EPiC Series in Computing

Volume 93, 2023, Pages 117–128

Proceedings of Society 5.0 Conference 2023

Examining the Barriers and Enablers of AI Adoption in a Multimedia Organization

Thandazile Mkhize[1], Grant Oosterwyk[1]
[1] and Popyeni Kautondokwa[1]
[1]University of Cape Town, Cape Town, South Africa
mkhtha176@myuct.ac.za, grant.oosterwyk@uct.ac.za,
ktnpop001@myuct.ac.za

Abstract

Decision-making is a complex process that significantly impacts an organization's success. In order to enhance the effectiveness of decision-making, organizations need to consider multiple perspectives, expertise, and experiences. Artificial Intelligence (AI) has received considerable attention from Information Systems (IS) research. Drawing from the General Systems Theory (GST), this qualitative study aims to examine the interplay between AI and decision-making and to identify the barriers and enablers of AI adoption in a South African organization. The data collection was guided by the findings from the literature review followed by a single case study approach using semi-structured interviews as the primary data source. A thematic analysis technique using NVivo software was adopted to facilitate the analysis process by grouping the findings into main themes. This research has identified the following barriers and enablers of AI adoption themes: efficiency, system capability, red tape, business support, job security, staff involvement, and accountability.

1 Introduction

Decision-making plays an important role in the success of an organization. Organizations can be viewed as a "web of decisions" that is structured to achieve organizational objectives (Shrestha et al., 2019). The quality of the decisions determines the future of the organization (Trunk et al., 2020) as "it is reasonable to believe that the quality of an organizational decision is largely a consequence of both the quality of the organizational intelligence and the quality of the decision-making processes" (Huber, 2009, p. 63). Furthermore, the quality of decision-making is strengthened by including a multitude of perspectives, expertise, and experiences. AI systems such as data-driven decision support tools and automation have been known to "replacing human work" and "enhances human intelligence by providing insight that can aid decision-making" (Enholm et al., 2022, p. 1720).

The adoption of AI in different industries in Africa is growing significantly. As an example, in the e-commerce space, customer decision-making is increasingly being influenced by AI recommendation models (Keding & Meissner, 2021). Also in the healthcare sector, for example, AI has seen a reduction in cancer diagnosis waiting lists in South Africa as the pathology reporting process has been automated (Gwagwa et al., 2020; Zhuo et al., 2021). Other industries have also jumped on the wagon such as the media industry in South Africa which is advancing the use of AI in their business operations (Munoriyarwa et al., 2021). The notion that AI, as a decision-making tool, is predicted to play a key role in the workplace, and thus collaboration among employees is crucial, especially with the growing concern regarding 'negative and unintended consequences' of these technologies (Jarrahi, 2018; Makarius et al., 2020; Papagiannidis et al., 2022; Mikalef et al., 2022). Information Systems (IS) practitioners and academics have opposing views on the social impact of AI in the workplace. Others argue that it poses a great threat to human jobs whilst there's a view that partnership between humans and machines is for the advancement of humans (Jarrahi, 2018; Duan et al., 2019). The purpose of the study is to examine the interplay between AI and decision-making within an organization and to capture the technology and social elements associated with the use of the General Systems Theory (Lee et al., 2015; Chatterjee et al., 2021; Oosterwyk & Brown, 2022). Furthermore, the objective of this research is to understand the enablers of AI-driven decision-making and to further highlight the potential barriers of this juxtaposition. We ask the following research question: "*What are the key barriers and enablers for the adoption of AI in a multimedia organization?*

2 Related work

Decision-making occurs at different levels of the organization. At the operational level decision-making is structured, and rule-based, whereas, at the executive level, it is a complex and dynamic process (Turpin & Marais, 2004). Strategic decision-making is characterized by a level of uncertainty and must adapt to complexity and even politics. This is in contrast with operational decision-making which highlights possible outcomes and probability (Arakpogun et al., 2021; Keding & Meissner, 2021)

Various decision-making theories classify decision-making into rational (bounded), intuitive, data-driven, and algorithmic decision-making (Turpin & Marais, 2004). Human decision-making behavior ranges between rational and intuition. As to which aspect is utilized is dependent on the complexity of the problem, the capability of the agent, and other environmental factors involved (Trunk et al., 2020).

