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Opinion Paper

Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda

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ABSTRACT

Artificial intelligence (AI) has been in existence for over six decades and has experienced AI winters and springs. The rise of super computing power and Big Data technologies appear to have empowered AI in recent years. The new generation of AI is rapidly expanding and has again become an attractive topic for research. This paper aims to identify the challenges associated with the use and impact of revitalised AI based systems for decision making and offer a set of research propositions for information systems (IS) researchers. The paper first provides a view of the history of AI through the relevant papers published in the International Journal of Information Management (IJIM). It then discusses AI for decision making in general and the specific issues regarding the interaction and integration of AI to support or replace human decision makers in particular. To advance research on the use of AI for decision making in the era of Big Data, the paper offers twelve research propositions for IS researchers in terms of conceptual and theoretical development, AI technology-human interaction, and AI implementation.

1. Introduction

The rise of Artificial Intelligence in recent years has attracted numerous controversial remarks. For example, CEO of IBM, Ginni Rometty, argues that AI technologies are "technologies to augment human intelligence…By and large we see a world where this is a partnership between man and machine and this is in fact going to make us better and allow us to do what the human condition is best able to do".[1] Stephen Hawking, on the other hand, remarked that "the development of full artificial intelligence could spell the end of the human race" (Cellan-Jones, 2014), and Bill Gates has also said that humans should be worried about the threat posed by Artificial Intelligence (Rawlinson, 2015).

These very different views from leading experts call for further investigation on how human beings can co-exist with AI and how to minimise the negative impact of the technology.

There is no commonly accepted definition of AI. It is normally referred to as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks. The terms AI and AI systems were first introduced in the 1950s. Since then, AI has experienced its ups ("AI springs") and downs ("AI winters"). With the rapid advancement of Big Data technologies, e.g. improved computing storage capability and super-fast speed of data processing machines, AI is being revitalised with the availability and power of Big Data.

Therefore, after years of hope and promise, AI is gaining meaningful traction within top corporations (Bean, 2018). It is reported that the take-up of AI-enabled systems in organisations is expanding rapidly (Miller, 2018a) and AI is transforming business (Daugherty & Wilson, 2018). The new wave of AI systems has improved an organisation's ability to use data to make predictions and has substantially reduced the cost of making predictions (Agrawal, Gans, & Goldfarb, 2018). According to Gartner's 2018 technology trend survey (Panetta, 2018), AI is listed as the No. 1 strategic technology. The ability to use AI to enhance decision making, reinvent business models and ecosystems, and remake the customer experience will drive the payoff for digital initiatives through 2025. The Gartner survey showed that 59% of organizations are still gathering information to build their AI strategies, while the remainder have already made progress in piloting or adopting AI solutions (Panetta, 2018).

Organisations that are engaged in using the new generation of AI systems "will find that AI faces the usual obstacles to progress of any unproven and unfamiliar technology," says Whit Andrews, Vice

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[1] https://www.youtube.com/watch?v=mNEQsl1-iZs.

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President and distinguished analyst at Gartner (Pettey, 2018). "However, early AI projects offer valuable lessons and perspectives for enterprise architecture and technology innovation leaders embarking on pilots and more formal AI efforts." (Pettey, 2018).

Overall, there are many white papers and reports from leading technology providers and articles in top management magazines, e.g. *Harvard Business Review* and *MIT Sloan Management Review*, that provide corporates with strategic and practical guidelines on how to benefit from AI. However, it appears that there are very limited academic research papers focusing on understanding the use and impact of the new generation of AI from the technology application perspective with rigorous academic investigation and theorisation. Moreover, much current academic writing seems ignorant of what happened from 1970 to 2000 despite the availability of extensive publications.

This research position paper aims to understand the challenges associated with the use and impact of the new generation of AI based systems for decision making and identify research opportunities for information systems (IS) researchers. The paper first provides a view of the history of AI through the relevant papers published in the *International Journal of Information Management (IJIM)*. It then discusses AI for decision making in general and the specific issues regarding the interaction and integration of AI techniques to support or replace human decision makers in particular. To advance research on the use of AI for decision making in the era of Big Data, the paper offers twelve research propositions for IS researchers in terms of conceptual and theoretical development, AI technology-human interaction, and AI implementation.

2. A view of the history of AI through *IJIM* papers

In this section, we present an historical perspective on the history and development of AI based on a review of relevant papers published in the *International Journal of Information Management (IJIM)*, including those under its former title of *Social Science Information Studies (SSIS)*. To achieve this, we carried out full-text searches on the *SSIS/IJIM* archive for the terms *artificial intelligence* and *intelligent*, plus the list of 25 more specific terms related to AI shown in Table 1. To develop that list, we began with selected terms from the list of categories of papers at AI conferences in Cantu-Ortiz (2014). We excluded those not specific to AI such as *bioinformatics* and *planning and scheduling*, and added a few other terms such as *recommender system* that emerged in the course of our search as alternative keywords in relevant papers.

