The Impact of Applying Artificial Intelligence on the Quality of Enterprises Decision-Making

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Abstract. Artificial Intelligence (AI) is becoming more heavily utilised in enterprise decision-making process, and it is being speculated that AI is on course to becoming capable of fully supporting autonomous decision-making. However, there are significant, non-replicable, human elements in a decision-making process, which are inherently absent in AI systems. This raises the question of the extent to which AI is able to support decision-making in its current form. AI has been heavily researched in the literature, but its role in enterprise decision making have only been very recently realised. It is important to realise where AI assisted decision-making process stands today. Most of the research conducted on AI decision-support systems have focused on the possibilities, opportunities, and challenges of being integrated into an enterprise decision-making process. What is lacking in the literature is an aggregate of the findings so that future research directions and investment opportunities can be better explored. In order to fill this gap, this research qualitatively analyses the very recent existing literature on AI's contribution to enterprise decision-making process. The methodology applied is secondary data analysis in the form of a literature review conducted using the PRISMA method. Seminal research papers have been reviewed, and their findings analysed and aggregated. The findings indicate that AI is most utilised in data processing as this requires little input from humans other than feeding large, fast-paced, real-time data. The findings further show that beyond the decision-making process, AI is used in market prediction, and in healthcare enterprises for making medical oriented decisions. Finally, the most common AI algorithms that are utilised to help in enterprise decision-making process are artificial neural networks and swarm intelligence. Based on the findings, this research also suggests future research implications for academics.

Keywords: artificial intelligence, machine learning, decision-making, quality of enterprises, digital competitors - e-commerce – marketing, PRIZMA.

1 INTRODUCTION

1.1 Background

Artificial intelligence refers to a system, usually a processor, that hast the ability to think and learn (Russell & Norvig, 1995). The learning process occurs through a set of predefined algorithms which are facilitated by tools and techniques built into the core functionality of the system (Jarrahi, 2018). Artificial intelligence is a term that is used to describe any or several of

a complicated set of processes, each of which can serve their own purpose. For instance, artificial intelligence can be used for pattern recognition, prediction, and deep learning (Jarrahi, 2018). The predictive ability of artificially intelligent systems has become accurate and reliable enough that they could potentially displace human workers (Brynjolfsson & McAfee, 2014). Researchers have commented that computer science is constantly in the search of developing algorithms that can allow enterprises to get closer to a fully autonomous decision-making process (MacCrory, Westerman, Alhammadi, & Brynjolfsson, 2014). However, the acceptability of a fully autonomous decision-making process, based on machine learning algorithms and focused on the best profitable outcome for enterprises is still fairly low, as humans are still seen to be an active part in the decision-making process (Guszcza, Lewis, & Evans-Greenwood, 2017). Therefore, the question is how well artificial intelligence can support enterprises in their decision-making skills when worked in tandem with the human workforce. This problem statement is further explored in the next section.

1.2 Problem Statement

Artificial intelligence (AI) is being applied to industries across the board, but no system is entirely autonomous. For instance, in cancer detection, sole AI prediction reflected an error rate of 7.5%, while pathologist error rate reflected 3.5%. When combined, this was brought down to 0.5% (Wang, Khosla, Gargeya, Irshad, & H., 2016). In terms of decision making, AI based decision-making processes are analytical, but lack intuition. Humans, on the other hand, are able to factor in intuition from learned experiences, foresight, and common-sense. Common-sense is inherently going to be a missing factor in artificial intelligence. Thus, AI and humans working in tandem can present robust decision-making processes. This study explores the contribution of AI in supporting humans in enterprise decision making process. While there has been some research on the extent to which AI can aide humans in decision making, the incredibly fast-paced progress of AI demands constant research to keep track of the progress made in recent years.

This study is therefore significant as it analyses the most recent published literature on AI in the decision-making process of enterprises and presents an overall conclusion on the impact that AI has on enterprise decision making process. The research question is therefore: "How has the recent integration of AI analytics capabilities assisted the human workforce in enterprise decision-making process?" The objectives to answer this research question is presented in the next section.

1.3 Research Objectives

The objectives of this study will answer the research question as outlined in the Problem Statement section. The objectives are as follows:

- Conduct a literature review on existing research on AI in enterprise decision making process.
- Compile and present the findings of the research explored in the literature review.
- Draw conclusive remarks on the impact of AI on enterprise decision-making process.

1.4 Research Importance

This research is important due to the following contributions:

- Provides numerical data on the impact of AI on enterprise decision making thus showing support that the recent integration of AI has helped enterprises in decision making process.
- Provides qualitative analysis of the literature on AI in enterprise decision making by aggregating previous seminal findings thereby understanding the existing trend in AI research, and also paving the way for future research.

The next section discusses the literature review "most recent and relative work that was used to conduct this study and join it with the current work.

2 LITERATURE REVIEW

In enterprise decision-making processes, humans play a significant role on being intuitive, which AI systems are always falling behind. While AI systems are very good at predicting outcomes, these predictions are based on the assumption that there are no disruptions on the ongoing structure of the market. However, global crises fly under the radar of AI systems, and even the most robust cognitive technologies are not able to analyse a probabilistic outcome to base a decision on that can factor in global crises (Guszcza, Lewis, & Evans-Greenwood, 2017). This was discussed in the literature by Campbell (2016) who observed the strength of AI analytical abilities in strategic board games where there are only a possible set of outcomes considering combinations of every single possible moves but having limitation in real world scenarios which have far too many uncountable factors. Human beings on the other hand can recall from experience and apply qualitative analysis in decision making process and can often refer to their intuition or common sense, which cannot be quantified in any measurable variables (Sadler-Smith & Shefy, 2004).

Artificial intelligence allows for a system to learn complex situations. The number of variables that can be processed by an AI system is always increasing, and the computational power is becoming faster. The speed with which an AI system is able to analyse information is beyond the cognitive ability of even the most intelligent human asset available to an enterprise. AI additionally utilises big data, algorithms, and learning mechanisms to factor in variables it previously had not considered. This is achieved by the learning process. Marwala (2015) discusses how AI is able to achieve better prediction in cases where variables are limited, albeit many. Through these algorithms, AI systems are able to reduce complexities in problems to determine causalities, correlations, and probabilities. A significant advantage of AI systems that have been identified in the literature is observed when large datasets are needed. Through a process of deep learning, and neutral networks, AI systems are able to make complex analytical decisions which would be humanly impossible owing the large and fast volume with which data needs to be processed in real-time (Jarrahi, 2018).

As a result of the above facts, it is difficult to propose a novel artificial intelligent system that does not have at least some form of known intelligence dynamics. For instance, swarm intelligence, often seen in groups of animals in nature are often used as a model for structuring artificial intelligence. While individual humans are able to intelligently make decisions, large datasets are better handled when swarm intelligence are mimicked in the algorithm for the AI. Notable work on how humans can aggregate knowledge by utilising artificial swarm intelligence in the pursuit of better enterprise decision making process was explored by Metcalf et al. (2019). Artificial swarm intelligence has been observed to be capable of elevating the overall intelligence of an enterprise when large groups of humans work in tandem with the AI. Artificial intelligence presents further complications. The swarm size of the network of decision trees that is implemented through the algorithm needs to be determined, keeping in mind the cost and resources that need to be allocated for operating the AI. The dilemma of choosing the correct swarm size was explored by Flostrand (2017). Additionally, there are known and unknown factors which come into consideration during enterprise decision making processes. AI systems need time, a valuable resource, to incrementally improve over iterations, and finally be able to assist human intelligence in business decisions (Baierle, Sellitto, Frozza, Schaefer, & Habekost, 2019). This was explored in the literature by Schoemaker and Tetlock (2017). There are further complications when it comes to being analytical and being intuitive, as was suggested in the literature by Ransbotham et al. (2017), and Borison and Hamm (2010).