Therefore, organizations seek tools to enhance the quality of their decision-making with the aim of having a competitive advantage. Data-driven decision-making refers to the analysis of data without the realization of intuition (Osman & Elragal, 2021). By employing data-driven decision-making, organizations experience positive outcomes such as exponential growth in customer acquisition and retention to list a few (Papagiannidis et al., 2022). Computer-aided decision-making increases the quality of decision-making (Huber, 2009), which could lead to an "organization-wide respect for measuring, testing, and evaluating quantitative evidence in decision processes" (Puklavec et al., 2018, p. 241).

The advancement of Big Data technologies with their computing and storage capacity has motivated AI, specifically in decision-making (Duan et al., 2019; Arakpogun et al., 2021).

Whilst AI is incorporated into decision-making, the decision outcome is considered the responsibility of the practitioners involved, thus adequate understanding of its weaknesses and its strengths is crucial (Papagiannidis et al., 2022). The structure of an organization needs to be carefully measured as AI (algorithmic) decision-makers are becoming key organizational actors (Huber, 2009). There are five key decision-making conditions: (1) *specification of the search space*, (2) *interpretability of the decision-making process and results*, (3*) size of the alternative set*, (4) *speed,* and (5) *replicability.*

As an example, under the specificity of the decision space, AI requires well-defined objectives as data changes become complex, and defining training data for the AI models is difficult (Trunk et al., 2020). In human intuition and judgment, objectives are not well defined and various variables are not explicitly well explained (Trunk et al., 2020). With these decision-making conditions, options for AI-embedded decision-making structures are proposed (Shrestha et al., 2019) which highlights how AI and humans interchangeably make decisions within an organization. There's however, a scarcity of literature observing the social interplay or harmony of the unique strengths of the two players (Jarrahi, 2018). A more recent study identified explainable AI (XAI) as an emerging research theme in an attempt for end-users to understand system recommendations (Haque et al., 2023). This contributes to the claim that AI is disrupting the organizational structure which led to the argument that some roles that were previously assumed by various IS managers will either be transferred to an AI model, partially or fully (Keding & Meissner, 2021). The AI-driven decision-making phenomenon is relatively new, frameworks that guide research to explore the interplay of AI and decision-making are still in their infancy (Mikalef et al., 2022). Existing studies have found conflicting outcomes on the acceptance of AI-driven in the workplace (Ochmann, 2022) which lead to a constrained relationship between the interplay of humans and AI (see Table 1).

As AI becomes embedded in organizational decision-making, understanding the views of employees, managers, customers, policymakers, and the communities under which the organization operates is crucial (Keding & Meissner, 2021; Papagiannidis et al., 2022). It is more critical for AI as it can act autonomously in decision-making. The lack of "explainability" of AI decision outcomes raises concerns around trust, accountability, and potential biases in the decision outcome (Keding & Meissner, 2021; Mikalef et al., 2022).

Proposition	Description	Source
Management Support	When a firm optimizes its firm-level resources and adopts AI technological innovations, it results in business value and competitive advantage. Senior Management's comprehensive understanding of AI and its potential resulted in support for the technology investment	(Makarius et al., 2020; Papagiannidis et al., 2022)
Efficiency	The high accuracy of AI has not only been achieved due to an increased performance of hardware but also because of increasingly complex algorithms used in deep learning approaches.	(Meske & Bunde, 2020)
Ethical consideration	To minimize harmful outcomes of automated decisions, ethical consideration is important throughout the stages of implementing an AI solution.	(Marda, 2018)
Organizational structure	Organizational structure designs need to consider human and AI co-existence to maximize its benefits and minimize risks.	(Dolata et al., 2021)
Trust, Transparency, Fairness	The lack of "explainability" of AI decision outcomes raises concerns, there is a general mistrust in the decision outcome.	(Keding & Meissner, 2021)
Accountability	There is no clear line of accountability for autonomous AI deployment.	(Keding & Meissner, 2021; Mikalef et al., 2022)

Table 1: Propositions for AI-driven decision-making in organizations as observed in the existing literature.

