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"HUMAN-MACHINES INTERACTION IN MANAGEMENT DECISIONS WITH RESPECT TO AI"

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ABSTRACT

Artificial intelligence is establishing a more permanent presence in our culture as a result of the recent big data explosion and the ongoing desire for innovation. The computerised features of this tool open up novel avenues for resolving a wide range of organisational problems. It also presents additional difficulties regarding its applications and limitations. The purpose of this thesis is to provide light on how AI and humans collaborate to make decisions within an organisation. Firms that rely heavily on the transfer of knowledge are the primary subject of this study. This new era of autonomous vehicles is the result of revolutionary improvements in the Automotive engineering sector brought about by advances in robotics and sophisticated controls.

A variety of issues in vision, navigation, and control must be resolved before autonomous vehicles can be used safely in today's traffic and in severe conditions. Sensors gather data about their surroundings, computers analyse it, and actuators control the car's mechanical systems in driverless vehicles. There has to be a low- or no-cost mechanism for the introduction of autonomous vehicle technology into the current academic and research landscape. To get driverless cars inside universities and labs, we need a technology that can work with the automobiles already out there. To accommodate the potential and implementation of autonomous vehicles in the Indian scenario, we need a flexible mechanical design to be incorporated into current vehicles. In order to facilitate the creation of autonomous vehicles, the authors of this paper propose a modular mechanical design that can be easily built and installed into preexisting vehicles.

Using specialised actuators, regular automobiles can be converted into autonomous vehicles. Motors are commonly utilised actuators in automotive automation. Apart from the motors, the envisaged platform will be automated by a pneumatic system. The mechanical framework of an autonomous vehicle must be

modified and designed such that it remains stable under dynamic conditions. With more work, we can get this technology ready for mass production.

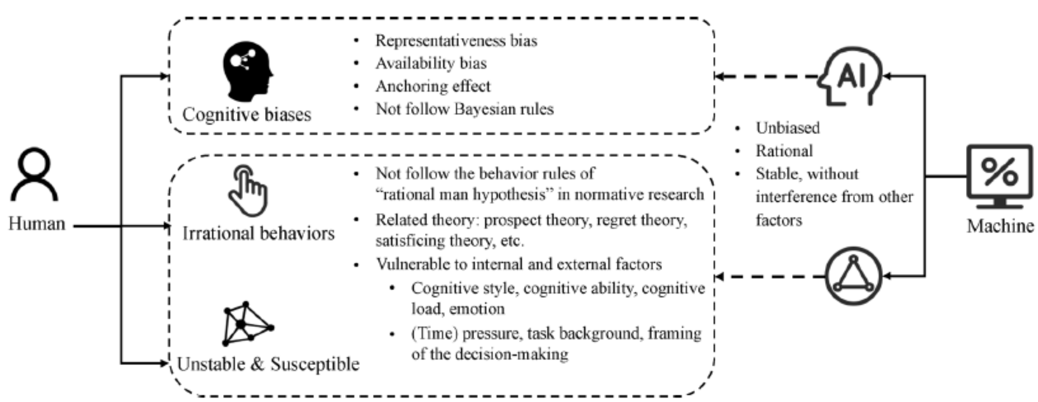
INTRODUCTION

Decision making with human and machine input The cognitive constraints of humans in making potentially hazardous choices

A choice's outcome can be affected by a variety of factors (March and Shapira, 1987). Thus, the quality of a decision is also dependent on the way in which the decision-maker deals with uncertainty, both aleatory uncertainty, which is inherent in the random phenomenon underlying a risk event, and epistemic uncertainty, which arises from a lack of knowledge about the phenomenon in question (Apel et al., 2004). It has been established that humans use cognitive biases and simple heuristics when making decisions.

People's judgements do not always follow the Bayesian rule (Grether, 1992; El-Gamal and Grether, 1995; Griffiths and Tenenbaum 2006; Charness et al., 2007), and they are susceptible to biases like representativeness bias, availability bias, and anchoring effect when assessing the likelihoods and consequences of a risk event.

Operations management, medical diagnosis, business strategy, and investing are just few of the many areas where cognitive biases have been revealed in empirical studies (Wickham, 2003; Chen et al., 2007; Croskerry, 2013; Blumenthal-Barby and Krieger, 2015; Tong and Feiler, 2017). Moreover, individuals are susceptible to restricted rationality since they do not always follow the norms proposed by prospect theory (Kahneman and Tversky, 1979), regret theory (Bell, 1982), and satisficing theory (von Neumann and Morgenstern, 1944; Wakker, 1989) while making decisions.