It has been suggested in the literature that artificial swarm intelligence addresses these issues and businesses see improvements in their decision-making process. Both large and small groups are compatible in AI based on swarm intelligence. The collected intelligence of both small and large groups have been observed to be processable by AI using swarm intelligence. However, in order to achieve higher accuracy in predictions, AI will prefer larger group sizes. This has been observed since very early literature by Ho and Chen (2007). However, larger group sizes are not always achievable in practical applications, as larger group sizes indicate sharing of information. This information needs to be from external sources, which often are proprietary in nature (Metcalf, Askay, & Rosenberg, 2019). Small group sizes would also present some restrictions on the predictive capability of AI as small group sizes indicate internal groups who are often more likely to think alike and have limited intelligence, based on the enterprise under which they are working (Frith & Frith, 2012). Therefore, in order for AI to assist in business decisions, intelligence gathered from small groups are preferred to be from experts in the field. They provide the insight, knowledge, and their own foresight and understanding of the market based on their intuition from experience, and the AI provides the analytical support through processing the information and finding patterns and offering predictions (Metcalf, Askay, & Rosenberg, 2019).

The analytical operations performed by the AI also has the potential to be real-time, where data from each member of the human intelligence group is analysed in parallel pattern to each other and offering predictions based on where the decision is converging. This was studied in the literature by Tetlock and Gardner (2016), and Schoemaker and Tetlock (2017). Schoemaker and Tetlock (2017) further commented that AI plays a significant role on being able to weigh the opinions of human intelligence sources (such as, individuals in a group of analysts) based on the accuracy of their predictions. This can improve the decision-making process as analysts are allowed self-reflection, the opportunity to learn, and the option to revisit their analysis methodology to be more in line with existing market mechanics.

Jarrahi (2018) comments that AI systems' computational skills can provide the predicted outcome, and human beings' intuition, judgement, and insight can further decide whether further actions need to be taken. In the news and entertainment industry, AI systems and human intelligence work in tandem to base their decisions on whether news and entertainment related articles are reliable or false (Gray & Suri, 2017). The decision for social media website executives to make their platform trustworthy was observed during the 2020 US presidential elections, where falsely reported news, contested claims, and conspiracy theories were flagged consistently across all major social media platforms. Hoffman (2016) had previously commented on the symbiosis of AI and human intelligence that comes into play in social media enterprises regarding false news. The AI is used as a filter to strain the controversial social media posts which gain popularity and can potentially spread misinformation. Human intelligence is then used to determine whether the news is actually false or reliable. For example, The executive decision by Twitter remove posts related to false information regarding the 2020 U.S presidential election is an example of AI and humans working together to make enterprise decisions.

Regarding decision making, a classic problem of equivocation, an instance where multiple conclusions are reached due to diverging opinions, experience, and perspectives from a multitude of industry experts, still exist in AI and human combination for enterprise decision making. This is also occurred when human emotions are going to be affected by AI decisions, where an analytically sound decision suggested by the AI might be seen as unacceptable to human stakeholders. Decisions such as buyout agreements, magnitudes of layoff, negotiations for alliances, can be made by AI, but if it goes against the interest of the executives, whose priorities are larger profits for themselves, then they, as stakeholders, would be inclined to defer to their own intuition rather than analytics (Campbell, 2016). Additionally, while AI systems can factor in socio-economic and political factors if the variables are so defined, humans are

more than likely to feel they are more equipped and hence, superior to the AI when politically motivated enterprise decisions need to be made Jarrahi (2018).

Hung's (2003) comments on the decision-making process of executive support systems are still relevant in the age of AI today. Hung (2003) suggested that executive support systems work best to merely support human decisions and Martin (2009) agree with Hung's analysis of how machines and humans should work together for enterprise business solutions. A complementary solution to how AI and humans can work together was provided by Jarrahi (2018). Jarrahi (2018) is suggest that humans can make fast intuitive decisions when unknown variables are significant, while AI can provide real time access to information for detecting anomalies in the pattern it has recognised. This can help to reduce uncertainty. Additionally, humans can cite the sources of information and can determine which dataset is most reliable in order for an AI to process and analyse the data in real time. This can help reduce the complexity of enterprise decision making. Finally, humans can negotiate, gather support, and gain consensus of their decisions, while AI systems can analyse the various branches of decisions that are taken by the human experts and offer its own understanding of the decision outcomes. This can help address the equivocality aspect of enterprise decision-making.

AI has received particular attention in the healthcare industry in the most recent literature. Manava et al. (2020) investigated the possibility of applying AI for detecting radiological data to radiologists. The authors commented on the eventual necessity to integrate AI into the healthcare industry in order to perform computations that do not require medical expertise. On other hand, in Manava et al.'s (2020) study, the authors believed that for radiology purposes. AI alone was not sufficient to make medical decisions. In response to the COVID-19 outbreak, several papers were published as well. In this application, AI lacks in making crucial decisions. This is a case where AI struggles due to the novelty of a virus outbreak. The common criticisms of AI in tackling COVID-19 were observed to be the same common restrictions that have always limited AI. Some of these limitations were lack of data (Lai, Yeung, & Celi, 2020), lack of validation (Li & Xia, 2020), technically complex (Kallianos, et al., 2019), resource-intensive (Chen & See, 2020), ethically questionable (Naudé, 2020), and legally complicated (Yu, Beam, & Kohane, 2018). Jaykumar et al. (2021) analysed the effectiveness of AI decision making for orthopaedic patients. The results of the study for Jaykumar indicate that AI helped make better decisions in collaborative efforts with humans, AI also improved satisfaction among patients, and produced better functional outc

omes at around 6 months. However, AI did not improve the consultation times that were needed for the patients or were not consistent in its treatment suggestions. Longoni, et al. (2019) suggested that patients in general prefer AI to human-made analysis when it comes to medical decisions. Pezzo and Beckstead (2020) however, commented that this is not always the case, but is instead observed more robustly in patients who knew about the instances when AI outperformed humans in medical tasks. The literature reflects that AI in medical enterprise decision making is also functional at perform in best when humans and AI collaborate. The findings by Pezzo and Beckstead (2020) and Longoni et al. (2019) however suggest that patients prefer AI decisions. However, this is not a reflection of what the medical enterprises prefer. Human-AI collaboration is still the preferred decision-making strategy in medical enterprises.