3 Theoretical Background

3.1 The IS Artefact

Lee et al. (2015) posit the IS artefact model, highlighting the symbiosis between technology and social subsystems, where information is integral to system behavior. Applying the general systems theory (GST) the relationship between the social and technology subsystems can be conceptualized as the interaction between AI and decision-making. Open to environmental interactions, the IS artefact facilitates an understanding of technology's diverse impacts (Chatterjee et al. 2021) and its relationship with social actors can either be affording or constraining. In the AI context, the technological subsystem comprises tools and data, while the social subsystem includes various stakeholders. The role of information is paramount, offering insight and enriching an understanding of AI's impact and adoption as it relates to organizational value (see Figure 1).

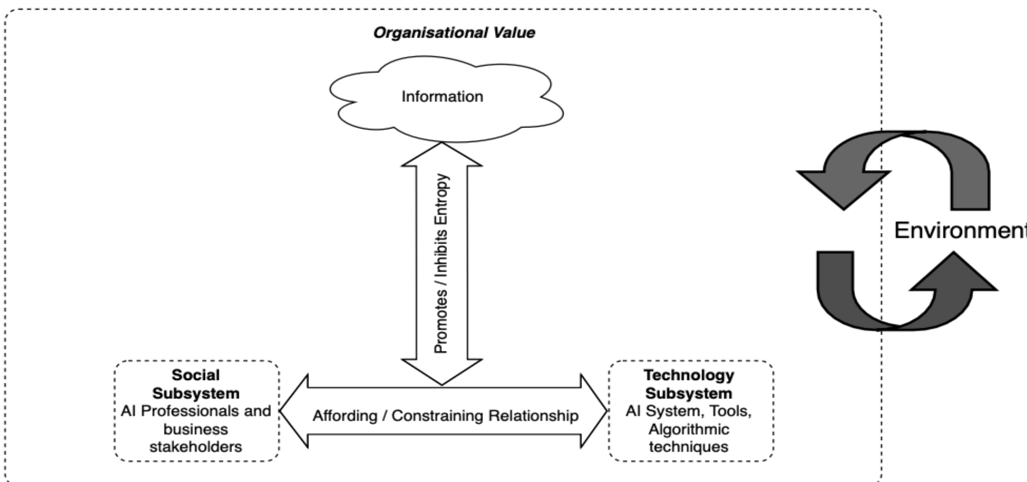

Figure 1: AI and Decision-making as an Information System (adapted from Chatterjee et al. 2021; Lee et al. 2015; Sarker et al. 2019).

4 Research Design

A South African multimedia organization was used as a single case where semi-structured interviews were conducted as the primary technique for data collection (Dawson, 2009). This study adopted the thematic analysis approach to facilitate the analysis process (Braun & Clarke, 2006). The participants were selected based on their experience working on existing AI implementations and projects within the organization. To ensure diverse views were obtained, the participants were a mix of different job roles across the organization. The full list of the participants and their respective roles are listed in Table 2.

Participant ID	Job Title	Years of Experience
INT1	Principal AI Manager	2
INT2	Content Production Architect Manager	4
INT3	Manager for Machine Learning	1

INT4	Senior Specialist for Machine learning	2
INT5	Senior Manager Sporting channel	11
INT6	Hearing-impaired subtitle creator	3
INT7	Senior Specialist AI & Robotics	4
INT8	Hearing-impaired subtitle creator	1
INT9	Hearing-impaired subtitle creator	10
INT10	Principal Business Analyst	3

Table 2: Interview Participants

5 Data Analysis and Findings

Building on the legacy of the sociotechnical perspective given the nature of AI adoption, various barriers and enablers have been identified to understand the mutual interaction between the social and technical components of the phenomenon. These will be discussed below.

5.1 Efficiency

The empirical data demonstrated *efficiency* as a technical construct that is an enabler for AI decision-making. The participants stressed how AI execution speed superseded that of humans.

> "*We were able to save around eight hours per show for subtitling. and the way that time was repurposed, was to take on more work so they could finish the subtitles of the shows quicker and they could produce more volumes of shows.*" [INT1] and as mentioned by [INT9] and [INT2], respectively, "*It definitely adds a lot more time if you don't have AI to help you. I've experienced both, where doing the job without AI and doing the job with AI. It's a big help and a big improvement.*" While another explained "*We had two people editing this, sitting in a room editing. It's now one person at most and then if you do a magazine show, maybe two people.*"

Furthermore, participants highlighted how the efficiency of AI encouraged *use,* which further created a dependence on AI for their daily tasks.