A preliminary screening removed papers where the term *intelligent* had nothing to do with AI, and papers where the term that had been found appeared only in a cited reference and the citation did not refer to any AI aspect. This gave a total of 123 *SSIS/IJIM* papers. We categorised these into those in which AI was a substantive part of the paper (52 in total) and those in which AI was mentioned only in passing (71). The latter category comprised papers ranging from those mentioning an AI system as just one type of system in a list of those systems an organization does or might use, or as one example system in the literature review part of a paper, to those in which one of the search terms simply appeared in an author affiliation or as a research interest. We believed that even the articles from the second category were worth including in the counts, both as an indication of the visibility of the subject, and because even a single sentence can be of great interest, as we will see shortly.

Table 1
Terms used in the full-text search of the *SSIS/IJIM* archive.

1	case-based reasoning	14	logic programming
2	computer vision	15	machine learning
3	cognitive computing	16	machine vision
4	cognitive science	17	natural language processing
5	data mining	18	neural network
6	data science	19	pattern recognition
7	expert system	20	recommendation system
8	fuzzy linguistic modeling	21	recommender system
9	fuzzy logic	22	semantic network
10	genetic algorithm	23	speech recognition
11	image recognition	24	support vector machine/SVM
12	k-means	25	text mining
13	knowledge-based system		

Fig. 1 shows the breakdown of the 52 substantive AI papers and the other 71 that mention AI in passing, in four-year periods from the first mention of AI in passing, by Seeger (1983) when discussing the future of information professions, up to the end of 2018.

As may be seen, the number of papers published remained fairly constant from 1983 to 2010, at roughly two papers per year (57 papers in 28 years). Fewer than half of these were substantive AI papers. However, the period 2011–2014 showed a considerable increase, to 24 papers against the previous average of 8.1, and the most recent period, 2015–2018, shows a larger increase still, to 42 papers. Even more significantly, 25 of those 42 were substantive AI papers, the same number as had appeared from 1983 to 2013 inclusive. This is a very clear indication of the rapid recent growth in research in AI in the era of Big Data.

We will now look in more detail at the techniques that make the AI systems work, the domains to which they have been applied, and the changing terminology used to describe them. In order to do this, we look most closely at the 52 substantive papers, though we triangulate those findings with the other *IJIM* papers and the wider literature. Table 2 categorizes these 52 according to the type of paper; note that six papers fitted into two categories. For techniques, we focus especially on the 22 of the 52 papers that concentrate on a specific example of an AI system (21 pilot studies and one fielded application), as these give the most precise evidence on the techniques actually in use. While other types of paper may mention AI techniques, especially review papers, it is often not clear whether those other papers are describing systems that had been developed, were being developed, or simply that might possibly exist someday.

2.1. Techniques

In this section we consider the techniques that comprise the forms of knowledge representation and/or the algorithms used to build the AI systems described. We only include those techniques mentioned and discussed by name. It is important to note that this does not necessarily measure how widely they are used, even in *IJIM*'s research domain, as some papers use terms like knowledge-based system or machine learning without describing the specific techniques employed.

2.1.1. Rule-based inference

Despite that caveat, the most common technique used in the AI systems reported is definitely rule-based inference. The very first system described in detail in *IJIM* (Lu & Mooney, 1989) was a rule-based expert system. In addition, the first mention in *IJIM* of an AI system in practical everyday use was also a rule-based system. This came in a paper by Bowonder and Miyake (1992), discussing information management in Japan's Nippon Steel Corporation. They noted that Nippon Steel had been the first in the world to use an AI system for blast furnace control (see Yui, Watanabe, Amano, Takarabe, & Nakamori, 1989).

Nearly all of the AI systems mentioned up to the year 2000 use rule-based inference, and this element of AI techniques remains with us today; three of the specific AI systems in articles from 2017 and 2018 (Araujo & Pestana, 2017; Kao et al., 2017; Rekik, Kallel, Casillas, & Alimi, 2018) are also rule-based.

The main change over time is that originally the rules were usually elicited from human experts by a human knowledge engineer, whereas now they are more likely to have been developed using an automated method such as CART (Classification and Regression Trees) (Kao et al., 2017) or association rule mining (Rekik et al., 2018).