Human decision-maker's limitations and machine's potential to enhance risky decision-making

Theory (Simon et al., 2004). (Simon et al., 2004). In addition to the decision-cognitive maker's style (Hunt et al., 1989) and skill level (Cokely and Kelley, 2009), other factors, such as cognitive load (Deck and Jahedi, 2015), emotion and pressure (Zinn, 2008; Ordóez et al., 2015), and the framing of the decision task (Payne et al., 1993; Dörner and Wearing, 1995), can influence the approach taken. By way of illustration, public decisionmaking can elicit powerful emotional reactions (Gregory et al., 1996) and moral difficulties because the costs of the decision will be shared by others (Tetlock, 2003). We can't always make the most well-informed choices, and sometimes the outcomes we do choose aren't the ones we'd want.

Artificial intelligence's (AI) popularity is skyrocketing, and with it come new difficulties and possibilities for improving people's daily lives eXplainable AI (XAI), which emphasises AI's explanability, is quickly becoming a must-have component of every AI-based system. Research into the effects of AI on real-world problems must take into account the human partner in this human-AI collaboration. Humans provide context and meaning to data collected by machine learning (ML) techniques and approaches. Since complicated ML models can be incomprehensible to individuals who engage with AI's outcomes XAI plays an important role in the human reasoning process concerning AI's findings. Designing technology that gives people agency while also taking advantage of AI's impressive potential is a fundamental challenge. In addition, individuals need to know what to expect from technology, have faith in it, and feel like they have some level of control over it. The finest outcomes are achieved by collaboration between AI and humans, which opens up novel avenues of thought for both humans and machines.

Previous research found that the terms "transparency" and "interpretability" were used interchangeably in the literature as synonyms of XAI, typically in the context of algorithms or ML models. One paper that demonstrates the use of transparency as a synonym for XAI is. This paper discusses the use of transparency in order to investigate intelligibility through interaction and instructions for blind users, and the results show promise for a more effective and efficient computer vision system. In order to promote model verification and debugging techniques using a visual analytics system, the authors of investigate visualisation and model interpretability. Interpretability and transparency are just two of many criteria that can be considered for a XAI approach, especially when the human-AI collaboration is taken into account. They could be the most important traits for a specific group of individuals (data scientists, for example, may find interpretability particularly useful) or an end goal (legal considerations surrounding XAI are typically linked to transparency, for example). But it doesn't mean they're sufficient for any XAI technique.

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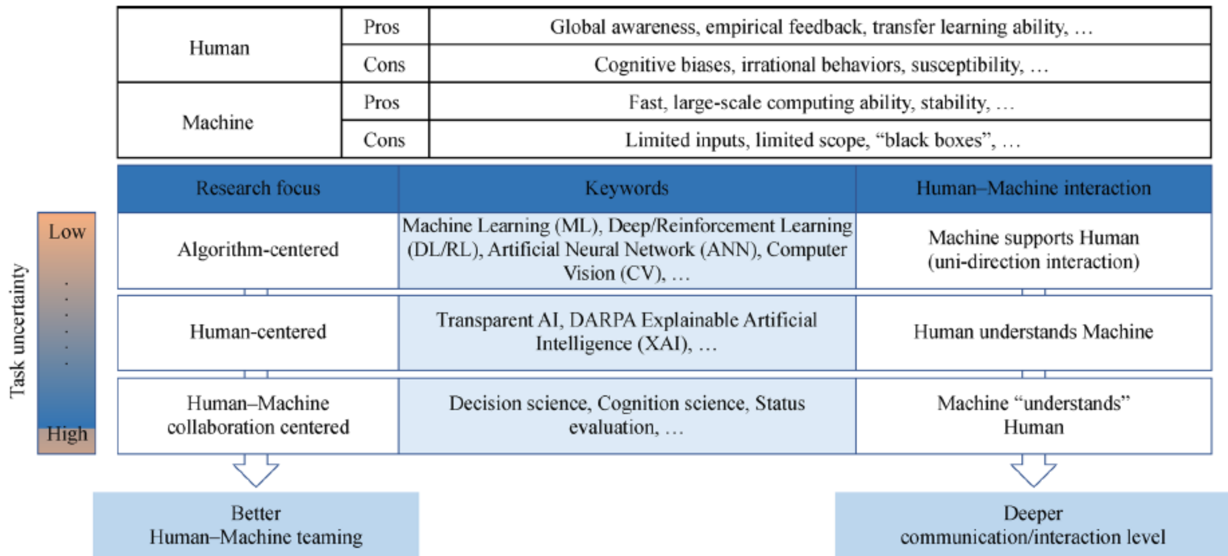


Expert System research opportunities Expert system on human–machine collaboration in risky decision-making.