Several techniques of AI have been observed in the literature. The most common among these is rule-based inference (Araujo & Pestana, 2017). Bayesian inference technique is another common AI method observed in the literature (Ramírez-Noriega, Juárez-Ramírez, & Martínez-Ramírez, 2017), and neural networks (Yaqoob, et al., 2016). While it has been argued that many AI systems are increasingly becoming more capable of handling decision-making entirely on its own and thereby automating an enterprise's decision-making process (Złotowski, Yogeeswaran, & Bartneck, 2017; Wilson & Daugherty, 2018), researchers consistently want to explore the possibility of human-AI hybrid decision making processes (Jarrahi, 2018; Duan, Edwards, & Dwivedi, 2019).

Research on the role of AI in enterprise decision-making is abundant in the literature. The majority of these studies focus on the role of AI in aiding humans make decisions. This is expected as a fully autonomous AI system for crucial enterprise decision making strategies is never going to be fully reliable. As identified in the literature, the problem involved in trying to fulfil this would require a level of sentiment and consideration, which AI are not equipped to do yet. AI decisions are purely analytical, while human beings apply sentiment and common sense. From the findings of the literature, a hypothesis can be drawn that exemplifies this observation. AI are programmed in a manner that makes it so that it easy, tailors its decision making with the best interest of the enterprise alone, and this may not necessarily include its stakeholders. Therefore, in a situation where there is a global crisis which causes massive losses to an enterprise, the AI's decision might act towards minimising the size of the labour force. While this makes financial sense for the sake of the profitability of the enterprise, it does not take into consideration the morality and ethics of laying off a massive labour force, and the consequences on the economy it might have in the immediate future. In this case, human intervention is crucial. It can be argued that when AI decisions are based on analytics with no consideration for human sentiment, autonomous AI decision making strategies work counterintuitively to how technology should be assisting humans for the betterment of society. Most of the research in the literature have focused on this point. There are still considerable gaps in the research. In order to identify this, it is fruitful endeavour to visualise the literature review in terms of most recent findings so that future research directions can be suggested. This is discussed in the results chapter.

3 RESEARCH METHDOLOGY

This section is an overview of the methodology applied in this study. The research methodology and its justification are presented in the next section. This study is qualitative in nature and it is performed by conducting a literature review. In order to apply such literature review, a review process called PRISMA is applied. PRISMA stands for Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Moher, et al., 2015). The process involves searching for journal articles in multiple databases and external sources, removing duplicated, screening records and excluding articles after first screening, assessing eligibility of articles after reading the full text and excluding articles after second screening, and compiling the literature review from the final number of articles retrieved.

4 ACHIEVED NUMERICAL RESULTS

The findings from the literature review are presented in the form of numerical results. The key statistics discussed in this section are, the areas where AI is applied most for enterprise decision making, the various AI processes and how much they are used in enterprise decision making, and the percentage improvement in enterprise decision making due to AI with additional focus on AI's contribution to medical enterprise decision making.

4.1 AI Applications and its Processes

The histogram in Fig. 1 shows occurrences in the literature of AI in various areas of application. The identified areas from the literature are as follows:

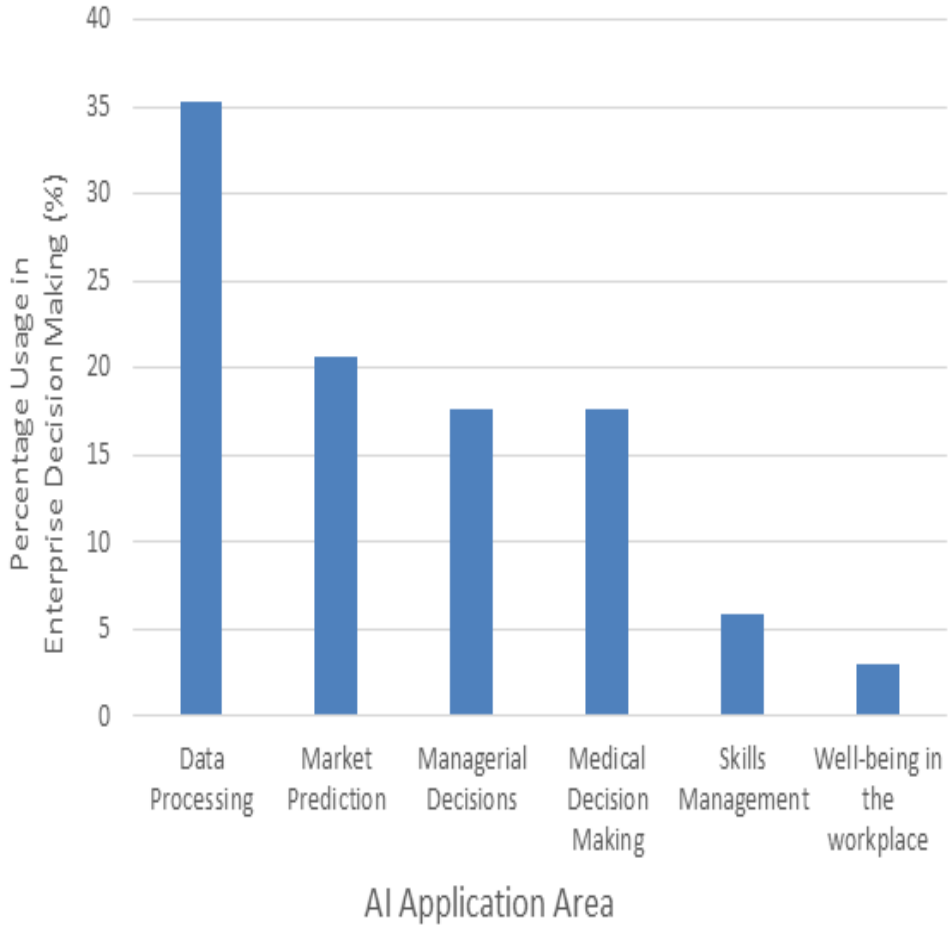

Fig. 1. Distribution of areas AI application related to enterprise decision-making.

The histogram in Fig. 1 shows that data processing and market predictions are the most researched applications of AI in enterprise decision-making process. Data processing is a predecessor to all the other applications. This means in order to make market predictions, managerial decision, medical decision making, skills management and well-being in the workplace, the first process will always be data processing. This is indicative of the focus of the research direction that has been given in the most recent literature. AI is most popularly considered for data processing. This is expected as most studies agree that AI is best used as a support for human decision-making process, meaning those work that can be reliably asked of an AI would be most researched. Market prediction and managerial decisions have also been researched in recent literature. In these areas, AI have been given higher control for decision-making as these have gone beyond the data processing. Similarly, for medical decision-making processes, it is an application of the processed data. AI's potential for decision making in the medical field has been explored so heavily because of the recent COVID-19 pandemic.

The preferred AI processes for enterprise decision making is represented by the histogram in Fig. 2. This is based on the relative importance that has been given in research on AI processes.

