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Towards a Socio-specific Artificial Intelligence Adoption Framework

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Abstract

Organisations need to be able to adopt AI successfully, but also responsibly. This requirement is not trivial, as AI can deliver real value to adopters. However, can also result in serious impacts on humans. AI's technical capabilities make AI powerful, still the implementation of AI in organisations is not limited to the technical elements and requires a more holistic approach. An AI implementation within an organisation is a socio-technical system, with the interplay between social and technical components. When AI makes decisions that impact people, the socio considerations in AI adoption frameworks are paramount. Although technical adoption challenges are well researched and can overlap with aspects associated with traditional IT implementations, artificial intelligence adoption often faces additional social implication. This study focuses on these social challenges, which is a problem frequently experienced by many organisations. The study investigates how an organisation can increase adoption of AI as part of its quest to become more data-driven. This study was conducted at an automotive manufacturer's analytics competence centre, located in South Africa. This paper describes the first iteration of a larger research effort that follows the design science research methodology. A socio-specific artificial intelligence adoption framework was created and can be used by organisations to help them succeed with their AI adoption initiatives in a responsible manner.

1 Introduction

Organisations have to transform into data-driven entities [15, 54], with most organisations only in the beginning stages of utilising the full potential of data analytics [30, 41]. Data-driven organisations are entities that act on observed data rather than gut feeling [2]. Furthermore, advanced levels of data-drivenness include forward-looking analysis, where organisations utilise artificial intelligence (AI) to predict the future and automate decision making [7, 2]. These automated decisions might impact humans and will lead to important legal and ethical questions whose answers affect both producers and consumers of AI technology [14]. Therefore, it is important to acknowledge that AI adoption should be done in a responsible manner, and it is the duty of AI researchers to ensure that the future impact of AI is beneficial [40]. Even though there are many theoretical frameworks to support technology adoption [50, 39, 46], they are not tailored towards AI adoption, nor do they mention the ethical implications. Organisations need to be able to adopt AI successfully, but also responsibly. This requirement is not trivial, as AI can deliver real value to adopters [33, 7], but can also result in serious impacts on humans [14].

Given the requirement for organisations to successfully adopt AI and the socio-technical nature of AI adoption, the following research question arises: *From a socio-perspective, how can an organisation increase adoption of AI as part of its quest to become more data-driven?* The successful increase of use of AI in an organisation in the context of this paper, is referred to as organisational AI adoption. In the light of the research question, we propose to create a socio-specific artificial intelligence adoption framework (SAIAF) that is targeted at both academics and practitioners. This paper describes the first iteration of a larger research effort that follows the design science research (DSR) methodology. The study is conducted at an automotive manufacturer's analytics competence centre, located in South Africa. This organisation is seen as a worldwide leader in industrial digital transformation [4]. This paper is about the analytics competence centre's input to the socio-perspectives of how an organisation can increase the adoption of AI and become more data-driven.

The remainder of the paper is structured as follows: Section 2 elaborates on related research, and Section 3 explains the research approach, followed by Section 4, which covers the DSR cycle and artefact development. Section 5 discusses the results and is followed by the conclusion in Section 6.

2 Literature Review

Big data offers organisations opportunities to utilise analytics to achieve new levels of competitive advantage in several different ways [11]. Organisations that are becoming data-driven acquire a better understanding of their costs, sales potential, and emerging marketplace opportunities [28]. However, many organisations are struggling to adopt AI as part of their analytics portfolio [41]. Additionally, being a responsible organisation also requires considering the potential negative impact of adopting AI [14].

Many theoretical frameworks on technology adoption exist, such as the technology acceptance model (TAM) [16], the theory of planned behaviour (TPB) [44], the theory of reasoned action (TRA) [20] and the TOE framework. The TAM, TPB and TRA are focused on the individual's adoption of technologies. However, the TOE framework allows for an organisational level paradigm [45]. The implementation of AI in organisations will impact humans and the environment, therefore, the adoption of AI in organisations should not be limited to the technical elements or the individual's adoption, but rather requires a more holistic approach [14]. As the TOE framework includes the technical, organisational, and environmental considerations, the TOE is specifically useful to explain technology adoption in organisations with a holistic perspective [45]. The TOE framework is relevant to this study; however, the TOE framework does not explain how or why the adoption of technology gains momentum and spreads, whereas DOI theory, on the other hand, does cover it [39]. The definition of diffusion in the context of innovation theory is the process by which an innovation is communicated through certain channels over time among the members of a social system. The idea is that innovation must widely be adopted until it reaches a critical mass and is self-sustained [39]. The innovation adoption decision process is the mental process that an individual passes through, namely: knowledge, persuasion, decision, implementation, and confirmation [19].