The human-AI cooperation is especially important in the context of decision making, especially for high-stakes procedures (i.e., decision making processes that may have a large impact on people's lives) [8]. AI can offer a new perspective on evaluating and categorising a wide variety of data for use in high-stakes decision-making, such as medical diagnosis and forensic investigations. A doctor's or investigator's final task is to make a decision regarding someone's health or future, respectively, or to testify in court. A justification of the decision must be given to others in those situations. If the choice relies on or is influenced by an AI-system result, then providing context for how the AI arrived at that result is crucial for establishing credibility. Those making the call need to be aware of how the AI-system could influence their choice.

In this position paper, we consider the importance of building the human-AI relationship in decision-making scenarios and discuss the role of XAI, our vision of Decision-Making with AI-system in the loop cycle, and one case presented in the literature about how XAI can impact people justifying their decisions. Considering the significance of establishing a rapport between humans and artificial intelligence, we chose one intriguing case from the high-stakes medical domain decision-making to investigate and debate the potential impact that XAI could have in supplying inputs for people to rationalise their choices. Decision-making and artificial intelligence are the subjects of our discussion and the sections that follow. We then introduce and discuss the XAI features in the context of a time-sensitive choice. We wrap up the study with some concluding thoughts on the role of XAI in decision making and the human-AI interface.

For direction, we developed three more specific questions: (1) How can we best utilise both human judgement and AI in making important decisions? (2) How might AI be used into organisational design to aid in decision making? Thirdly, how might AI aid decision makers in knowledge-intensive companies in overcoming obstacles, and what fresh difficulties arise from incorporating AI into the decision-making process?

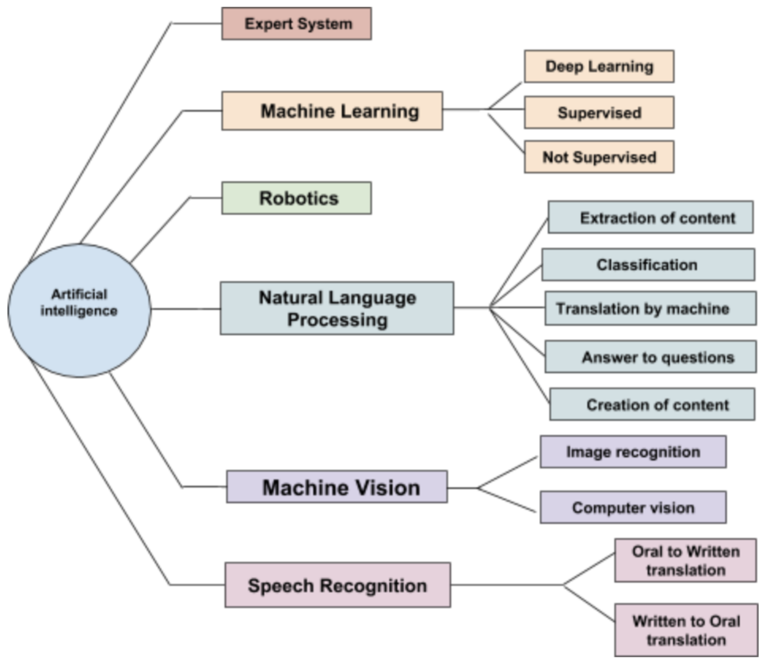
Section 3 explains how we combined an interpretivist paradigm with a qualitative investigation. We conducted interviews and surveys at two large IT companies and two real estate technology startups employing AI to explore this area of study. Six semi-structured interviews were performed to help us learn more about the decision-making process in knowledge-intensive companies and the roles that people and AI play in it. From this literature study, we were able to derive the theoretical framework shown in the next section, which served as the basis for our in-depth interviews.