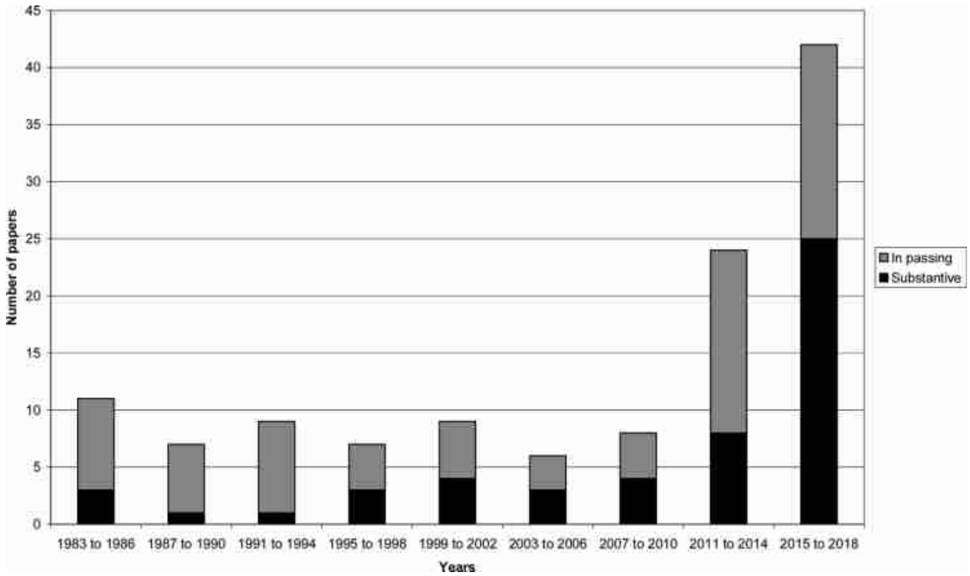

Fig. 1. AI papers published in SSIS/IJIM by year.

Table 2
Substantive AI papers categorized by type.

Type of paper	Number
Conceptual paper	12
Theoretical development	3
Pilot study/proof of concept	21
Fielded application	1
Survey	7
Management/organizational issues	3
Review	11

2.1.2. *Semantic linguistic analysis*

Almost as pervasive are the various methods of semantic linguistic analysis. The use of maps to help understand natural language in documents for information retrieval was one of the techniques identified in a review by Wormell (1984). These soon afterwards became known as semantic networks. More recent systems such as those by Tadeusiewicz, Ogiela, and Ogiela (2008) for medical diagnosis and Ogiela and Ogiela (2014) for analysing financial data use versions of this approach, sometimes with theoretical extensions such as the latent semantic analysis used by Ahmad and Laroche (2017).

2.1.3. *Bayesian networks*

Bayesian networks are based on probabilistic inference, with the conditional probabilities associated with each path between nodes in the network adapting in the light of new data, thus encompassing learning. Specific use of this term is relatively recent, with papers such as Zhao, Tang, Darlington, Austin, and Culley (2008) on evaluating information in engineering documents and Ramírez-Noriega, Juárez-Ramírez, and Martínez-Ramírez (2017) using a Bayesian network as the design for an intelligent tutoring system. However, it is likely that some of the unspecified inference methods in earlier expert systems or knowledge-based systems papers used this approach.

2.1.4. *Similarity measures*

The concept of identifying examples that are similar or close to a new observation is at the heart of case-based reasoning, which has been an active area for most of the period (Tseng, Chen, Hu, & Lin, 2017; Zantout & Marir, 1999). Similarity measures are the metrics for similarity/closeness. Bouakkaz, Ouinten, Loudcher, and Strekalova (2017) compare several similarity measures for textual analysis, and find that the k-means approach produced the best results in their experiment. The k-means approach also has the advantage of being conceptually very simple. It divides a set of observations into a predetermined number of clusters (k) by an iterative process. First a random set of k points are chosen to be the centres of the clusters, then each observation is assigned to its closest centre. Once all observations have been clustered, the mean point of each cluster is recalculated and these become the new set of cluster centres. The process is repeated until no observation changes cluster.

Support vector machines (Ragini, Anand, & Bhaskar, 2018) are another commonly used similarity measure approach; in this case examples are categorized by maximizing the width of the gaps between the clusters.

2.1.5. *Neural networks*

Neural networks, more precisely artificial neural networks (ANN), are intended to mimic the way the human brain works, and are at the forefront of the current expansion in AI even though applications can be found as far back as the 1980s (Ford, 1989). Interestingly, few papers in *IJIM* address specific applications of ANN, exceptions including Liébana-Cabanillas, Marinković, and Kalinić (2017), Mostafa and El-Masry (2013). ANN are more likely to be discussed in general summary and review articles (Frias-Martinez, Magoulas, Chen, & Macredie, 2006; Gottschalk, Filstad, Glomseth, & Solli-Sæther, 2011; Yaqoob et al., 2016).

2.1.6. *Other techniques*

Techniques discussed in *IJIM* that have also been commonly used elsewhere include frame-based representation (Dugdale, 1996), and genetic algorithms (Lebib, Mellah, & Drias, 2017). Frames allow richer forms of knowledge representation than rules, but the inferencing process is more complex, so less straightforward and harder to understand. Genetic algorithms mimic the process of Darwinian natural selection, with a population of solutions undergoing processes equivalent to inheritance, reproduction, mutation, and cross-over, until the best solution emerges. Neural networks and genetic algorithms are both examples of techniques inspired by biology: a review of those and others may be found in Kar (2016).

2.2. *Domains*

Some of the domains in which AI systems were being applied, or at least considered, have featured throughout the period. This is most likely because of the potential economic rewards from a successful system. These include: manufacturing, such as the 1992 Nippon Steel example discussed above and clothes manufacturing (Ying, Pee, & Jia, 2018); health care, from Thornett (2001) looking at computer support for general practice to Kao et al. (2017) on risk factors for cardiac arrest survival; and legal practice (du Plessis & Toit, 2006).