More specifically, Bettoni et al. propose an AI adoption model to support data-driven transformations and the adoption of AI [9]. This model includes digitisation, data strategy, human resources, organisational structure, and organisational culture as the main elements [9]. This framework is helpful to identify elements that are required to be addressed but does not include prescriptive information of what can be used to enable the organisation. The same is also true for other frameworks found in the literature [34]. Not specifically related to AI, but useful for data-driven transformations is Pillay et al.'s big data-driven decision-making model [37]. It includes a theoretical and organisational support model that demonstrates what needs to be in place within the organisation to enable an efficient big data-driven decision making-process [37]. On the industry side, Google cloud's AI adoption framework offers a framework that covers aspects such as the power of AI, the creation of value and AI maturity [22]. Even though this framework seems to be comprehensive, Google cloud's framework lacks social considerations, such as trust, ethics, and fairness [14]. Google has guidelines on responsible AI practices [23]. However, their adoption framework does not specifically mention them [22].

AI's technical capabilities make AI powerful, but the implementation of AI in organisations is not limited to the technical elements and requires a more holistic approach. An AI implementation within an organisation is a socio-technical system, with the interplay between social and technical components [53]. When AI makes decisions that impact people, the socio-considerations in AI adoption frameworks are paramount.

3 Research Approach

This study aims to create a framework to support responsible organisational AI adoption while bringing together theory and practice [26]. To be of theoretical value, the framework should be grounded in theory, and to be of practical relevance, the proposed solution should cater for the specific considerations that the adoption of AI raises in organisations. Furthermore, the proposed solution should not only include the elements that influence adoption but should also include prescriptive knowledge [6] on how to enable the adoption of AI in organisations.

To allow for a systematic research and design approach, this study follows the DSR cycle steps as described by Vaishnavi et al., namely "awareness of the problem", the "suggestion of a solution", the "development of a solution", the "evaluation of the solution" and finally a "conclusion" [49]. The model introduced by Peffers et al. [36] includes similar steps; however, Vaishnavi et al.'s DSR cycle is selected for this study since it adopts a reduced process model and allows for a simple iterative approach [49].

As input to the DSR cycle, the technological-organisational-environmental (TOE) framework [45] and the diffusion of innovation (DOI) theory [39] are used as the theoretical foundation. Three related studies are used as input to create the SAIAF. The first study covered a systematic literature review on the critical success factors of AI adoption [24]. The other two studies are part of the larger research effort and form part of the case study at the analytics competence centre. One of the two studies investigated the barriers to AI adoption [43] and the other the socio-enabling factors leading to organisational AI adoption [42]. Purposively sampled industry focus groups from the analytics competence centre are used to evaluate and develop the framework further. The research approach followed is graphically depicted in Figure 1 and the DSR cycle content is described in detail in the artefact development section.

4 Artefact Development

4.1 Awareness of the Problem

Although the adoption of technologies is an extensively researched topic [32], AI has some characteristics, such as its ability to learn and act autonomously, making it unique [8]. In addition,

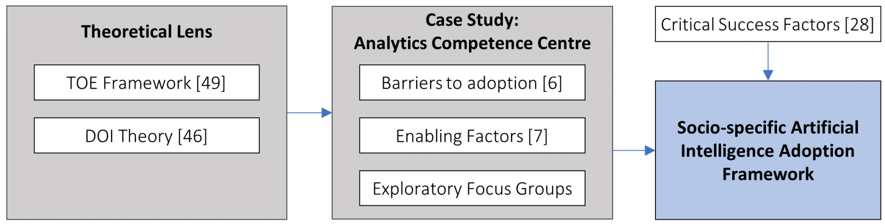

Figure 1: Input to the DSR cycle

AI is not to be referred to in a monolithic sense [1]. Different types of AI can be classified based on intelligence (artificial narrow intelligence, artificial general intelligence, and artificial super-intelligence), based on technology (for example, machine learning, deep learning, and natural language processing) or based on function (conversational, biometric, algorithmic, and robotic) [7]. Both scholars and industry agree that in organisations, the trend in the short term is not that AI will replace humans, but that AI will instead allow for augmented analytics within a human machine-partnership [29, 25]. Moreover, in the quest for organisations to become more data-driven and adopt AI, organisations should be mindful that AI at a fundamental level is not only the technical and social practices [5] but also impacts the institutions, infrastructures, politics, and culture around it [14]. These complexities lead to several challenges, for example, AI's deployment problem, talent issues and social dysfunctions [7]. Therefore, there is a need for a better understanding of the accepted approaches and techniques for managing organisational transformations into data-driven entities and the responsible adoption of AI. Furthermore, from the literature review, it seems that the socio-aspects are not well represented in the current AI adoption frameworks. The implications of neglecting the social aspects and impacts of AI is well documented in Crawford's book on "ATLAS of AI" [14].