> "*It definitely adds a lot more time if you don't have AI to help you. I've experienced both, where doing the job without AI and doing the job with AI. It's a big help and a big improvement.*" [INT9]
>
> "*There are days, one or two, and it's not a lot of days that the system was down, and we needed it, the thought that you need to start from scratch for all of us, we wanted to die.*" [INT8]

The derived business value was noted as a result of less staff required to execute a task. Furthermore, there's a belief that AI is giving the organization a competitive advantage.

> "*While the game is happening, you would have an editor, in an edit suite he would be clipping highlights, and if there is more than one match, of course, they would be giving that person different matches to cut. This system could do that on the fly without any person.*" [INT2]
>
> "Y*ou can do English subtitles again, translated to Portuguese. So we're one of the first in Africa to do this at scale*" [INT1].

As positive as the sentiments were for the efficiency of AI, a counter-argument emerged that highlighted how at times AI falls short concerning efficiency. *INT10* highlighted how long it took for the subtitling editors, to upload the audio files into the AI model, and to receive the output with subtitles. The time to convert the video into subtitling format was not reduced by the fact that the video was shorter (e.g., movie trailers), in such cases, manually subtitling proved more efficient. The analysis highlighted how AI's efficiency adds value to the business, where there's evidence of cost-cutting by reducing the number of staff required to execute a task, or by the increased throughput. In parallel, the participants shared positive sentiments related to the impact of AI model efficiency.

5.2 Staff Involvement

A social construct, staff involvement emerged as the second prominent enabler for AI decision-making. Participants claimed that involving staff from the initial stages of implementation made them feel part of the solution.

> "*We started including the team from the start, once we had this technology, so it was a team's responsibility to evaluate the technology along with us as specialists."* [INT1].
>
> "*That's not the approach that we are taking here. We are saying we are building all these solutions for you guys to enable you guys to work better and to save the company money.*" [INT7]
>
> "*I feel to even have the input of this is how you can improve, which is where our part, the six of us that you can interview came in every week or every month. We would have a session with the AI team to say listen, I see the improvement here. I think it could do better here if it uses American English.*" [INT6]

Involving staff further dispersed any preconceived fears about the threat to their jobs.

> *"So, every test that we did, every set of results, they were included, and they could see that the AI is not 100%. Right? There's always needs to be a human in the loop to make corrections."* [INT1].

Demonstrating the value AI will bring into people's lives leads to a positive outlook from the staff.

> "*but there's still a lot of room for improvement and I guess in a sense, we have been hopeful because it is a What do they call it? Machine learning. It is self-learning. we have that hope that it will improve as time goes*." [INT10]

Involving staff in the early stages of implementing AI yielded positive findings in that they were more cooperative and owned the solution. It further allowed staff to use their domain knowledge and judgment to guide the AI teams on other implementation decisions.

5.3 Business Support

The empirical data demonstrated that for organizations to advance technologically, business support in terms of capital investments is an enabler to the successful implementation and adoption of AI.

> "*It's the willingness to explore new technology, new ways of doing things so they open to new technology.*" [INT2].
>
> *"Yeah, there is sufficient support, especially if you have a use case. Business does give support for POCs pilots, and even for production. So, I would say we do get enough support."* [INT1]

Business support is an enabler for AI adoption. However, this theme was not prominent in the dataset.

5.4 AI Governance

The data did not highlight that AI governance involves technical and social factors. It was also mentioned as a future consideration to alleviate some of the blockers of AI-driven decision-making.

> "*So currently, no, we don't have guidelines on that one. But we are working on a framework right for AI ethics and governance."* [INT1]
>
> "*You know we have the centre of excellence for AI… they're responsible to make sure that whatever we engage, whatever we do prediction on it follows certain standard guidelines and process and we followed that from the group guideline perspective*." [INT7]

The data indicate a need to establish a body within an organization to formulate AI governance guidelines to be followed groupwide.