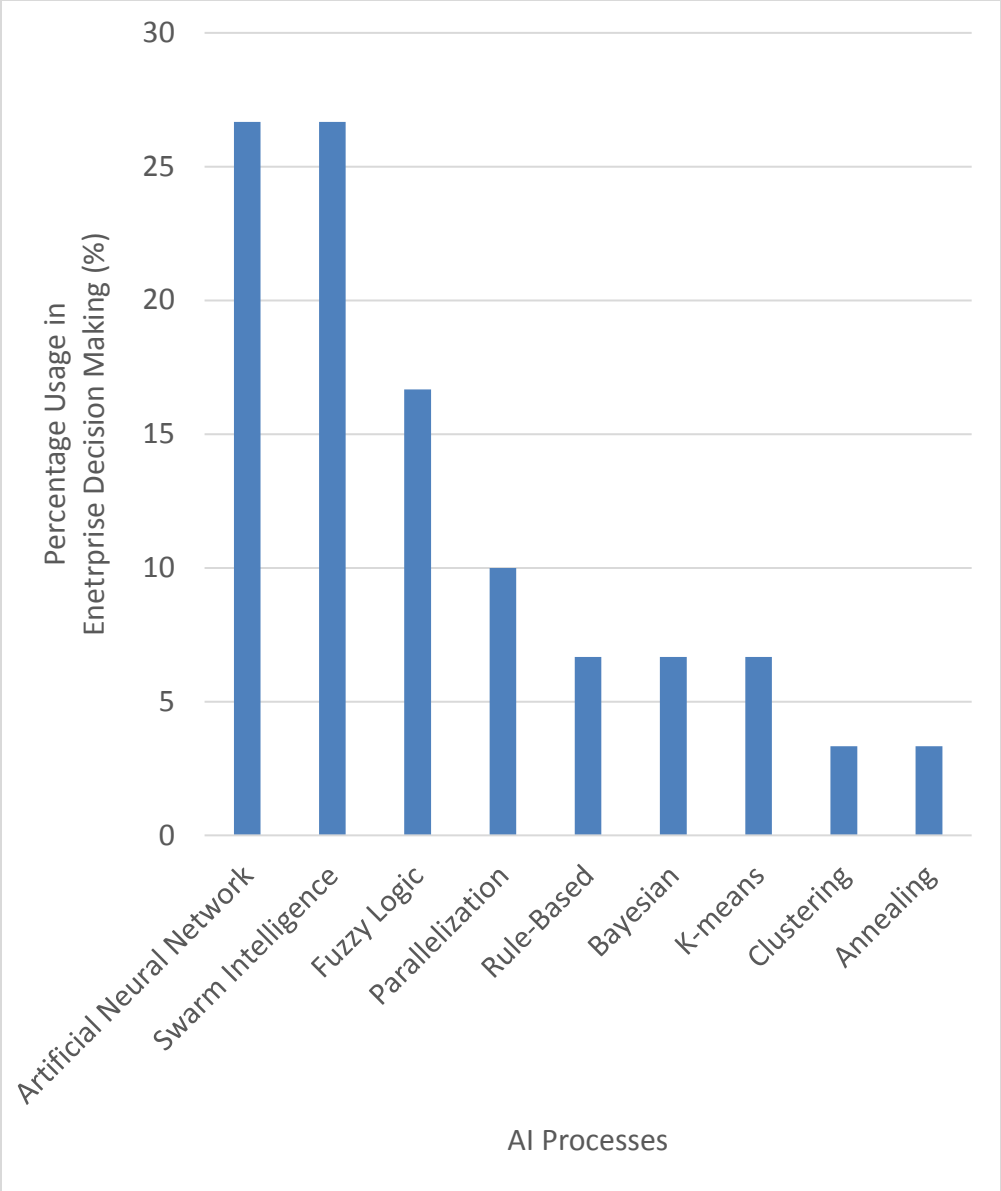

Fig. 2. Types of AI Algorithms researched in the literature and their occurrences.

In enterprise decision-making, the most popular forms of algorithms involve artificial neural network and swarm intelligence. These algorithms offer powerful learning capabilities to the AI system. Artificial neural network is a learning process whereby new branches and nodes are created that simulate a learned objective which can later be used to process data effectively and more efficiently. Swarm intelligence simulates swarm behaviours in nature. These methods, along with Fuzzy logic method are very effective for managing large datasets and are therefore common choices for researchers to consider when large, unstructured, fast flowing data are needed to be processed in the decision-making procedure. Algorithms which have appeared less frequently in the literature are similarly capable of strategising a decision-making procedure, but their applications are limited, and depend heavily on statistical knowledge of the operator. The block diagram for data processing is presented in Fig. 3.