Recommender/recommendation systems have also been common throughout the period, but with a change in emphasis. Earlier systems tended to tackle major investments such as property (Lu & Mooney, 1989) or stocks and shares (Dugdale, 1996), but their practical use was limited. Systems addressing higher-volume but lower-value decisions are now in everyday use, and central to the success of organizations such as Amazon and Netflix, who have capitalized on the Big Data that they acquire. *IJIM* papers similarly now cover topics such as which books to read (Kim, Kim, Oh, & Ryu, 2010), which videos to watch (Choi, Oh, Kim, & Ryu, 2016) or which kitchen appliances to purchase (Ahmad & Laroche, 2017). Often these are offering technical improvements in the methods used.

As is fitting given the scope of *SSIS/IJIM*, intelligent information retrieval has been a concern since the earliest days (Wormell, 1984). Improvements in natural language understanding have facilitated progress here, which continues with articles such as those by Chung (2014) and Bouakkaz et al. (2017).

Some domains reflect changes in the wider world and its technology, such as the appearance of papers on website quality (Heradio, Cabrerizo, Fernández-Amorós, Herrera, & Herrera-Viedma, 2013; Rekik et al., 2018).

Other domains reflect the technology finally reaching the tipping point for practical usefulness, such as the work of Araujo and Pestana (2017) on employee health and well-being, and of Ragini et al. (2018) on disaster response and recovery.

In a different direction, Mostafa and El-Masry (2013) is the first *IJIM* paper to use AI as a research tool, with various data mining methods being used to analyse a survey about e-government in Egypt. Other papers using AI to analyse results include (Liébana-Cabanillas et al., 2017; Rekik et al., 2018).

Nevertheless, some domains remain at the “potential” level. As far back as 1997, Martinsons (1997) was discussing the potential for using knowledge-based systems in human resource management, and commenting that it “remains unrealized” (p.35). Many systems have been developed and indeed implemented for job matching and screening applications, but there continues to be scepticism about their use. This extends to the latest developments; the use of chatbots to respond to queries from applicants, for example by L’Oréal (Thibodeau, 2019); and use of AI based interviews for London City jobs particularly in financial sectors. This is posing a new challenge to job applicants as training for AI-based interviews is costing them about £9k (Blunden, 2018).

2.3. Terminology

We can identify three overlapping eras in the *IJIM* literature. Broadly speaking, the central terms in each era are respectively expert systems, knowledge-based systems, and a combination of artificial intelligence/machine learning/data mining.

2.3.1. Expert systems rule! (Up to 2000)

The three systems described in *IJIM* in detail up to 2000 (Dhaliwal & Tung, 2000; Dugdale, 1996; Lu & Mooney, 1989) were all expert systems. Examining the other *SSIS/IJIM* papers over that period confirms that AI was more or less synonymous with expert systems.

Since 2000, the term expert system has become far less important as a label. It may still be a phrase mentioned in the text, but it does not appear in *IJIM* paper titles, abstracts or keywords.

2.3.2. Knowledge is power - but only in business and management? (1983 onwards)

This era overlaps both of the others. The term knowledge-based system (KBS) began to become popular with the launch of the UK Government’s Alvey Programme of IT research in 1982/3, and was used in early *SSIS* papers (Ingwersen, 1984a, 1984b; Nicholas & Harman, 1985). Some saw expert systems as a subset of KBS; others regarded the two terms as equivalent.

The start of the 21 st century saw the term expert systems decline in popularity in business and management in favour of knowledge-based systems. There were three reasons for this:

1 The bad reputation that some expert systems projects achieved, meaning that “expert system” was not an attractive label.
2 An increasing realization that the system often served to assist or support a human decision-maker, rather than as an expert telling the human what to do.
3 A shift in emphasis from “the expert” to “the knowledge”, with the growth in popularity of knowledge management in the late 1990s.

Ironically, systems using the rule-based technology common in early expert systems proliferated in the 21 st century. They were simply embedded in other systems, for example as “wizards” in software packages, and now as an engine powering recommendations, so that the user would not be confronted with the “cursed” term.

KBS was the most common term in use for an AI system in *IJIM* during the 2000s, and many business/management academics and practitioners still regard it as the most appropriate term to use. As Bimba et al. (2016, p.857) put it, “A system which represents knowledge is normally referred to as a knowledge based system.” Interestingly, this only seems to be true in business and management. In other domains, especially science and engineering, expert system is still the more common term. *Web Of Science* lists more than 10,000 publications since the year 2000 that include the term *expert system(s)*, as opposed to fewer than 2000 including *knowledge-based system(s)*.

2.3.3. The rise of the intelligent machine - and data mining (during the 2010s)

During the 2010s, the term AI has come back into popularity as the overall label. This may in part be the result of the fact that deep learning systems such as multi-layer neural networks do not produce explanations that humans can understand easily, or indeed at all. Arguably, therefore, these systems do not represent knowledge as in the definition in the previous subsection. They certainly do not represent human knowledge.