5.5 Accuracy

Another prevalent technical theme emerging from the empirical data was Accuracy. Accuracy is a major barrier to the adoption of AI for decision-making. The inaccuracies are generally experienced in the earlier stages of the implementation but improve with time.

> "*And because of the accents, AI is not always correct and the spelling of names which on the script we've got the correct spelling, there are a few ways to spell a name, and at least if you've got the script, you know the correct name. Spelling for the name, yeah" [INT8]*

The participants understood the concept of machine learning, in the sense that they needed to feed it more data for it to improve. They noted the improvement over time.

> "*...but it has improved over time. So, since I started it was OK. a bit messier and now it gets cleaner by the day."* [INT8]

Other participants demonstrated more frustration and mistrust of AI models due to the inaccuracies.

> "*…and it's not really accurate and Sometimes it's so bad that I opt to type from scratch rather than using it, and so on*". [INT10]

Inaccuracies further created an element of mistrust of the AI models; as efficient as the models are, participants strongly believe that human judgment is still necessary to cross-check the AI models' output or decision.

> "*I'm gonna be honest, I wouldn't say that 100% trust yet, because even when it is quite accurate, ...the thing is I still can't trust this script like even 80% because if I do that and I miss*." [INT9]
>
> "*My view on that is like I said, I think that for at least a while, we still do need a little bit of the human element…*" [INT10]

Contrary to these negative sentiments, it was argued that some agents opted to use the chatbot rather than existing systems as the source of information.

> "*When a customer calls in and they want to know how much a decoder is, agents, ask the chatbot for a question like how much is the decoder, and then it will return all the relevant information associated with that."* [INT7]

The inaccuracies of decisions or outputs of AI mainly resulted from the lack of "training data" for the AI models. One of the AI experts stated that to address inaccuracies, they retrain the models regularly and are working on automating the "Feedback Loop" to continuously improve the accuracy of AI models. However, currently, the "feedback loop" is not formalized.

> "*Currently we generate this prediction in an Excel format and send it to them and they provide feedback in excel Which sometimes is not effective because if someone goes on leave for a month, there is no visibility to see.*" [INT7]

The accuracy was the reason participants felt secure about their jobs for the near future; they believed that AI still had a long way to go before it could operate autonomously. The following participants, in answering the questions regarding their sentiments on AI and their job security, exhibited negligible concerns.,

> "*... But when I see right now like the type of mistakes that AI make, I see that there's still a long way to go, but I do foresee that obviously in the near future it will, it will eradicate my job but the only difference is that I've mentioned that there's still a long way to go…*" [INT10]
>
> *"My view on that is that I think that for at least a while, still, we do need a little bit of the human element… in situations like that you do need a little bit of a human ear to pick up those things."* [INT9]
>
> *"The thing is, I was stressed when I heard it's working like that and it's improving by the day but I think it will never be perfect.*" [INT8]

5.6 Contractual Obligations

A significant barrier to AI implementation was contractual obligations. The multimedia has contractual obligations with its different stakeholders. Stakeholders include the subscribers, who are the customers, advertisers who contribute extensively to the organization's revenue stream, and the production studios who own the content aired by the multimedia. The multimedia must abide by all the various rules and terms of engagement with these stakeholders. The empirical data suggested how these rules impeded utilizing the AI's full capabilities.

> "*So as part of our rules with the studios, we can't send content to the cloud for processing, right?... You can't send that content out of the building to be subtitled… So that was one of the biggest challenges we had, technically. So we had to build a solution that could do it in-house on our premises.*" [INT1]

Furthermore, empirical data highlighted that due to contractual obligations, the organization was limited in running AI models autonomously; human judgment is required in the decisions taken by the AI models. Other platforms, such as YouTube, can get away with inaccuracy in spelling, but for this organization, business and customer obligations only allow for such mistakes.

