhancing tasks only machines can do. Among the primary studies of this study, P55 would be a good standout of this, studying the use of deep learning to enhance customer targeting effectiveness (Zhang & Luo, 2019). The paper asserted that given some pilot tests deep learning models would be superior in sales performance compared to the more common industry practices of targeting customers by past purchase frequency or spending amount. These activities involve data analysis at such speeds and at volumes that no human would be possible to process.

Cognitive engagement applications of AI were the value attributed to the least number of primary studies within our sample. This is likely partly due to the cognitive engagement dealing more with customers, and businesses being more conservative with customer facing technology (Davenport & Ronanki, 2018). The idea of having frustrating conversions with a chat-bot that just can't seem to understand what the user is saying still quite strong in the public consciousness, never mind the high-profile failures such as Taybot (Badjatiya, Gupta, Gupta, & Varma, 2017).

Our findings provide an overview of the current state of research when it comes to AI use in the organisational setting, but also helps to draw some interesting points for future research. One of the main findings in our synthesis concerned the lack of definitions when it comes to AI in empirical studies. Since AI applications cover a breadth of different techniques, technologies, and set a different set of requirements on data, infrastructure and leveraging them in the organisational setting it is important that future research accurately frames the definition of AI that is used. Apart from enabling a better comparison between empirical works, clearly articulating definitions can also allow for a better understanding of the assumptions and constraints that characterise the body of work.

Adding to the above, the different applications of AI largely dictate the type of business value that can be expected. This is a point that is mentioned also in the article of Davenport and Ronanki (2018) but is largely overlook in empirical studies. Providing exact definitions on what type of AI application is studied is critical for business value research. In addition, it is important that studies define the exact use and application of the technology since this has an important bearing on how business value is realised. This point also relates heavily to the choice of theory used to support business value generation, as well as the context in which these technologies are deployed.

Specifically, on the use of theories in studying business value, much of the work that has been published to date remains untheoretical. This poses a major issue as the boundary conditions and context in which AI applications are studied are not grounded on established theoretical frameworks. It also makes the comparison between findings and the identification of complementarities much more difficult. Adding to the above, major themes that have been under-reached remain difficult to identify with an absence of theoretically grounded work. For instance, there is limited work on the diffusion and assimilation of AI application in organisations following longitudinal studies. This creates a large gap in our understanding of how AI applications are gradually assimilated in operations and how business value may evolve depending on the different stages of maturity.

5.6. Implications for practice

Our findings, apart from their research relevance also raise some important practical implications. Specifically, our analysis documents the types of AI applications that are most pursued by organisations and therefore of highest interest to researchers. The specific applications and technologies of AI that are mostly researched provide practitioners some indication about the future deployments and common technologies in organisations. The fact that machine learning applications are the most researched technology within the AI domain provides some indication about where future investments should be directed, as well as the expected type of business value that they can deliver. Having such insight can allow IT managers to start experimenting with such techniques within their organisations and making appropriate investments to gradually deploy such solutions in business areas where they could be of high value.

In addition, the review of studies points out to those that can enable practitioners to obtain important lessons learned from deployments of AI technologies, identify ways in which methods have been applied and what common challenges emerge, as well as identify those that present general advice and best practices. The broad and extensive literature on AI in organisational settings make it challenging for many practitioners to identify empirical studies that are of value to them. With the synthesis of findings and the presentation of studies based on a thematic categorisation, practitioners are more easily able to identify those studies that contribute to the challenges they and their organisations face when it comes to AI deployments.

In section 2.2, we noted other SLRs conducted in IS concerning artificial intelligence. Rzpeka and Berger (2018) consolidated research streams within IS research that had previously been treated separated and aggregated insights regarding the interaction with different AI-enabled system types. Hofmann et al. (2019) found that nearly every step in the radiology value chain could be improved with the use of machine learning. Borges et al. (2021) found that the strategic use of AI had not been well explored yet and created a preliminary conceptual framework to aid managers in exploring that. Karger (2020) was a first attempt to investigate how block chain and AI could combine. This study took a step back from any specific industry domain to research how AI and machine learning was being defined and used in a broader level, uses a framework adapted from Shaw (2003) and Paternoster et al. (2014) to see the contributions to literature from AI studies in IS and creates a research agenda for future research.

6. Future research agenda

In the following section, we critically evaluate the literature related to our research questions and highlight potential gaps for further study to identify the opportunities for future AI research and thus fulfil the fourth and final aim of this paper. We develop an agenda of future research that build from the identified gaps. This research agenda is presented in Table 14 and was primarily formatted to correspond to the framework provided by Dejoux and Léon (2018) that has been used throughout this study, with the addition of two key areas that warrant further research.

AI is seeing a small consolidation in how it is defined; as something that exhibits human intelligence, which can be seen in the definitions used by the papers in section 4.1. But the subject and definition of human intelligence is something that is still heavily debated even now. It has been noted that AI technology has tended to "*become a somewhat broad church where many forms of automation and limited intelligent machines are labelled as AI*" (Dwivedi et al., 2021). There is a gap there for researchers to give more clarity in defining AI, even if that means redefining it away from traditional human intelligence. Section 4.2.1 also points to a resurgence in interest in AI in recent years, though many of the studies here are heavily focused on the technology and performance aspect of AI. More research should be done on the societal and

Table 14
Future research agenda for AI.