Within AI, the terms machine learning and data mining are also in much more common use nowadays. In part, this reflects technological developments. Machine learning used to be seen as highly-technical jargon, but the success of machine learning systems widely reported in news stories such as the AlphaGo system defeating one of the best human players of the game Go (Koch, 2016) and IBM’s Watson system beating the human champions on the US TV quiz show “Jeopardy” (Gabbatt, 2011) has done much to improve its image. Data mining is a newer term than any of the others. Its original meaning in the field of economics was trying various models to see which fitted the data best. The more general usage did not become widespread until the mid-1990s.

More confusingly, these changes also overlap with another area of terminological change, relating to the rise of the term analytics. Some authors now regard machine learning as a form of analytics (for example Lismont, Vanthienen, Baesens, & Lemahieu, 2017), while some of the techniques discussed in Section 2.1 are now referred to as data mining when in the 1990s they would simply have been called statistical techniques.

It can be argued that there are subtle differences between expert systems, knowledge-based systems and AI systems, but some of the changes in terminology are surely no more than simply “fashion”. For example, what were often referred to in the 1980s or 1990s as production rules are now called business rules or just rules. Similarly, Kao et al. (2017) refer to the CART decision tree approach used to develop their rules as a data mining technique, whereas in the 1990s it would have been referred to as a rule induction algorithm.

3. An overview of using AI for decision making

The promises made to develop machines capable of outperforming humans in several tasks in a few years and the real accomplishments achieved have been reported widely (McCorduck, 2004). Despite what can now be thought of as excessively optimistic promises for AI outcomes during the 1950s and 1960s, steady progress has been sustained over the last four decades in the main areas of AI (Cantu-Ortiz, 2014).

Using AI for decision making has been one of the most important applications in AI history. The roles of AI have been classified in various ways. Broadly speaking, AI systems can be used either to support/assist the human decision makers, or to replace them (Edwards, Duan, & Robins, 2000). More specifically, the early publication by Bader, Edwards, Harris-Jones, and Hannaford (1988) identified six roles for knowledge based systems: Assistant, critic, second opinion, expert consultant, tutor, and automaton.

Edwards et al. (2000) conducted an analysis of expert systems for business decision making at different levels and in different roles based on experiments carried out two decades ago. The roles of AI (e.g. expert systems) are examined using the three organisational decision making levels, i.e. strategic, tactical and operational decisions. Their findings show that:

- Expert systems in a replacement role are effective at the operational and tactical decision levels, but have limitations at the strategic level.
- Expert systems in a support role can help users make better decisions at all three decision making levels, but their effectiveness can only be fulfilled through their users.
- An expert system acting in a support role does not necessarily save a user’s time, but an expert system in a replacement role does improve the efficiency of decision making.
- The users of expert systems in a support role did not believe that they had learned from using the system.

The role of AI systems, e.g. expert systems, for decision making is also discussed based on the structure of decisions that is named by Simon (1987) as structured, semi-structured and unstructured decisions. The findings by Edwards et al. (2000) suggest that AI (e.g. expert systems) can be used to replace human decision makers for structured or semi-structured decisions, but it would be better to be used as a decision support tool for dealing with unstructured decisions at the strategic level in organisations.

In a relevant assessment on the potential use of AI in organisations in 1985, Lee (1985 (p.8)) commented “Because mechanical inference relies on a stable, fixed semantics, the utility of an idealized, fully integrated, knowledge-based inference system will be limited to organizations in completely stable environments.” and “integrated information systems will only be of use for those aspects of the organization’s activities where semantic stability can be maintained. This conclusion corresponds to the empirical observations made by Gorry and Scott-Morton (1971).” This indicates that with the limitations of early AI technologies in dealing with dynamic environments, AI for organisational decision making was more effective in working in stable and familiar conditions.

In a recent joint research with Deloitte, Davenport and Ronanki (2018) examined 152 AI deployment projects that are making use of AI-based systems across a wide range of business functions and processes. Based on the survey results, Davenport categorises AI system applications into three categories:

- Cognitive Process Automation: Automation of back office administrative and financial activities using ‘Robotic Process Automation’.
- Cognitive Insights: Detecting patterns in data and interpreting their meaning using statistically-based machine learning algorithms.
- Cognitive Engagement: Engaging employees and/or customers using natural language processing chatbots, intelligent agents and machine learning.

As the progress of AI technology enables researchers to create advanced machines, it is possible for AI to undertake more complex tasks that require cognitive capabilities such as making tacit judgements, sensing emotion and driving processes which previously seemed impossible (Mahroof, 2019). As a result, an increasing number of jobs are autonomously performed by AI systems without human control and supervision (Złotowski, Yogeeswaran, & Bartneck, 2017). There are many reports on the benefits of AI for decision making because AI is believed to be able to help organisational employees to reach better decisions, to boost our analytic and decision-making abilities and heighten creativity (Wilson & Daugherty, 2018). However, “with the resurgence of AI, a new human-machine symbiosis is on the horizon and a question remains: How can humans and new artificial intelligences be complementary in organizational decision making?” (Jarrahi, 2018 p. 579).

4. Research Propositions for addressing challenges and opportunities

This section discusses the challenges and research opportunities of AI based systems for decision making in the era of Big Data from the use and impact perspective. As AI development and applications cover a wide range of areas, future research directions can be diverse. To help IS researchers in their endeavour to advance our knowledge and understanding on how to maximise the benefit of the new generation AI systems for decision making, twelve research propositions are offered, based on three areas: conceptual and theoretical development, AI technology-human interaction, and AI implementation.