> *"I'm not sure you could completely go hands-off… So, the production team vets the clips before it is released to Facebook or Twitter. That is mainly to make sure that there's nothing contractual, there's no breach of contracts…And there's sponsorship agreements and stuff like that they need to make sure it all in place So, in essence, there is still an element of human interaction or involvement that is required."* [INT2]

> *"… Some of the shows you watch on other platforms use AI and people are fine because you can, at least if you now and again hear what's going on or can read, it's OK. I don't know if our organization will ever get to that point where that would be OK."* [INT8]

5.7 Red Tape

In the context of AI project management, red tape emerged as a significant impediment to successful implementation. Participants, including AI specialists and senior roles, expressed frustration at this bureaucratic hurdle, characterized by an excess of approval procedures. These procedures were deemed more obstructive than the standard protocol for IS implementations, highlighting the criticality of this theme as two employees explained:

> *"The most challenge was red tape, internal red tape, so deploying the solution for production there is quite a number of boards that you have to go through, explaining the business value, explaining the type of technology, and that that takes a long time to get.*" [INT1] and "*But because there's a lot of processes and historic systems and people that you need to include in the conversation. It just takes much longer so it's mostly I would say corporate red tape. And I'd say it's, well, just how the business is so big, we had to present to about four or five forums before we could even do a POC.*" [INT2].

5.8 Accountability

Accountability came strongly as a social barrier in the adoption of AI decision-making. The multimedia battles with who needs to own the AI models and subsequently account for the decisions or output of the AI models.

> "*So that's the second challenge I would say is that who looks after this operationally and I think it's still a challenge for us today.*" [INT2]

The sentiment that businesses still shy away from taking responsibility for decisions taken by AI is further affirmed by other participants.

> "*We need someone that is accountable if something goes wrong, so you cannot really push back to the tech team, right? It is that business sponsor that needs to take responsibility for any initiative in production.*" [INT1]

To respond to this issue of accountability, the multimedia's AI Centre Of Excellence is in the process of formulating an AI governance framework.

> "*…No, they still bring it back to the tech team. So, I think as part of this new AI ethics and governance framework that we're putting in business will be accountable, and they will be an executive sponsor.*" [INT1]

5.9 System capability

The system capability of the AI models, a social construct, emerged as one of the barriers to successful AI adoption. Firstly, the AI model lacks integration with other business systems. An external customer, for example, expects that after engaging with the tool, e.g., the AI bot, the decision taken would be effected instantaneously to the rest of the systems, but this is only sometimes the case. Another participant added that negative customer experience directly impacts the business [INT7]:

> "*When a customer reconnects as an example, they expect to be reconnected now, but what they don't understand is when they reconnect on the AI bot, that information needs to be integrated into other systems to reactivate the customer account and rend the shows to their tv set."* [INT7]

Secondly, sourcing data for the AI models was noted by various participants as a barrier. There needs to be more diversity in the data used while building the AI models to avoid many inaccuracies when the models are operationalized.

> "*I think the first challenge from a machine learning perspective is the availability of data. So that is quite a massive challenge. Also, when you get the data, it is in a format that is usable and understandable to a person who's not necessarily a data steward.*" [INT7]

The issue of training data was also raised by how AI could not transcribe local accents correctly initially but improved with more data fed through it.

> "*It isn't perfect yet because there's a lot of accents that it doesn't pick up quite yet.*" [INT9]
>
> "*Because of the accents and those things AI is not always correct.*" [INT8]

An outlier aspect of the system capability theme was the audibility/traceability of the AI chatbots; chatbots are implemented with an autonomous workflow as a feature; it is, therefore, crucial to be able to trace the steps of the actions taken by the AI bot when processing a customer request. Furthermore, the authentication capability of the AI bot is an important enabler for customers to trust the tool. This feature was vital for the AI team to get buy-in from the business.

> "*There is auditability. In terms of what actions were taken by the system, by the system I'm referring to the bot.*" [INT7]
>
> "*For the bot to be autonomous, it needs to have certain controls built into it, and some of those control is to have the ability to authenticate the customer.*" [INT7]

6 Discussion

In an attempt to examine the interplay between AI and decision-making in an organization, various barriers and enablers were identified. The data highlighted that AI relies on pre-coded features to execute and operates mainly at the operational decision-making level. Most AI implementations discussed by the participants within the case study were primarily involved in operational decision-making. This aligns with existing literature, which suggests that at the operational level, decision-making is mostly rule-based.