The findings and results from the interviews are organised similarly to the literature review and offer useful information for resolving the research issue. Our empirical findings are reported and a chart is included in appendix we utilised the general analytical process for qualitative studies to examine and discuss these results. The three subquestions are mirrored in the organisation.

The thesis explains how humans can be enhanced and make better decisions through the integration of AI into the organisational decision-making process of knowledge-intensive organisations. It appears that AI is employed as a decision-making assistance rather than a fully autonomous decision-maker, and that businesses adopt smoother and more collaborative designs to maximise its potential inside the decision-making process. Artificial intelligence (AI) is a useful tool for handling complicated problems, yet humans still seem to have the upper hand when faced with ambiguity and uncertainty. Furthermore, there is a moral and legal ambiguity around AI that presents new challenges for businesses to navigate.

The AI Decision-Making Process Case

Given the significance of developing the human-AI relationship in such circumstances, we chose one case of XAI proposals from the literature to address the human-AI relationship for justification of judgements. The case study comes from the medical field and was conducted by Xie et al.



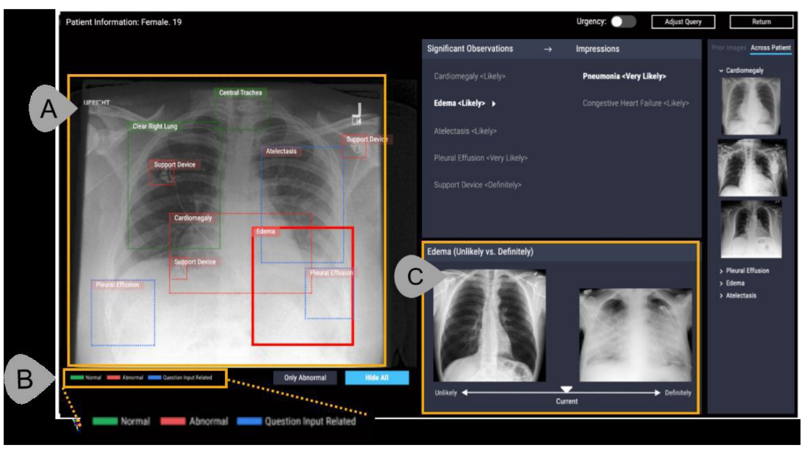
Mechanism linking periodontal infections to vascular tissue inflammation

Xie et al. present CheXplain, a system that aids doctors in navigating and comprehending AI-enabled chest X-ray data. Physicians who are not radiologists but who refer patients to radiologists for additional diagnostics or treatment make up the user base. One common reason referring doctors contact radiologists is to ask for clarification on a particular issue. While a radiologist's expertise is indispensable, a physician's ability to interpret a chest x-ray (CXR) and integrate it with data from other diagnostic tests is where this effort is best spent.

When interpreting a CXR, doctors often seek justification rather than an explanation. This idea for explainable AI-enabled interactive chest X-ray analysis will allow doctors to see where the AI looked and what it thinks the CXR shows to determine the result, as well as understand precisely what is revealed in CXR images and why. CXR images are often ordered by physicians with a specific query in mind, with essential contextual information gleaned from other exams in some cases (e.g., clinical exams, patient observation, history, etc.) As useful as the CXR is, it is not the only tool a doctor has at his disposal. There is background data, which is crucial to the doctor's judgement. In determining a diagnosis, the CXR is merely one piece of information among several.

We focused on the three elements of CheXplain depicted in Figure 2. The first option involves marking certain regions of the CXR image with markers that indicate which parts of the image the AI examined and what those parts might be (Figure 2-A). If a doctor has never looked at a CXR before, this is a fine place to begin, and it can be supplemented with additional data regarding the patient's condition. The classification of CXR indicators as normal, aberrant, and question-input related is another intriguing aspect (Figure 2-AB). As a radiologist would, it provides an overview of the CXR and frees the doctor to concentrate on answering the patient's specific question. The CXR may corroborate or refute a physician's preconceived notions about the patient's condition, which are reflected in the questions the doctor enters into the system. If the hypothesis is correct, the doctor can utilise the CXR results to justify the following stages in the patient's treatment.

Third, we emphasised CheXplain's ability to place observations in context through the use of contrasting instances (Figure 2-C). In accordance with standard practise, this aspect (Physicians mentioned that comparing abnormal and normal CXR images is common in teaching radiologists). With this method, the human and artificial intelligence (AI) mental models can be better aligned, which is essential for the XAI approach.