4.1. Conceptual and theoretical development

4.1.1. Defining the key concepts and terms

AI has been applied in many different domains and numerous terms are used to describe AI based systems for decision making, such as: expert systems, knowledge-based systems, intelligent decision support systems, intelligent software agent systems, intelligent executive systems, etc. However, as AI is constantly evolving and advancing, names of AI based systems for decision making have changed over the years as shown in our review of *IJIM* papers in Section 2. Many names for AI based decision systems have disappeared or have been replaced with new names. It can be argued that defining AI and its related terms has become a moving target.

To clarify any conceptual confusion and controversy, there is a need to have a systematic review of AI related definitions and terms and to re-define them to reflect the new generation of AI in the era of Big Data. We make the following proposition:

Proposition 1. *Defining AI can be difficult, so it is necessary and beneficial to re-define the concept of AI and related terms to reflect the changing nature of AI development and applications in the era of Big Data.*

4.1.2. Understanding, theorising and measuring AI use and impact

With the rapid increase in AI applications, many claims are made by AI developers and large corporates about its substantial benefits and impact. For example, according to Davenport and Ronanki (2018), a survey of 250 executives who are familiar with their companies’ use of cognitive technology (a term Davenport and Ronanki explain as "next-generation AI") shows that three-quarters of them "believe that AI will substantially transform their companies within three years" (p.110).

As most similar claims are not substantiated by measurable empirical evidence and rigorous academic research, it is difficult to know how, why and to what extent AI systems are being used and impacting on individual and organisational decision making and transforming organisations. This raises a challenge on how to measure the benefits and impact of AI for decision making from short to long term, and from social, economic and political perspectives. What would be the implications for future business executives in making strategic decisions?

Therefore, the following proposition is offered:

Proposition 2. *Measuring the benefit of AI and its impact is very difficult, but possible. Therefore, there is a need to develop and test theoretically sound and practically feasible AI impact indicators to measure its benefits.*

Overall, to have a systematic understanding on how and why AI based systems are being used and affecting individual and organisational performance, an appropriate theoretical framework should be developed.

Proposition 3. *It is necessary to theorise the use of AI and its impact on decision making, therefore an integrated conceptual framework is needed to provide a systematic understanding of AI for decision making.*

4.2. Technology-human interaction

4.2.1. The role of AI for decision making

For the early applications of AI in the business and management field, Edwards (1992) points out that the spread of expert systems (representing and applying expert knowledge using AI) into management and administrative applications from the scientific/technical domains of the early systems was very slow. The view put forward in his paper was that for expert systems to be applied to problems in management or administration, the traditional 'closed-world' picture of an expert system was usually inadequate. The real manifestation of the expert system's role (and indeed that of the human expert) in management involves much more negotiation and interaction than in scientific/technical domains. The consequences for the resulting system are that it looks much more like the traditional picture of a decision support system than a classic standalone expert system.

In an early published paper in *IJIM*, Seeger (1983, p.205) voiced a concern that is still current "complex programmes of the kind developed in the field of artificial intelligence may lead to information system designs where the intellectual procedures of information work will be performed by machines. This could make a significant part of human information input obsolete."

In the era of AI and Big Data, Miller (2018a) argues the imperative of a new human-machine symbiosis and calls for the rethink of "how humans and machines need to work symbiotically to augment and enhance each other's capabilities." (p.2).

There has been an increased interest in examining the role of AI in recent years, i.e. automation or augmentation. Some AI practitioners and researchers argue that AI should be used to augment the human judgement rather than automation (Miller, 2018a; Wilson & Daugherty, 2018) and "AI systems should be designed with the intention of augmenting, not replacing, human contributions" (Jarrahi, 2018 p. 584), but this assertion should be further supported with rigorous research and investigation with empirical evidence on how and why AI is best at providing augmentation in supporting human judgement rather than decision automation.

Wilson and Daugherty (2018) argue that companies that deploy AI mainly to displace employees will see only short-term productivity gains. What is the evidence for this claim? If this is true, why and how will using AI for replacing employees not deliver the long term gains and how can this shortcoming be overcome?

Wilson and Daugherty (2018) also claim that companies can benefit from optimizing "collaboration between humans and artificial intelligence" and develop employees' "fusion skills" that enable them to work effectively at the human-machine interface. However, some AI systems don't have the capability to explain the reasoning process of decision making, how to solve the Blackbox issue, i.e. knowing why decisions are made in a certain way (Davenport & Ronanki, 2018) and provide explanations to AI users? To address this issue, Miller (2018b) observes that there has been a recent resurgence in the area of explainable AI because researchers and practitioners seek to make AI algorithms more understandable.