For an organization to derive value from the technology investment, it needs to understand the key factors leading to achieving that objective. The study found that the efficiency of AI is an essential factor in the successful adoption of AI. The study highlighted the extent to which (Papagiannidis et al., 2022) efficiency influences the economy to create a competitive organizational edge. Furthermore, it affected how the staff engaged with the tool; where signs of inefficiency existed, it was generally rejected, but where it showed to improve the speed, it was embraced.

The output of the decisions performed by AI models had a lot of inaccuracies. However, further research needs to investigate ways to improve the quality of training data. Claims such as employees' role in “self-learning” led to negative sentiments towards the use of an AI tool.

Business support is an enabler to the successful implementation of AI for decision-making. Support in the form of capital investment in AI initiatives was considered significant. Further investment in newer AI initiatives among participants' projects nurtured a culture of innovation.

Barriers to realizing AI’s full potential is contractual obligation. The data revealed that there are contractual obligations that a multimedia organization needs to adhere to, which restrains and slows down the speed of AI implementations and further limits the full capacity and use of AI technologies.

7 Proposed Model

The study identified various barriers and enablers for AI adoption in a multimedia organization. In identifying the subthemes, the proposed model (Figure 2) presents the barriers and enablers which were further grouped into the main themes: AI-driven decision-making, social, instrumental and humanistic objectives. Figure 2 serves as a graphical representation demonstrating how the researchers progressed from raw data to the proposed themes as guided by the method.

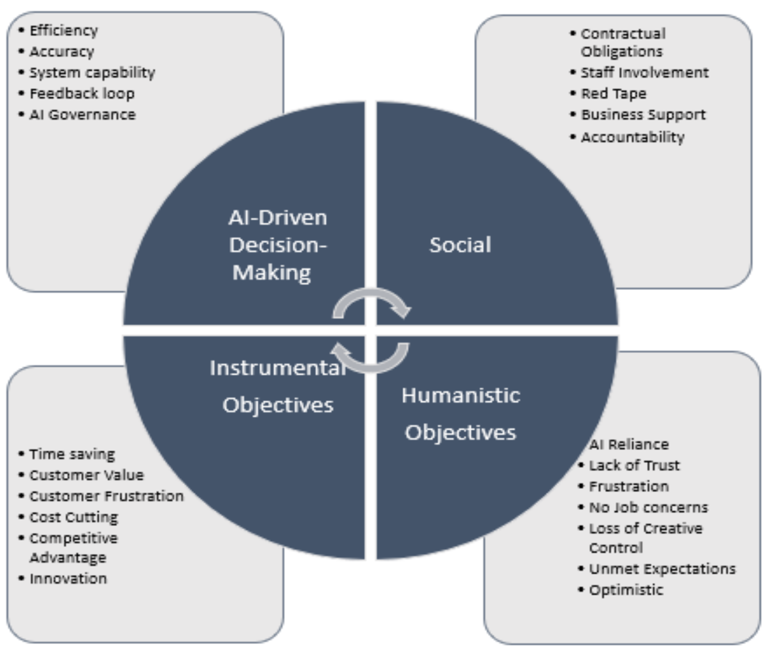

Figure 2: Proposed model for barriers and enablers in AI adoption

8 Conclusion

The study initially aimed to examine the interplay of AI and decision-making within a South African organization and identify the barriers and enablers for adopting AI in a multimedia organization. The data collection was guided by the findings from the literature review, followed by a single case study approach using semi-structured interviews as the primary data source. A thematic analysis was used to facilitate the analysis process by grouping the findings into main aggregated themes. This research has identified the following barriers and enablers of AI adoption: efficiency, system capability, red tape, business support, job security, staff involvement, and accountability. The findings suggest that various constraining factors play a role in adopting AI. As with most papers, this study came with a few limitations. The study's findings indicate that AI's impact on decision-making within IS research is currently in its nascent stages. Furthermore, we recommend investigating the potential biases associated with using machine learning algorithms, particularly in the context of decision-making within various industries and not limited to multimedia organizations. Moreover, there is a need to identify effective strategies for effectively integrating the technical and socio-cultural aspects of decision-making.

References

Arakpogun, E. O., Elsahn, Z., Olan, F., & Elsahn, F. (2021). Artificial Intelligence in Africa: Challenges and opportunities. *Studies in Computational Intelligence*, *935*, 375–388.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101.