CheXplain: The high-fidelity prototype

relationship. The AI will tell doctors of its references for each mark in the CXR by displaying a "unlikely-definitely" range on the interface. The doctor can see if his or her own concepts of "unlikely" and "absolutely" correspond to those of the AI. The authors suggest that showing doctors two (radiographically) similar photos is one method to provide context for the AI's conclusion and help them understand it.

The CXR is used by the doctor to help make a diagnosis. CheXplain equips the user with the rationale needed to defend the examination's findings. In this scenario, the highlighted features show the doctor where in the image the AI has determined to be important in relation to the doctor's question. Aside from that, AI provides its references with contrasting cases that allow the doctor to access the CXR results and decide if they may be used as input for validating a patient's diagnosis or not.

Research design

Quantitative and qualitative approaches are the two primary types of data collection. To begin with, the qualitative approach thinks about things like time and place when conducting research. Using an interpretivist perspective, the qualitative approach yields credible results. The validity of a study is determined by how well it represents the phenomenon being studied. Quantitative research, on the other hand, is an exacting method that can be conducted at any time and in any place. There is a strong consensus around the findings produced by the quantitative approach, which is typically connected with the positivist paradigm. If the study is duplicated, there should be little to no variation, and this is what we mean by reliability.

Since we are using an interpretivist worldview, a qualitative approach is ideal for this research. We are also interested in learning more about AI, KIF decision-making processes, and the ways in which these factors interact with KIF organisational structures. Our goal is to amass comprehensive and accurate data.

Analysis and discussion

Here, we'll examine those observations and results in light of the hypotheses we laid out in the preceding section. The following sections evaluate and explore the core tenet of our thesis, which is the interplay between AI and humans in the decision-making process within KIFs' organisational structures. (3) new issues associated with AI in decision making (1) the function of the decision maker and organisational challenges (2) organisational design suitable for AI in KIFs

The majority of interviewers saw AI as a method that strives to replicate the human brain. However, they also highlighted the special talents it possessed. As AI relies on algorithms and computers to carry out its jobs, it has a distinct competitive advantage over human beings. To begin with, AI's computer capacity allows it to store more data and digest it faster than human brains, resulting in superior analysis. As an added bonus, it has access to data in real time, so there's no need to worry about storage space. All of this is consistent with our theory that AI will soon be able to detect patterns, give meaning to data, and handle massive amounts of data more effectively than humans. The more data is fed into an AI system, the more accurate its analyses will be. This is especially helpful now, in the era of Big Data and digitization. Second, artificial intelligence is unbiased, completely rational, and flexible in its use. Atos's interviewees explained that machines make decisions without the usual pitfalls associated with human cognition, such as prejudice, uncertainty, and uncertainty about the future. Artificial intelligence (AI) relies solely on verifiable facts in its analysis, as the data is analysed in accordance with its algorithmic rules to determine the optimal solutions to a given problem. Consistent with Parry and colleagues, AI is scalable in that once a problem has been solved, the system can rigorously translate its manner of thinking to a similar problem while evaluating the singularity of the new problem via its objectivity capabilities (2016, p. 577). Machines are able to make accurate predictions based on the present and the past because of their objectivity and analytical prowess. According to one startup worker's observation, AI's ability to make predictions using probabilities and margins of error may allow it to outperform human futurists (Parry et al., 2016, p. 580).

The preceding discussion of AI's benefits provides evidence that AI already possesses and can perform better than humans on a number of decision-making skills. As a result, it's fair to question whether or not AI can act independently when making choices. Based on our findings, it appears that AI has reached a level of autonomy where it can make small-scale judgements on its own, at least according to the IT consulting business professionals we spoke with. These determinations are typically mundane and unappreciated by society. As they only necessitate qualities that machines excel at, such as objectivity and dealing with massive amounts of data, they are amenable to being totally automated. It is true that AI is utilised in businesses as part of GDSD to handle "regular operational decision processes that are quite well structured" (Parry et al., 2016, p. 573).

Such fully automated decisions are already in use in high frequency trading and inventory management.