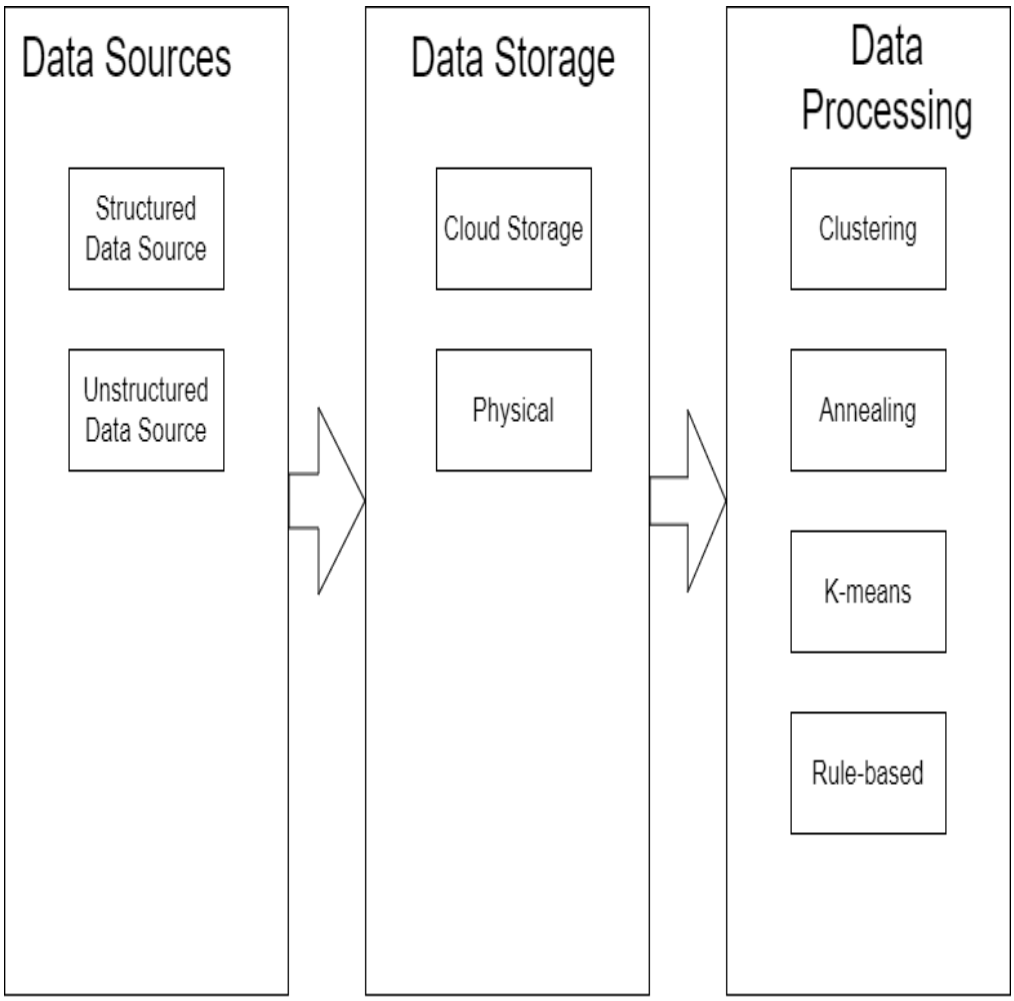

Fig. 3. Data Processing Block Diagram

The process begins with first accessing large volumes of fast and real time data. These are the unstructured data sources. They can include real-time data from social media, news feeds, articles, blogs, reviews, and commentaries. Unstructured datasets comprise of texts, images, videos, and metadata which have no recognisable patterns. Structured data sources are those that are generated from reports such as industry reports, white papers, research papers, publications, and studies. Structured datasets can also be real time, for example, information about the stock market. Before being processed, these are stored either on the cloud or on a physical drive. The data processing then involves gathering, converging, separating, and classifying the data. These are performed using clustering, annealing (Yaqoob, et al., 2016), k-means (Duan, Edwards, & Dwivedi, 2019), or rule-based processes (Araujo & Pestana, 2017) (Di Vaio, Palladino, Hassan, & Escobar, 2020).

AI's data processing techniques are then used for generating insights for the business. In order to generate insight, the AI algorithms execute a number of processes. Artificial neural network is the most commonly used process to generate insights that enterprises can base their decision-makings on. The block diagram of Artificial Neural Network is given in Fig. 4.

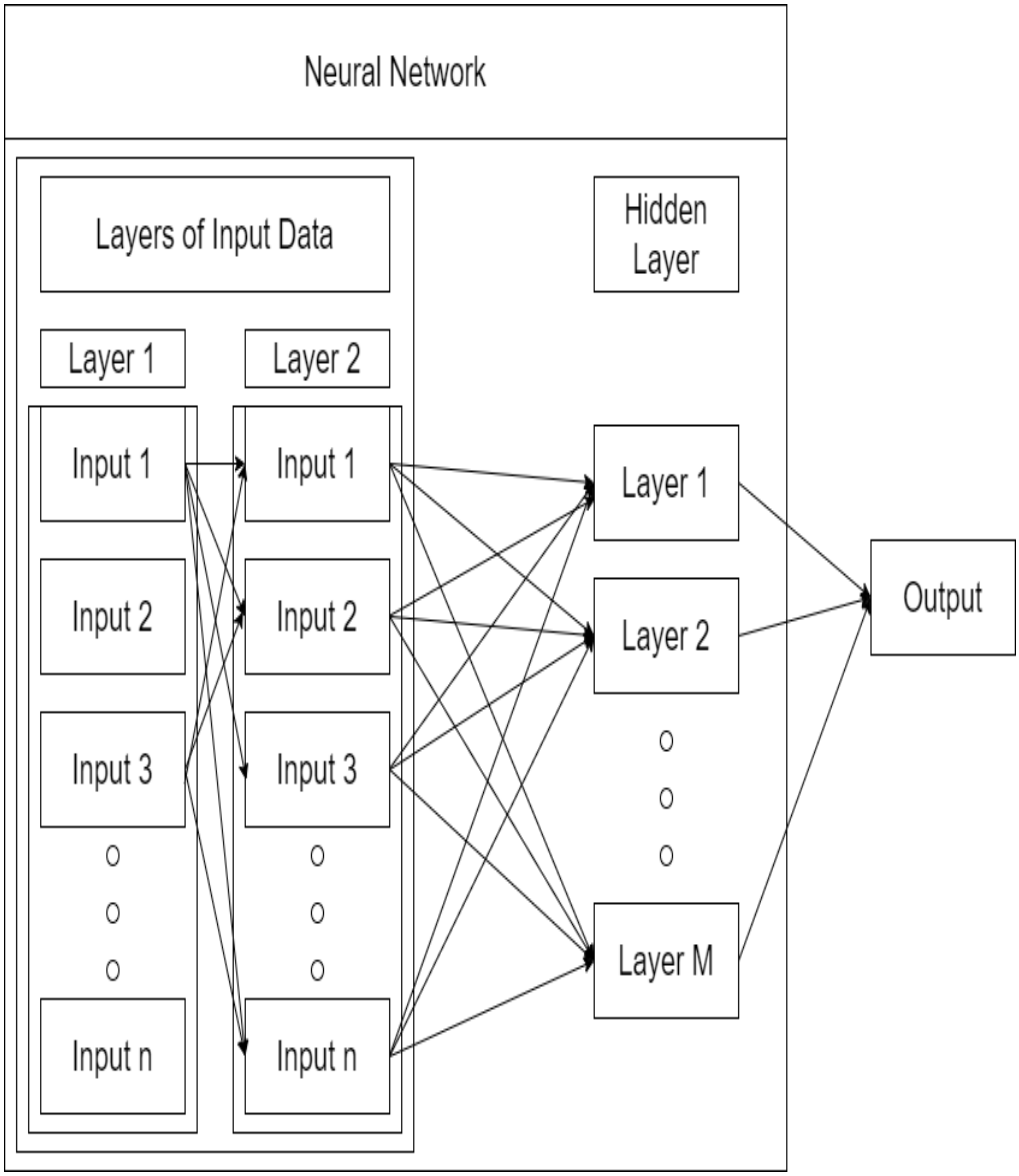

Fig. 4. Artificial Neural Network Block Diagram

The artificial neural network (shown in Fig.4) process describes the creation of nodes in between various layers of input data. These nodes create the first network links. These are then connected to various hidden layers, which performs the calculations decided by analytical expressions determined during the designing and training of the program. The hidden layers further increase the neural network size. The hidden layer finished the computation, and the output is generated. It is worth noting that sometimes there can be multiple outputs, in which case the output, too, would be a layer.

Swarm intelligence is another process that is capable of generating outputs. The block diagram of swarm intelligence is provided in Fig. 5.