4.2 Suggested Solution

We suggest combining the TOE framework and DOI theory as the basis to create SAIAF. This proposal is followed because the required framework should include information on what influences the adoption and how to enable the organisation. Although not specific to AI adoption, the combination of innovation diffusion theory and a TOE framework has successfully been adopted in several studies [51, 55, 56].

On this theoretical basis, the results of three AI adoption-related studies are added to create the SAIAF. As mentioned in the research approach, the first of the three AI adoption-related studies [24] covered a systematic literature review on the critical success factors of the adoption of AI. The study used the TOE framework as basis and identified 12 success factors to the technological dimension, 13 related to organisational and 11 to the environmental dimension of the TOE framework [24].

The second study, part of the larger research effort, applied the TOE framework and focused on the barriers to adoption and highlights the extent to which fairness, accountability, transparency and explainability influence trust in AI and consequently AI adoption [43]. Online questionnaires involving analytics and AI experts were analysed using structural equation modelling (SEM) as the underlying statistical methodology. This study identified that trust is one of the main barriers to adopting AI in organisations. Furthermore, it found that organisations that ensure fairness, accountability, transparency and explainability as part of their AI adoption initiatives will lead to a higher level of adoption.

The third study, also part of the larger research effort, used the DOI theory to identify the enabling factors that contribute to the successful adoption of AI [42]. It was based on the five stages of the innovation-decision process, as postulated in the diffusion of innovations theory [39].

4.3 Development of the Solution

The findings from the three related studies [43, 42, 24] are combined into a framework. The proposed SAIAF includes four main areas (see Figure 2). The first is an introduction to AI in a data-driven context, which is followed by a high-level overview of the AI adoption decision stages [42]. Then measures to support AI adoption momentum are listed [42], and lastly, the AI adoption considerations based on the TOE framework are given [24, 43].

4.3.1 AI in a Data-driven Organisation

In the context of the SAIAF, a data-driven organisation is defined as an organisation that uses analytical tools and abilities, that creates a culture to integrate and foster analytical expertise and acts on observed data to achieve benefits [43]. The goal is not that AI replaces humans, but rather that AI can support data-driven organisations within a human machine-partnership [29, 25] while supporting or automating some decision making [7]. Furthermore, true data-drivenness should include forward-looking analysis, where organisations not only use data to report on the past but utilise models to predict the future in a responsible manner [2].

4.3.2 Adoption Decision Stages

During the decision stages of AI, decision-makers go through the following stages: increase knowledge of AI, form an attitude towards AI (persuasion stage), a decision to adopt or reject the use of AI, then to implement AI (or not implement AI), and lastly the confirmation and evaluation of the decision [42]. AI technologies are ever evolving; therefore, the stages are repeated in cycles. The framework shows each decision-making stage and the enabling factors that support adoption. The first of the five stages is the “increase knowledge stage”. During the “increase knowledge stage”, the communication of benefits is imperative and can be achieved via numerous channels, for example, forums, workshops, and training [42]. Furthermore, training is a key enabler to build more capabilities in AI [12] and should not only include awareness of AI but also how-to and principles knowledge [39]. Training initiatives should include training on AI tools, training on AI platforms, training covering AI products and AI concepts [42]. The training should be focused not only on employees but also on management [39], as knowledge in AI is a precondition for creating strategic value from AI [29]. The “persuasion stage” includes highlighting the benefits of adopting AI. This can be achieved by the same types of communication channels as during the knowledge phase. Secondly, showing real-life examples will boost confidence in AI and can be achieved by using workshops, demos, and pilots [42]. Lastly, the importance of top management support should not be underestimated [17]. In the “decision to adopt stage”, the future benefits and a positive business case is key to the adoption decision process [12]. Furthermore, the reduction of risks is also an enabling factor [42], for example addressing issues of trust, explainability and fairness. During the “implementation stage”, the specific focus is on increasing the probability of a successful go-live or implementation. This includes aspects such as involving business and getting implementation support from external providers if the specific knowledge of AI is not within the organisation [42]. The “confirmation stage” of AI adoption is all about evaluating if the business value and goal achievement are at

Socio-specific Artificial Intelligence Adoption Framework

AI in a data-driven organization

A data-driven organization is an organization that uses analytical tools and abilities, that creates a culture to integrate and fosters analytical expertise and acts on observed data to achieve benefits. AI is centred around the idea that mental processes can be simulated or replicated in computers. AI allows for augmented analytics within a human machine-partnership.