Although AI is autonomous throughout the entire decision-making process, all respondents believe that its reasoning and judgements are nevertheless constrained by the rules of the algorithms developed by humans. Decisions are made in accordance with predetermined rules. Decisions made by machines are limited to the parameters of their instruction manuals. In this approach, developers are forewarned about the choices made by machines; they have built the algorithms to always result in the same answer to a given set of information. In this case, the word "choice" might not be the right one to use when referring to machines, since the decision was made by their designer and the robots just replicated it. Weak AI can only make autonomous decisions at this time. Respondents stressed that AI lacks a holistic understanding of the issues at hand and that humans must always play a part in decision making by making the ultimate call and regulating AI activities (such as cutting power if things go horribly wrong). Without human oversight, contemporary AI is bound to make mistakes, casting doubt on the reliability of these powerful tools.

Humans' Crucial Decision-Making Role

There are a variety of justifications for why people, and not machines, should make final decisions. Robots make decisions in accordance with a rigid rational process that mimics the logic of their creators. However, humans can bypass the cognitive processes involved in decision making by relying on their emotions and the automatisms they've developed from their experiences (Kahneman, 2003, p. 698). As a result, they can make choices based on mental operations that computers can't replicate.

Intuition appears to be linked to a wide range of traits that limited AI cannot replicate, including sensitivity, originality, practicality, discernment, and imagination. Since neither of them can be translated into code, people will continue to hold the reins in terms of making important decisions. While ML may transform computers into subject-matter experts for making rule-based decisions, these systems nevertheless lack the intuitive reasoning abilities of human beings. Our findings suggest that this is why people are the de facto 'owners' of the decision. A machine may be required to make the call, but only within the parameters they establish. In this way, people employ their special skills to guide the work of AI, such as by leveraging their common sense to generate feasible solutions. Humans also adjust AI judgements to the world as it is; for example, they can use their knowledge of ethics and morality to stop AI from enacting solutions that would be unacceptable to the majority of people.

Finally, interviewers from all the companies mentioned that humans had an advantage of legitimacy over AI in decision making. Decisions made by peers are generally more respected than those made by robots, however this may change in the future. Having a human being with ultimate decision-making authority is reassuring to customers and workers alike. This topic will be expanded upon in the following section. In conclusion, the theory's two-system decision making method suggests that robots can mimic human thinking but not intuition, and that AI mimics human reasoning in a limited but effective fashion. All judgements that involve human qualities, such as management ones, are thus inappropriate for robots and should be left to humans. In addition to being distinct and unrepeatable, human intelligence is characterised by an insatiable drive to "push the frontiers of what is possible," as explained by IBM worker 1.

Conclusion

This master's thesis primarily aims to learn more about the decision-making process within KIFs and how artificial intelligence (AI) and humans interact with one another in that setting. Our overarching question is, "How can AI re-design and develop the process of organisational decision making within KIFs?" and we state this explicitly in the introduction. For more clarity, we've posed three essential queries: (1) How can we best balance the use of human judgement with that of AI in making important choices? (2) How can AI be used to aid in decision making inside an organization's design? Thirdly, what new difficulties develop when AI is used to make decisions in KIFs, and how might AI help decision makers overcome the difficulties they currently face?

Our qualitative research yielded several important takeaways. We determined that decision-making tasks are currently beyond the capabilities of AI. True, AI provides faster and deeper analysis on very particular issues than humans, but it cannot incorporate parameters that are emotional and ethical, and it cannot solve a dilemma or a new problem outside its realm of competence without human inputs and training. So, humans still play a significant role in the decision making process, while AI plays the role of an aid and support in the analysis and formulation of alternative decisions. Humans' critical thinking, common sense, and contextualization skills make them uniquely suited to offer the problem to AI and frame a query. Then, using their own value-based, ethical, creative, and intuitive compass, people select the most optimal option from those presented by AI, or they consider solutions not shown by the technology.

The findings also show that KIFs can benefit from using AI to aid in decision making when the organisation is constructed in an actor-oriented fashion. To the contrary, this organisational structure helps spread the word about KIFs and its central ideas—knowledge and the power it gives actors to make decisions. Actors in KIFs have a fundamental understanding of AI's capabilities and a sensitivity to digitalization; in addition, they have a wide range of "soft talents" such as social intelligence, collaborative ability, transdisciplinarity, sense-making, critical thinking, and empathy and creativity. Results, however, highlight the fact that actors in KIFs today need more than just soft and hard skills; they also require the cognitive flexibility to quickly absorb and use new information. When it comes to the commons, knowledge commons play a crucial role since they allow people to manage the production and distribution of new information. When it comes to managing both explicit and tacit information, crucial factors include the accessibility of reliable communication networks and computer servers, agile management, and knowledge management methods.