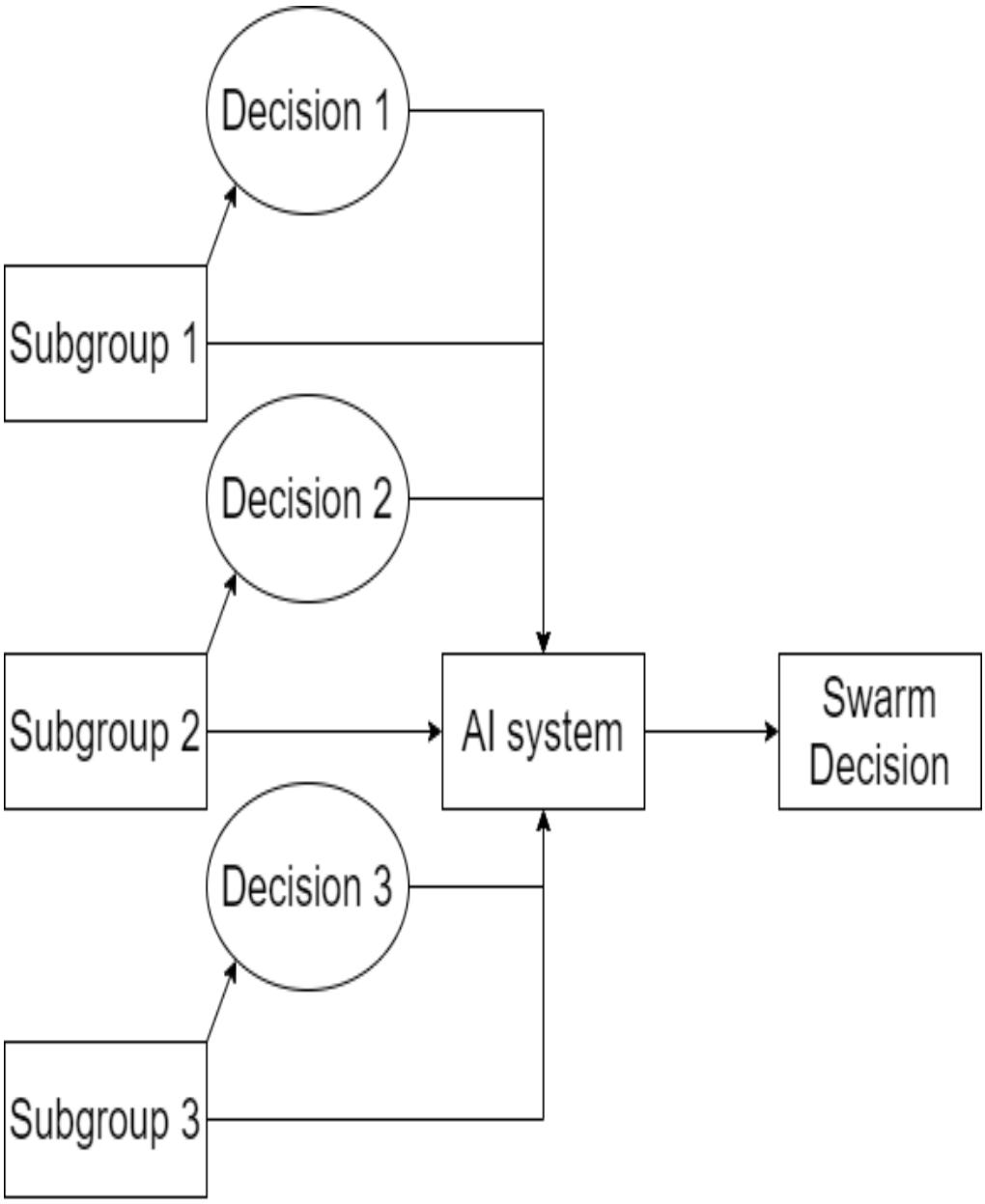

Fig. 5. Swarm Intelligence Block Diagram

The subgroups represent groups of human decision makers. They provide their decision metrics and accompanying reasonings and the AI, through its algorithms, determines what the swarm decision is. This swarm decision is the calculated best outcome for the enterprise. Swarm intelligence is heavily used in enterprises where human intervention is crucial, for example, in stock market analysis. This is also why swarm intelligence is so highly researched and applied in enterprise decision making when AI-human symbiosis is critical.

Over the years, these various AI processes have been slowly adopted in enterprise decision-making, but the results vary vastly across industries. The graph in Fig. 6 shows the contribution of AI in enterprise decision making across various areas of applications.

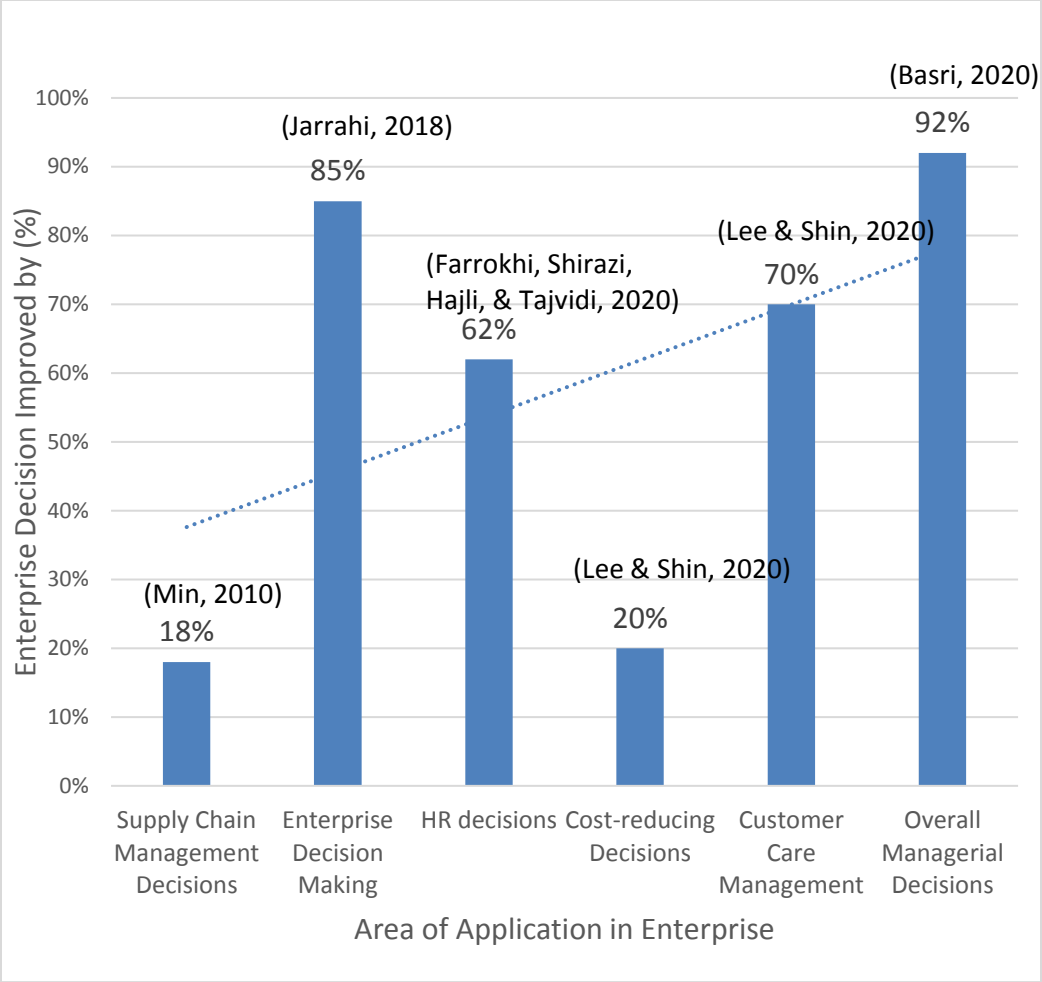

Fig. 6. Improvements in enterprise decision making process due to AI-Human Symbiosis

The inconsistencies of the contribution of AI in improving decision-making processes in enterprises is evident in the shape of the bars in the histogram. The histogram is organised in terms of the date of the study was conducted. All of these instances, except for Lee & Shin (2020) are for AI-human symbiotic enterprise decision-making process. The performance metrics for improvements are based on the qualitative reports of enterprise executives and managers who provided their insight regarding the level of extent that they believed AI has helped them make better decisions. In this regard, there is no absolute decision that AI has made enterprise decision making processes better, as studies never focus on one specific industry. In its early days, AI still managed to improve decision making process by 18% (Min, 2010), in supply chain management. But the study by Jarrahi (2018) report overall enterprise decision making processes by 85%. In human resource departments, the application of AI is seen to improve enterprise decision making processes by 62%. Cost reducing enterprise-based decision-making processes are improved by 20% and customer care management services are improved by 70% (Lee & Shin, 2020). In the case of the customer care management study, an AI was used to provide customer care services based on its own decision-making process. According to the latest study, overall managerial decisions are improved by 92% in the year 2020 (Basri, 2020). The dotted linear trendline shows that overall, the application of AI is

towards improving enterprise decision making when humans are also involved in the decision-making process.