Chatterjee, S., Sarker, S., Lee, M. J., Xiao, X., & Elbanna, A. (2021). A Possible Conceptualization of the Information Systems (IS) Artifact: A General Systems Theory Perspective. I*nformation Systems Journal*, 31(4), 550-578.

Dawson, C. (2009). *Introduction to Research Methods A Practical Guide for Anyone Undertaking a Research Project*.

Dolata, M., Feuerriegel, S., & Schwabe, G. (2021). A sociotechnical view of algorithmic fairness. *Information Systems Journal*, *32*(4), 754–818.

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.

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, *24*(5), 1709-1734.

Gwagwa, A., Kraemer-Mbula, E., Rizk, N., Rutenberg, I., & Beer, J. (2020). Artificial Intelligence (AI) deployments in Africa: Benefits, challenges and policy dimensions. *The African Journal of Information and Communication*, *26*, 1–28.

Haque, B., Islam, N., & Mikalef, P. (2023). Notion of Explainable Artificial Intelligence - An Empirical Investigation from A User's Perspective. In *Proceedings of the European Conference on Information Systems (ECIS),* Kristiansand, Norway.

Huber, G. P. (2009). A theory of the effects of advanced information technologies on organizational design, intelligence, and decision making. *Knowledge, Groupware and the Internet*, 221–254.

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

Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change*, *171*.

Lee, A. S., Thomas, M., & Baskerville, R. L. (2015). Going back to basics in design science: From the Information Technology Artifact to the Information Systems Artifact. *Information Systems Journal, 25*(1), 5–21.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273.

Marda, V. (2018). Artificial Intelligence policy in India: A framework for engaging the limits of data-driven decision-making. *Philosophical Transactions of the Royal Society*, *376*(2133).

Meske, C., & Bunde, E. (2020). Transparency and trust in human-AI-interaction: The role of model-agnostic explanations in computer vision-based decision support. In *Lecture Notes in Computer Science* (pp. 54–69).

Mikalef, P., Conboy, K., Lundstrom, J. E., & Popovic, A. (2022). Thinking responsibly about responsible AI and `the dark side' of AI. *European Journal of Information Systems*.

Munoriyarwa, A., Chiumbu, S., & Motsaathebe, G. (2021). Artificial Intelligence practices in everyday news production: The case of South Africa's mainstream newsrooms. *Journalism Practice*.

Ochmann, J. (2022). Just like you like it—The effects of transparency and decision outcome on the evaluation of human and algorithmic decision-making. *Wirtschaftsinformatik*.

Oosterwyk, G. and Brown, I. (2022). Examining the interplay between decision-making and big data analytics in driving decision value: a critical realist case. In *Proceedings of the Australasian Conference on Information Systems (ACIS),* AIS, Melbourne, Australia.

Osman, A. M., & Elragal, A. (2021). Smart cities and big data analytics: A data-driven decision-making use case. *Smart Cities*, *4*(1), 286–313.

Papagiannidis, E., Dremel, C., Mikalef, P., Krogstie, J., Merete Enholm, I., & Mikalef, P. (2022). *Toward AI Governance: Identifying best practices and potential barriers and outcomes*.

Puklavec, B., Oliveira, T., & Popovič, A. (2018). Understanding the determinants of business intelligence system adoption stages an empirical study of SMEs. *Industrial Management and Data Systems*, *118*(1), 236–261.

Sarker, S., Chatterjee, S., Xiao, X. & Elbanna, A. (2019). The sociotechnical axis of cohesion for the IS discipline: Its historical legacy and its continued relevance. *MIS Quarterly 43*(3), 695-719.

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson education.

Shrestha, Y. R., Ben-Menahem, S. M., & Krogh, G. (2019). Organizational decision-making structures in the age of Artificial Intelligence. *California Management Review*, *61*(4), 66–83.

Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision making. *Business Research*, *13*(3), 875–919.

Turpin, S. M., & Marais, M. A. (2004). Decision-making: Theory and practice. *ORiON*, *20*(2), 143–160.

Zhuo, Z., Larbi, F. O., & Addo, E. O. (2021). Benefits and risks of introducing Artificial Intelligence into trade and commerce: The case of manufacturing companies in West Africa. *Amfiteatru Economic*, *23*(56), 174–194.