Traditional organizations are struggling to implement AI as part of their analytics portfolio. The Artificial Intelligence Adoption Framework (AIAF) provides organizations with a practical guide to assist them in adopting AI and transforming it into more data-driven and do so in a responsible manner.

Adoption decision stages

Improve knowledge	Persuade	Decide	Implement	Confirmation
Communicate benefits	Highlights benefits	Future benefits	Execution support	Measure business value
Multiple channels	Show examples	Positive business cases	Involve business	Measure adoption
Training and awareness	Management support	Business buy-in		Measure goal achievement
		Reduce risks		

Adoption momentum

AI adoption should be seen as a continuum. To conserve AI adoption momentum, organizations should ensure the following takes place: show value, management direction, remove barriers, continuous improvement mindset.

TOE considerations

Technological	Organisational	Environmental
IT infrastructure	Top management support	Industry pressure
Relative advantage	Competencies	Governmental regulations
Quality data	Resources	Customer readiness
Tool availability	Fairness	Trust
Transparency	Absorptive capacity	Accountability
Explainability	Culture	

Figure 2: Socio-specific artificial intelligence adoption framework proposal

a satisfactory level [42]. This is important as some people in the organisation might view the business case for adopting AI as unproven, and therefore might be reluctant to take the first step towards adoption [10]. The measurement of business value, the level of AI adoption and the level of goal achievement are all enabling factors to confirm if the adoption of AI was of a satisfactory level [42].

4.3.3 Adoption Momentum

As AI is a moving target and at the frontier of computational advancements [8], it is essential for the continuation of adoption to implement a continuous improvement mindset. This can be supported by an innovative company culture [31, 12], by ensuring that the value of adopting AI is known [42] and constantly removing barriers that might hamper the adoption process [12].

4.3.4 TOE Considerations

The TOE considerations are elements that organisations must consider when adopting technologies [45], which also apply in the case of AI. Even though the SAIAF is a socio-focused adoption framework, the framework also includes technological considerations. For example, not having the correct technological elements in place can be seen as a barrier and should be removed when adoption is required [11]. From a technological perspective having the correct IT infrastructure in place is one of the success factors to the adoption of AI [24]. This includes the setup, the right data ecosystem and building or buying appropriate AI tools [12], that can result in a relative advantage. Furthermore, from a technological context, the characteristics of the technology should allow for observability which enables transparency and explainability [43]. AI solution development should be done in a manner that renders the models more understandable to stakeholders and addresses AI interpretability needs [5]. As part of the organisational considerations, top management support [12], having the right skills, competencies, and resources are some of the key considerations in adopting AI [24]. In the context of an organisation's subjective norms, ensuring fairness in AI is another organisational consideration [43]. Other organisational considerations such as absorptive capacity [46], slack [38] and culture [15] play a role in adoption. Aspects such as industry pressure, governmental regulations and customer readiness are part of the key environmental considerations when trying to assist an organisation with the adoption of AI [24]. Accountability also forms part of the considerations, where for example, a regulatory environment insists that accountability in the organisation is set in place [43].

4.4 Evaluation of the Solution

The evaluation of the proposed SAIAF was achieved through three exploratory focus groups with six participants each [47]. The focus group took place over a period of five months. Note that the evaluation phase was mainly used to improve the framework. Using focus groups in the industry is of value to this study as it puts the researchers in direct interaction with domain experts and potential users of the framework [47], with the shared target to maximise knowledge, wisdom, and creativity [52]. The three focus group sessions were conducted and included AI experts of the same analytics competence centre as mentioned previously [43, 42]. The participants were selected based on their domain expertise, and as the study is focusing on the "how", the participants included both technology and management orientated experts [18]. Specifically, the groups comprised of site reliability engineers, agile masters, data engineers, business intelligence experts, data scientists, IT governance experts, technical team leads and management. As SCRUM is part of the organisation's agile working model, it was decided that the focus group sessions should be conducted in the form of sprint reviews [21]. A sprint review typically includes the evaluation regarding what has been achieved during a sprint, in this case, the SAIAF [21]. The concept of using sprints to harden the scientific rigour of DSR is introduced by Conboy et al. [13]; however, the use of actual sprint reviews to evaluate artefacts is a novel research method. In contrast, applying sprint reviews to evaluate artefacts is commonly used in practice. Due to the transdisciplinary nature of this research, the novel idea of combining focus groups and sprint reviews is appropriate [52]. Conceptboard, an effective online tool to perform collaborative engineering design by a geographically separated team [3], was used to support the collaboration and document the results for analysis.