There is however, one industry where several studies have focused on, which is the healthcare industry. Healthcare enterprises have been attempting AI integrations across various levels, and their outcomes so far are presented in Fig. 7.

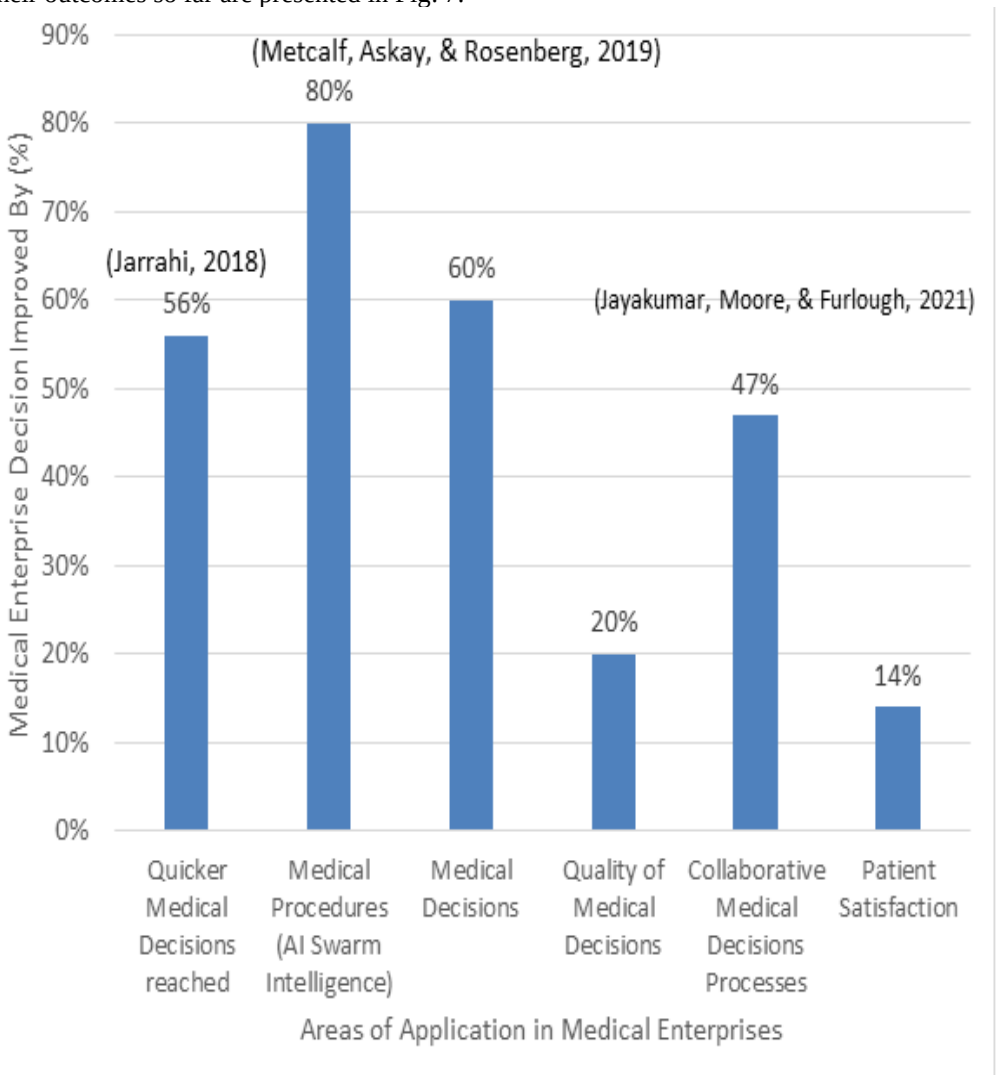

Fig. 7. Improvements in medical enterprise decision making process due to AI-Human Symbiosis

According the histogram shown in Fig.7, AI has helped the medical industry by increasing the speed of reaching medical decisions by 56% (Jarrahi, 2018). Through artificial swarm intelligence, AI is also able to suggest better medical procedural decisions by analysing the opinions of swarms of healthcare professionals. The improvement impact of this is 80% (Metcalf, Askay, & Rosenberg, 2019). The overall improvement in medical decisions is 60%. The latest study of the application of AI in medical enterprise decision making suggest that AI has improved the quality of medical decisions by 20%, has allowed for better collaborative decisions making processes by 47%, and has increased patient satisfaction by 14% (Jayakumar, Moore, & Furlough, 2021).

5 CONCLUSIOS

AI and human symbiosis have been commented as being the preferred combination for enterprise decision-making. While it will always be the eventual objective to have a fully autonomous decision-making AI system, the reality of it is that AI is limited in the knowledge and capability of its designer. However, designing sentiment, emotion, and common-sense in AI is still a feat yet to be achieved by any researcher. The various learning processes of AI systems reviewed in the literature indicate that through artificial neural network, and swarm intelligence, AI can assist humans in data processing, market predictions, and managerial decisions. Recently, there has been a high demand for research in the medical field where AI assisted decision-making processes are being increasingly used.

As progress of research gets farther, the possibility of a fully autonomous AI becomes higher. However, because of human nature where political, social, and economical influences trump over enterprise-centric decision, no AI systems can fully be trusted to make decisions that might not negatively impact stakeholders.

From the literature review it is further evident that the research focus is advancing fast towards data processing by applying artificial neural network and swarm intelligence. It can be commented that the applications of such algorithms are better understood for researchers, and therefore, further investment in research should continue in these fields.

The findings of this research are particularly of interest for academics as it lays down the groundwork for future potential research areas. However, since this research has given higher priority on the most recent literature, it is limited in its findings in terms of the history and rise of AI.

References

Araujo, J., & Pestana, G. (2017). A framework for social well-being and skills management at the workplace. *International Journal of Information Management, 37*(6), 718-725.

Baierle, I. C., Sellitto, M. A., Frozza, R., Schaefer, J. L., & Habekost, A. F. (2019). An Artificial Intelligence and Knowledge-Based System to Support the Decision-Making Process in Sales. *South African Journal of Industrial Engineering, 30*(2), 17-25.

Basri, W. (2020). Examining the Impact of Artificial Intelligence (AI)-Assisted Social Media Marketing on the Performance of Small and Medium Enterprises: Toward Effective Business Management in the Saudi Arabian Context. *International Journal of Computational Intelligence Systems, 13*(1), 142-152.

Borison, A., & Hamm, G. (2010). Prediction Markets: A New Tool for Strategic Decision Making. *California Management Review, 52*(4), 125-141.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* New York, NY: WW Norton & Company.