Many previous studies have examined the roles of AI before the era of Big Data. However, considering the super power of the new generation AI and the overwhelmingly mixed views and debate on the role of AI in decision making, it is imperative that the role of AI should be revisited and redefined, therefore we make the following proposition:

Proposition 4. *AI can play multiple roles in decision making, but AI will be mostly accepted by human decision makers as a decision support/augmentation tool rather than as the automation of decision making to replace them.*

4.2.2. System design criteria for supporting decision making

As the effectiveness of AI systems for decision making can only be realised through its acceptance and use by the end users (Edwards et al., 2000), the system design criteria for AI based systems has been an issue since the early applications of AI. For example, system design criteria have been an issue since the days of *SSIS*, before it became *IJIM* (Pejtersen, 1984). Based on our understanding of the roles of AI, whether for supporting, augmenting, replacing, or automating decision making, IS researchers need to propose the design criteria from technology-human interaction perspective for system developers to create ideal AI systems for human decision makers. For example, what are the ergonomic design issues for developing AI systems that are suitable for decision making? Therefore, we make the following proposition:

Proposition 5. *The ergonomic design of AI systems is important for their success, but the ergonomic issues are different between supporting, augmenting, replacing, or automating systems.*

4.2.3. Refining and improving AI system performance while in use by decision makers

The unique strength of human intelligence is its ability to learn and adapt to new environment and challenges. Refining and improving performance through continuing learning has been a challenge for advancing AI until the recent advances in deep learning and Big Data. Deep learning, as a subset of machine learning, has been one of the essential enablers for the renewed AI success. Can AI systems be refined and improved by deep learning while they are in use by decision makers? This question needs to be addressed by further research, so we make the following proposition:

Proposition 6. *AI systems performance for decision making can be refined and improved by deep learning while the systems are in use by decision makers.*

4.2.4. AI users' behaviour issues

Why do human decision makers accept/reject using AI for decision making? Previous research shows when people use AI as a supporting tool for decision making, different people may take different attitudes and actions on implementing the decisions recommended by AI system. For example, Davenport and Ronanki (2018) and Miller (2018a) identify the need for employees to adapt to the smart machines being used to partially or fully automate cognitive work. Davenport and Kirby (2016) introduce a model of 'Five Ways of Stepping' to help people renegotiate their relationship to machines and to co-exist with smart machines by aligning their contributions in the age of AI.

For example, senior managers' attitudes towards using AI can be critical as Ransbotham, Gerbert, Reeves, Kiron, and Spira (2018) suggest that scaling AI in the enterprise demands new ways to engage business experts with technology. Considering the importance of users' behaviour towards using AI, we make the following proposition:

Proposition 7. *AI users' personal traits and knowledge and understanding of AI will significantly affect the use and success of AI.*

4.3. AI systems implementation

4.3.1. Understanding the critical success factors

AI has been revitalised with Big Data and is becoming ever more powerful than before. However, while technology advancement may have no limit, its applications may encounter bottlenecks and unprecedented barriers. Although there may be many factors affecting the success of AI applications, it is important to identify what are the most critical success factors based on the empirical evidence collected from the real-world AI applications. These critical success factors will help organisations to be more focused by addressing the most critical issues. The critical success factors can also offer valuable guidelines for AI designers and developers in their effort to overcome challenges in order to provide the most effective and acceptable systems for decision makers.

Based on the work by Duan, Ong, Xu, and Mathews (2012) before the era of Big Data, the technical challenges related to supporting executive decision making using AI (intelligent software agents in this case) are the agents' capability to understand a business executive as an individual user with specific domain of work and information, and to fit the intelligence activities into the right content and context. They call for alleviating the limitations and bottlenecks of AI applications in terms of representing human intuition and judgement.

For example, understanding the technology can be critical for adoption success. Davenport and Ronanki (2018) argue that before embarking on an AI initiative, companies must understand which technologies perform what types of tasks, and the strengths and limitations of each.

Overall, factors affecting the use, impact, success and failure of information systems have been studied extensively (Dwivedi et al., 2015; Dwivedi, Rana, Janssen, Lal, Williams & Clement, 2017 Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2017; Hughes, Dwivedi, Rana, & Simintiras, 2016; Hughes, Dwivedi, & Rana, 2017; Hughes, Rana, & Dwivedi, 2019). There has been some work on critical success factors for implementing data mining systems (Bole, Popovič, Žabkar, Papa, & Jaklič, 2015), but across the board there is a lack of research on identifying the critical success factors affecting the current use of AI and its impact in the era of Big Data. Therefore, the following proposition is offered:

Proposition 8. *There are a set of critical factors that will significantly affect AI's success for decision making.*

4.3.2. Understanding the synergy of AI and Big Data

It can be argued that it is Big Data that has empowered AI for its current boom and the domain of cognitive computing will be incomplete without harnessing the benefits of Big Data analytics (Gupta, Kar, Baabdullah, & Al-Khowaiter, 2018). The Big Data era has added types of data that were not previously used in analysis, such as that from social media (Martínez-Rojas, Pardo-Ferreira, & Rubio-Romero, 2018; Ragini et al., 2018). On the other hand, AI makes Big Data meaningful through cognitive computing because analysis of Big Data by humans can be extremely time-consuming and thus the utilisation of AI techniques help to make sense of Big Data (Gupta et al., 2018). Yet AI is only one of many ways in which Big Data can be used (Yaqoob et al., 2016). Thus there is still a strong need to further explore and understand the synergy of AI and Big Data. More research is needed to establish the unique advantages obtained by the combination of these technologies and understand how AI can be further improved with the increasing availability of Big Data with its volume, variety and velocity. Therefore, we make the following proposition:

Proposition 9. *There is a necessity to fully understand the synergy of AI and Big Data and its implications for AI research and practice.*

4.3.3. Culture and AI applications

Culture has been recognised as an important influential factor in technology acceptance by many studies in the past. Does culture, such as national or organisational culture, and personal and religious values, also play a critical role in acceptance/adoption and use of AI applications? For example, Gerbert, Reeves, Ransbotham, Kiron, and Spira (2018) examine "Why Chinese companies approach AI differently". Liu, Chan, Zhao, and Liu (published online 2018) also find a significant influence of both organisational and Chinese national culture on knowledge management. If culture does play a role, how, why and to what extent does it affect the AI success? Thus, we formulate the following proposition:

Proposition 10. *The acceptance of AI for decision making can be affected by different cultures and personal values.*

On the other hand, will the wide use of AI for supporting and automating human decision making change culture? This is an area that has not been well explored so far, thus requiring further investigation with the following research proposition:

Proposition 11. *The acceptance and successful application of AI for decision making may result in a change of culture in organisations and in individual behaviour.*

4.3.4. Ethical and legal issues

Rapid advances in AI are raising serious ethical concerns. Remenyi and Williams (1996) was an early example of consideration of the ethics of an AI system published in *IJIM* over two decades ago. Ethical and legal concerns surrounding the applications of AI have become a major challenge. As this topic has received a substantial amount of attention and debate, a separate full paper would be more appropriate to this topic. However, as the role of government is critical for addressing the ethical concerns and legal challenges, particularly around responsibility for and explainability of decisions made by an automaton AI system, it is imperative that more research must be carried out on the role of the government in shaping the future of AI (Galston, 2018). How can the government develop adequate policy, regulations, ethical guidance and legal framework to prevent misuses of AI and their potential disastrous consequences on both individual and societal levels? Therefore, this paper makes the following proposition:

Proposition 12. *Government plays a critical role in safeguarding the impact of AI on society.*

5. Conclusion

As AI has become more popular today due to Big Data, advanced algorithms, and improved computing power and storage, AI systems are becoming an embedded element of digital systems, and more specifically, are making a profound impact on human decision making. As a result, there is an increasing demand for information systems researchers to investigate and understand the implications of AI for decision making and to contribute to the theoretical advancement and practical success of AI applications. This paper aims to address this need by analysing and highlighting the critical challenges and opportunities for IS researchers. Twelve research propositions are provided focusing on the use and impact of AI for decision making in terms of: theoretical

Table 3
A summary of research propositions.

Theoretical development	Technology-human interaction	AI implementation
1 Proposition 1 – Defining AI can be difficult, so it is necessary and beneficial to re-define the concept of AI and related terms to reflect the changing nature of AI development and applications in the era of Big Data. 2 Proposition 2 – Measuring the benefit of AI and its impact is very difficult, but possible. Therefore, there is a need to develop and test theoretically sound and practically feasible AI impact indicators to measure its benefits. 3 Proposition 3 – It is necessary to theorise the use of AI and its impact on decision making, therefore an integrated conceptual framework is needed to provide a systematic understanding of AI for decision making.	4 Proposition 4 – AI can play multiple roles in decision making, but AI will be mostly accepted by human decision makers as a decision support/augmentation tool rather than as the automation of decision making to replace them. 5 Proposition 5 – The ergonomic design of AI systems is important for their success, but the ergonomic issues are different between supporting, augmenting, replacing, or automating systems. 6 Proposition 6 – AI systems performance for decision making can be refined and improved by deep learning while the systems are in use by decision makers. 7 Proposition 7 –AI users' personal traits and knowledge and understanding of AI will significantly affect the use and success of AI.	8 Proposition 8 – There are a set of critical factors that will significantly affect AI's success for decision making. 9 Proposition 9 –There is a necessity to fully understand the synergy of AI and Big Data and its implications for AI research and practice. 10 Proposition 10 – The acceptance of AI for decision making can be affected by different cultures and personal values. 11 Proposition 11 – The acceptance and successful application of AI for decision making may result in a change of culture in organisations and in individual behaviour. 12 Proposition 12 – Government plays a critical role in safeguarding the impact of AI on society.

development, technology-human interaction and AI implementation. Table 3 provides a summary of the research propositions. Although the propositions are specifically for research in AI for decision making, most of them can also provide relevant directions for research on the use and impact of AI in general.

Like any publication, this opinion paper has certain limitations. First, it only reviews and discusses the history of AI through *IJIM* papers and so our findings may not be comprehensive and representative. Second, the paper only focuses on identifying the challenges and opportunities from the applications of AI for decision making; it does not cover issues related to advancing AI techniques and systems. Third, as an opinion paper, no primary data was collected or used to support the development of the research propositions.

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