Additionally, PPI enables efficient administration of knowledge commons. Actors in an actor-oriented architecture use the PPI and knowledge commons to make autonomous, decentralised decisions.

Uncertainty, complexity, and ambiguity have all been discussed as obstacles to organisational decision making. We've examined how AI can complement human efforts, and how humans can supplement AI, to meet these difficulties. Our research shows that (1) AI can clarify ambiguity as long as it is asked the right question; (2) machines have superior abilities to analyse complex data and give sense to it; (3) AI can reduce uncertainty through its ability to make objective forecasts, but humans' experience and their holistic approach are vital to make decisions within this context. New organisational and societal issues posed by AI advancement are highlighted by our findings. It's important to define AI's accountability for judgements it's made or helped make, both internally and legally. The ethical implications of imbuing computers with morality are numerous. Humans are sometimes resistant to the changes mentioned above since AI is a new technology revolution that will profoundly alter organisational practises and society. Our research focused on 'weak AI,' or the currently popular form of AI deployed in business settings. Strong artificial intelligence, sometimes known as superintelligence, is currently in development. It will make these problems even more severe and accelerate the need for effective solutions from institutions and the public at large.

Future Research

Theoretically and practically, the study's execution was fascinating. In addition, we learned a lot from this research about the interplay between people and AI in business settings. Since AI has the potential to become a strategic asset for businesses, we believe it is important and fascinating to learn about its current and future applications. We believe having two researchers in the study ensured its quality and was to its benefit. Since there were two of us working on the thesis, we were able to have in-depth discussions and debates as we gathered data and ran our analysis, which helped us check and balance each other's assumptions and assumptions we didn't make. We were able to learn a great deal about our issue thanks to this study. We agree that there is no shortage of interesting questions to investigate in the fields of artificial intelligence, strategy, organisation, and management. Thus, many studies in this area are possible along the road.

Doing a case study at a single company in the future would be a great way to go deeper into our topic. Additionally, other businesses or industries related to our study's issue could be the focus of future research.

While our study focused on KIFs, future work might examine whether or if AI and humans play similar roles in other types of organisations. The ethical, legal, societal, and culpability concerns brought by AI warrant more exploration in future qualitative investigations.

Given the relative lack of research into the role of AI in business decision making, we choose to perform a qualitative study to shed light on this important topic. However, we think that in the future some quantitative research should be undertaken to measure the influence of AI within decision making for businesses, such as its level of speed, accuracy, etc. In this regard, it might be instructive to compare the outcomes of different companies based on their AI adoption rates. Further study might also quantify the degree to which society and the workforce embrace the use of AI in decision making, as well as investigate the new issues presented by such technology. On the same note, more study is required of the policies adopted by commercial and legal institutions to meet these issues.

Limitations

Several caveats exist in our study. Our sample of interviews is a restricted type, which is the first constraint. The majority of our in-depth interviews for this qualitative research project were with native French speakers. In terms of background, our interviews are all rather similar to one another. In addition, we took our time selecting respondents in order to ensure that their experiences and perspectives aligned exactly with the theoretical framework we had just reviewed. As a result, the second restriction on the validity of our study is the relatively small sample size we were able to collect through interviews. It was challenging to track down experts in areas like artificial intelligence, decision making, and the KIF's internal structure. Other constraints, such as a lack of time and the novelty of AI in business and academia, explain the second limitation. Furthermore, we found another restriction connected to the interviews we conducted. There is some evidence to suggest that interviewees' candour may be called into doubt if a semi-conducted interview format is used.

Another flaw in our research is that our respondents came from a relatively small number of organisations in a relatively small number of industries. Actually, only high-tech service enterprises and real estate corporations are represented in our sample because this is the most convenient and fruitful sector for our research. This may cloud the truth about other sectors we haven't investigated. Finally, we only had one in-person interview. We performed the vast majority of our interviews via video conferences and the other two via phone calls. One could argue that using such approaches could reduce the quality of the data acquired because respondents might not feel at ease or give their undivided attention to the interview, and because researchers might miss important cues from the interviewees' lack of body language. When conducting interviews, for instance, Saunders et al. (1997, p. 215) suggest that the researcher can gain greater insight from the experience because of the one-on-one nature of the interaction.

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