Campbell, M. (2016, October 24). *20 years later, humans still no match for computers on the chessboard*. Retrieved February 23, 2021, from NPR: https://www.npr.org/sections/alltechconsidered/2016/10/24/499162905/20-years-later-humans-still-no-match-for-computers-on-the-chessboard

Chen, J., & See, K. C. (2020). Artificial Intelligence for COVID-19: Rapid Review. *Journal of medical Internet research, 22*(10), e21476.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research, 121*, 283-314.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63-71.

Farrokhi, A., Shirazi, F., Hajli, N., & Tajvidi, M. (2020). Using artificial intelligence to detect crisis related to events: Decision making in B2B by artificial intelligence. *Industrial Marketing Management, 91*, 257-273.

Flostrand, A. (2017). Finding the Future: Crowdsourcing Versus the Delphi Technique. *Business Horizons, 60*(2), 229-236.

Frith, C. D., & Frith, U. (2012). Mechanisms of Social Cognition. *Annual Review of Psychology, 63*, 287-313.

Gray, M. L., & Suri, S. (2017, January 09). *The humans working behind the AI curtain*. Retrieved February 23, 2021, from HBR: https://hbr.org/2017/01/the-humans-working-behind-the-ai-curtain

Guszcza, J., Lewis, H., & Evans-Greenwood, P. (2017). *Cognitive collaboration: Why humans and computers think better together.* New York, NY: Deloitte University Press.

Haenlein, M., & Kaplan, A. (2019). A Brief History of Artificial Intelligence. *California Management Review, 61*(4), 5-14.

Ho, T. -H., & Chen, K. -Y. (2007). New Product Blockbusters: The Magic and Science of Prediction Markets. *California Management Review, 50*(1), 144-158.

Hoffman, R. (2016, June 14). *Using artificial intelligence to set information free*. Retrieved February 23, 2021, from Sloan Review MIT: https://sloanreview.mit.edu/article/using-artificial-intelligence-to-humanize-management-and-set-information-free/

Hung, S. -Y. (2003). Expert versus novice use of the executive support systems: An empirical study. *Information and Management, 40*(3), 177-189.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577-586.

Jayakumar, P., Moore, M. G., & Furlough, K. A. (2021). Comparison of an Artificial Intelligence–Enabled Patient Decision Aid vs Educational Material on Decision Quality, Shared Decision-Making, Patient Experience, and Functional Outcomes in Adults With Knee Osteoarthritis: A Randomized Clinical Trial. *JAMA Network Open, 4*(2), e2037107.

Kallianos, K., Mongan, J., Antani, S., Henry, T., Taylor, A., Abuya, J., & Kohli, M. (2019). How far have we come? Artificial intelligence for chest radiograph interpretation. *Clin Radiol, 74*(5), 338-345.

Kerzel, U. (2020). Enterprise AI Canvas Integrating Artificial Intelligence into Business. *Applied Artificial Intelligence, 35*(1), 1-12.

Lai, Y., Yeung, W., & Celi, L. A. (2020). Urban Intelligence for Pandemic Response: Viewpoint. *JMIR Public Health Surveill, 6*(2), e18873.

Lee, I., & Shin, Y. J. (2020). Machine learning for enterprises: Applications, algorithm selection, and challenges. *Business Horizons, 63*, 157-170.

Li, Y., & Xia, L. (2020). Coronavirus Disease 2019 (COVID-19): Role of Chest CT in Diagnosis and Management. *American Journal of Roentgenology, 214*(6), 1280-1286.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. *Journal of Consumer Research, 46*(4), 629-650.

MacCrory, F., Westerman, G., Alhammadi, Y., & Brynjolfsson, E. (2014). Racing with and against the machine: Changes in occupational skill composition in an era of rapid technological advance. *Proceedings of the 35th International Conference on Information Systems* (pp. 295-311). Red Hook, NY: Curran Associates Inc.

Manava, P., Galster, M., Heinen, H., Stebner, A., & Lell, M. (2020). Artificial intelligence-based algorithms : Decision-making support for computed tomography of the chest. *Radiologe, 60*, 952-958.

Martin, R. L. (2009). *The design of business: Why design thinking is the next competitive advantage.* Boston, MA: Harvard Business Press.

Marwala, T. (2015). *Causality, correlation, and artificial intelligence for rational decision making.* Jurong East, Singapore: World Scientific.

Metcalf, L., Askay, D. A., & Rosenberg, L. B. (2019). Keeping Humans in the Loop: Pooling Knowledge through Artificial Swarm Intelligence to Improve Business Decision Making. *California Management Review, 61*(4), 84-109.

Min, H. (2010). Artificial intelligence in supply chain management: theory and applications. *International Journal of Logistics: Research and Applications, 13*(1), 13-39.

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticew, M., . . . Prisma-P. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews, 4*(1), 1-9.

Naudé, W. (2020). Artificial intelligence vs COVID-19: limitations, constraints and pitfalls. *AI Soc, 35*(3), 1-5.

Pezzo, M. V., & Beckstead, J. W. (2020). Patients prefer artificial intelligence to a human provider, provided the AI is better than the human: A commentary on Longoni, Bonezzi and Morewedge (2019). *Judgment and decision making, 15*(3), 443-445.

Ramírez-Noriega, A., Juárez-Ramírez, R., & Martínez-Ramírez, Y. (2017). Evaluation module based on Bayesian networks to intelligent tutoring systems. *International Journal of Information Management, 37*(1), 1488-1498.

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). Reshaping Business with Artificial Intelligence: Closing the Gap between Ambition and Action. *MIT Sloan Management Review, 59*(1), 1-17.

Russell, S., & Norvig, P. (1995). *Artificial intelligence: A modern approach.* Englewood Cliffs, NJ: Prentice-Hall.

Sadler-Smith, E., & Shefy, E. (2004). The intuitive executive: Understanding and applying 'gut feel' in decision-making. *The Academy of Management Executive, 18*(4), 76-91.

Schoemaker, P., & Tetlock, P. E. (2017). Building a More Intelligent Enterprise. *MIT Sloan Management Review*, *58*(3), 28-38.

Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., . . . Machtynger, L. (2020). Artificial Intelligence (AI) in strategic marketing decision-making: a research agenda. *Strategic Marketing*, *33*(2), 183-200.

Tetlock, P. E., & Gardner, D. (2016). *Superforecasting.* New York, NY: Random House.

Wang, D., Khosla, A., Gargeya, R., Irshad, H., & H., B. A. (2016). Deep learning for identifying metastatic breast cancer. *ArXiv*, 1-6.

Wilson, J., & Daugherty, P. R. (2018). COLLABORATIVE INTELLIGENCE Humans and Al are joining forces. *Harvard Business Review*, *96*(4), 115-123.

Yaqoob, I., Hashem, I. A., Gani, A., Mokhtar, S., Ahmed, E., Anuar, N. B., & Vasilakos, A. V. (2016). Big data: From beginning to future. *International Journal of Information Management*, *36*(6), 1231-1247.

Yu, K., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nat Biomed Eng*, *2*(10), 719-731.

Złotowski, J., Yogeeswaran, K., & Bartneck, C. (2017). Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources. *International Journal of Human-Computer Studies*, *100*, 48-54.