Figure 3 is a screenshot of the last focus group session using Conceptboard [3]. The area in pink on the left is used to present the framework to the participants. This contains the background, problem statement, the session objective, and an overview of the framework. The area in blue on the right allows the participants to provide feedback. The screenshot is intended to show a high level view of the board, the actual content is described below.

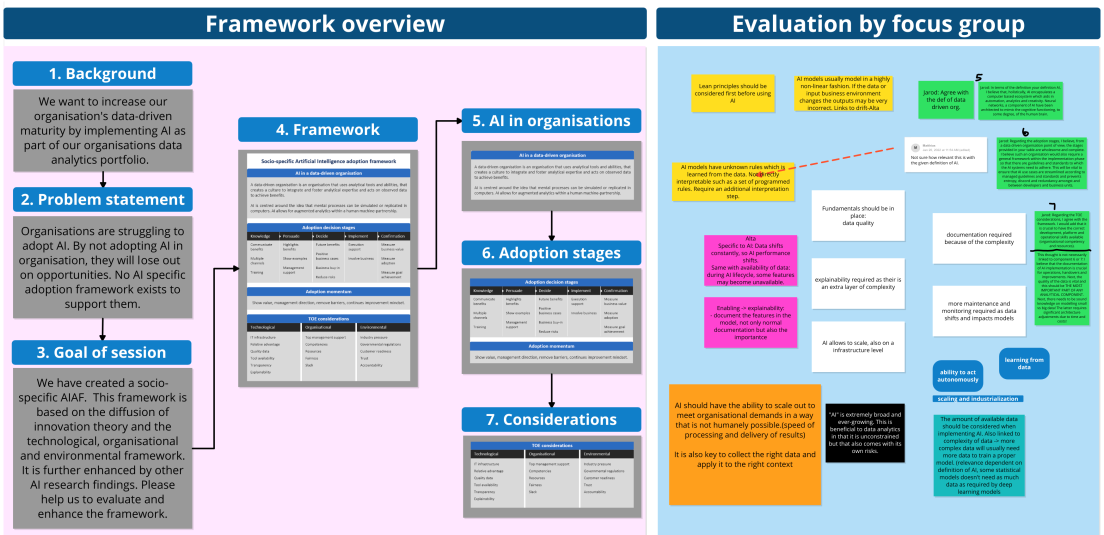

Figure 3: Screenshot of the Conceptboard tool used during a focus group session

All the focus groups indicated that AI is different from standard systems. They pointed out that this is because in AI continuous "learning" take place based on data, whereby standard systems are more rule based. Furthermore, they stated that AI encapsulates a computer-based ecosystem that aids in automation, analytics, and creativity. They additionally highlighted that AI is comprehensive and ever-growing. This is beneficial to data analytics because it is unconstrained, but it presents its own risks, such as algorithm bias. One of the focus group participants, who was responsible for training business units and senior management on AI and its possibilities, mentioned that several managers highlighted that the value or benefits of AI, must be made clear. This is in line with the proposed SAIAF that includes the benefits and value of AI in all but one adoption decision stage. The importance of highlighting the benefits of adopting AI is in line with the findings of previous studies [42, 45].

The focus groups further pointed out that the fundamentals should be in place. This includes the quality and amount of data, which confirms the findings of other research related to other industries [24, 37]. Additionally, one data scientist mentioned that more complex data structures will usually need more data to train a proper model. Over and above, documentation is highlighted as necessary due to AI's complexity. One focus group participant mentioned: "I believe that the documentation of AI implementation is crucial for operations, handovers and improvements". Other fundamental aspects include a scalable infrastructure, and normal continuous integration (CI) and continuous delivery (CD) concepts. CI allows for automatically testing code and CD supports pushing code into production [48].