Title	Research agenda description	Future Research Questions
AI definition	• Lack of consensus around the definition of AI	• Is comparing AI to human intelligence the most effective way of advancing AI research? • How can a first principles approach be used to define a more contemporary definition of AI?
Resurgence of interest	• Over focus on the technology and performance aspects of AI	• What are the societal and personal impacts of the recent advances in AI? • What can researchers and regulators do to keep up with the speed of these advances?
Machine learning	• Increase in use of machine learning as a methodology among researchers.	• How can a researcher measure the effectiveness of their machine learning approach?
Expert systems (ES)	• Move from "classical" ES to a more hybrid knowledge base.	• Is the change to a more hybrid knowledge base of expert systems more effective than the "classical" style? • If so, does the value added by this new style outweigh the resources and time spent on adapting to it?
Robotics	• Effects of extended use of advanced service robots on people is still relatively undeveloped.	• What are the impacts of the use of service robots on people, both those they are servicing and the people working alongside them? • What are the long-term psychological impacts on the increased use of service robots, both on an individual and societal level?
Natural Language Processing (NLP)	• Chatbots and intelligent agents have made great advancements in recent years, while the effects of these advancements still need to be studied.	• How can we quantify the value of more advanced chatbots and intelligent agents?
Machine vision	• Machine vision seems to be lagging in advances compared to strides made in other AI functions.	• How can the recent advances in AI and hardware further improve the use of machine vision?

personal effects these recent advances will have on people, both in the workplace and their everyday lives.

Researchers are increasingly using machine learning as a major component of their methodology when researching various topics, but currently there is a gap where much of this research could further expand on how and why they are using machine learning the way they are. For expert systems, there seems to be a shift away from the "traditional" style of ES with just a few experts managing a system to a more hybrid knowledge base that uses a variety of AI systems (Wagner, 2017). This increased complexity may also mean it will take more time and effort than usual to see a return on the time and resources invested.

Research into the full aspects of how service robots could potentially affect business and people is still lacking. Wider debate is needed into the interactive and psychological elements of robot-human interaction, especially in the long term, with some studies specifically showing that the strategic use of AI technologies for customer and employee engagement has not been well exploited yet (Borges et al., 2021; Gursoy, Chi, Lu, & Nunkoo, 2019). A specific domain that is currently lacking in research for robotics is technophobia; previous research has examined the fear of computers and have not accounted for new and evolving technologies such as robots (Sinha, Singh, Gupta, & Singh, 2020). Research into extensive interactions between advanced chatbots and humans is still immature, so researchers should take advantage of the increase in NLP capability and the usage of its technologies to do further research. Finally, machine vision doesn't seem to be taking advantage of some of the recent technological advances seen in the new studies in machine learning, so there's a gap there for researchers to see if and how machine learning could be improved. Additionally, much of IS literature recognises that IS alone is ineffective in generating value, so complementary assets are key to realising value from IS (Shea, Dow, & Chong, 2019). AI is one of these complementary assets with potential for transformative value in IS (Nishant, Kennedy, & Corbertt, 2020).

There is potential for AI in all its forms. Despite the interest in AI in recent years, there remains gaps in knowledge. However, AI does tend to encompass a broad array of ideas and practises, ranging from the specifics of the technology used to even how it is defined. Many forms of automation, machine learning and intelligent agents are thus labelled as AI. However, despite the great strides in AI noted in the, so called "strong" AI doesn't seem like it will be made a reality within the foreseeable future (Kurzweil, 2005). The future agenda of AI seems set on the further advancement of "weak" AI where specific tasks and decisions are attributed to machines, especially as much of the current research is focused on industry specific uses of AI i.e., AI in healthcare, AI in manufacturing etc. This leaves a gap for researchers to consider the use of AI in other domains, such as agriculture sustainability (Nishant, Kennedy, & Corbertt, 2020) and the public sector (Dennehy, 2020; Abubakar, Behravesh, Rezapouraghda, & Yildiz, 2019).

From the findings and analysis of this SLR, it highlights a need for a more coherent working definition of AI among academia. To improve the coherence and efficiency of research and communication, it is better to make our working definitions explicit.

7. Conclusion

This systematic literature review study provides a structured understanding of the state-of-the-art of AI research in IS. This was achieved by identifying 98 primary studies out of 1877 related AI articles over a fifteen-year period (2005 – 2020) and analysed them with respect to (i) definitions of AI, (ii) frequency of publication by year, (iii) publication channels, (iv) research method and data collection type, (v) contribution type, (vi) type of AI and (vii) business value.

A clear finding emerging from this systematic literature review is the need to (i) increase the number of rigorous academic studies on AI, especially regarding tools and models, (ii) be more detailed on the definition of AI used in studies, even when it is not the focus, and (iii) build on cumulative knowledge. Research on AI in IS is still largely unexplored. While there is a relatively sizable amount of literature concerning AI in some way, a comprehensive review of what is known about AI in IS is lacking. This is especially true for the way AI is defined in IS, which is still disparate. This study examines the body of knowledge about AI in IS. This work has developed one of the very few SLRs on AI in IS and has provided a structured analysis of trends and gaps in the field. The study provides new insights to the field of IS through the utilisation of conceptions of AI definition, mapping activities to AI, and value relating to AI. We identified gaps in knowledge in the context of AI research and IS, which provides a starting point for IS researchers and IS practitioners to advance the socio-technical knowledge surrounding AI. Thus, we make a call for future IS studies to examine AI, specifically to how AI is defined in contemporary IS research.

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