They agreed with the findings that fairness, accountability, transparency (FAT) and explainability in AI processes lead to trust and a higher rate of AI adoption [43]. Additionally, experts in the focus group highlighted that to ensure AI is implemented responsibly, the FAT factors and explainability should be incorporated into the teams' daily work and not come as an afterthought. The group suggested that fairness, accountability, trust and explainability should be included in a governance process of the organisation. This suggestion is in line with the recommendations from Ienca [27], who advocates that it is the responsibility of technology governance bodies to align the future of cognitive technology with democratic principles, such as fairness, accountability and transparency.

When evaluating the proposed framework, all focus groups agreed that the framework is useful as a high-level guide to help organisations on how to enable them to adopt AI. Some comments on the framework from a data scientist: "Regarding the adoption stages, I believe, from a data-driven organisation point of view, the stages provided in your table are wholesome and complete. I believe such an organisation would also require a general framework within the implementation phase so that there are guidelines and standards to which the AI systems need to adhere to. This will be vital to ensure that AI use cases are streamlined according to managed guidelines and standards and prevents entropy, discord, and redundancy amongst and between developers and business units" Other comments on the framework with recommendations from another data scientist: "I agree with the framework. I would add that it is crucial to have the correct development, platform, and operational skills available (organisational competency and resources)".

4.5 DSR Cycle Conclusion

The focus group sessions were used to communicate and gather feedback from practitioners. From the feedback in the focus group, it was clear that the framework was understandable and, in their opinion usable by practitioners to assist them to adopt AI in a responsible manner. However, some enhancements were recommended, such as a narrower definition of AI, the inclusion of governance processes [27], more focus on industrialisation and machine learning operations [48]. Furthermore, it is recommended to consider making the value-creating steps occur in tight sequence so that the product or service will flow smoothly toward the customer, which can be achieved via CI and CD [48]. Additionally, the framework can also be enhanced by stating its objective, which is in line with the findings from Pee et al. [35].

5 Discussion

5.1 Background and Findings

This study describes the first iteration of a larger research effort that follows the design science research methodology. The research question under investigation was: *From a socio-perspective, how can an organisation increase adoption of AI as part of its quest to become more data-driven?*

On the theoretical bases of DOI and the TOE framework, together with three related studies, a SAIAF was created. The SAIAF is intended as a high-level guide to support organisations with their AI adoption journeys. Exploratory focus groups evaluated the SAIAF and gave recommendations on how to improve the framework. However, it should be mentioned that the concept of a framework alone cannot increase AI adoption. Organisations will have to successfully apply the framework to responsibly increase AI adoption.

The organisation where the study took place has seven principles covering the development and application of AI, namely: "human agency and oversight", "technical robustness and safety", "Privacy and data governance", "transparency", "diversity", "non-discrimination and fairness", "environmental and societal well-being" and lastly "accountability". It was interesting to observe that the seven principles were well represented in the SAIAF and in the recommendations from the focus groups.

5.2 Implications for Research and Practice

The study specifically highlighted social aspects that need to be considered when adopting AI in organisations. Even though other AI adoption frameworks exist, the socio-specific considerations or impact of adopting AI are not sufficiently addressed [23, 9, 34, 37]. The expected contribution of the SAIAF artefact is two-fold. Specifically highlighting the socio-specific considerations, on the one side, the framework can be used by academia, and provides a high-level view of identified social elements essential for enabling the responsible adoption of AI. On the other hand, the framework can be used by practitioners as it provides them with a high-level guide to assist managers and change mediators with guidance on how to support the responsible adoption of AI and transform a traditional organisation into more data-driven.

6 Conclusion

The scope of this study was limited to an analytics competence centre. However, the creation of the framework is grounded in information systems theory. Furthermore, the organisation at which the study took place has very high digital transformation maturity and experience. Therefore, the experience and findings can be used by other organisations to support the responsible adoption of AI as part of their analytics portfolio. Furthermore, the theoretical contribution of this paper is achieved by combining the TOE framework with concepts of the DOI theory while evaluating the relevance it has to AI adoption in organisations. Lastly, it makes a modest contribution to design science research theory by demonstrating the usefulness of using SCRUM review sessions [21] and collaboration tools such as Conceptboard [3].

A future study is underway to build a website that will support the communication, evaluation on the improvement of the SAIAF. What constitutes AI is growing and ever evolving. Therefore, it is recommended to investigate how this framework can evolve and improve over time. Lastly, one limitation of this study is that it was conducted at one organisation and only in one industry. Future studies could investigate the validity of this framework in other companies and industries.

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