Artificial Intelligence Beyond the Hype: Exploring the Organisation Adoption Factors

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Abstract

The adoption of artificial intelligence (AI) has increasingly taken hold across global businesses. Although research exists in this domain, very little is known about the adoption factors and necessary AI specifications to ensure successful organisational adoption of this technological innovation. The present study fills this gap in the literature through the analysis of the adoption process of AI. The conceptual framework of this research is based on the technology–organisation–environment (TOE) framework and the diffusion of innovation theory (DOI) for assessing the adoption process of AI from an organisational perspective. The conceptual framework was tested and validated through the use of semi-structured interviews conducted in Australia with18 expert interviewees regarding its applicability to the AI adoption process. The findings indicate that relative advantage, compatibility, top management support, management obstacles, organisational readiness, and government regulatory support are important determinants of AI adoption. In terms of academic contribution, this research provides an improved understanding of the critical factors relating to the adoption of AI from the perspective of organisations. The empirical results further support the applicability of using the DOI and the TOE framework at the organisational level, to further understand AI adoption. With regards to practical implications, this research provides Australian organisations with relevant suggestions with regard to how the adoption of AI can be improved.

Keywords AI adoption, Artificial Intelligence, Organisation, TOE, DOI.

1 Introduction

Artificial Intelligence (AI) is a revolutionary technology which has the ability to enhance and boost the performance of organisations by developing "artificial" solutions to address complex business challenges, with "intelligence" being a replica of human intelligence (Rai et al., 2019). The adoption of AI promises organisations several advantages in terms of their business value, including increased revenue, reduced costs, and improved business efficiency (Gartner, 2019). In addition to cost and effort benefits, AI also provides process automation (e.g., chatbots and computer vision), cognitive insight (e.g., classification), and cognitive engagement (e.g., process optimisation and automated tasks).

As it has for many other countries, AI also offers a substantial opportunity for Australian businesses. A recent report by PricewaterhouseCoopers, one of the big four accounting firms, estimated that by 2030 AI's potential contribution to the global economy will increase by 14% (US$ 15.7 trillion). The study also estimates the capacity for the Australian economy to benefit US$ 2.2 trillion from AI and automation by 2030 (Rao, 2017). However, despite the successful growth of AI, a study by Alphabeta industry leaders showed that only 9% of Australian organisations are making significant investments in AI and automation compared to more than 25% in the US (Alphabeta, 2018). In addition, a recent industry survey by Gartner (2019) indicates that the majority of organisations are still gathering information about what AI is, and how to adopt AI. Thus, a holistic view with regard to the adoption of AI and the related variables have not yet been developed within the Australian context.

Inevitably, AI has drawn the attention of the Information System (IS) academic community, contributing to the growth of an increasing body of knowledge at the intersection of industry and technology (Alsheibani et al., 2018). Despite the already highly-developed understanding of AI techniques, this is not the case when it comes to the adoption of AI in organisations (Pumplun et al., 2019); yet such an understanding is extremely important for organisations attempting to pragmatically overcome the underlying AI challenges that prevent organisational adoption. The intention of this study is to fill the current gap by exploring organisational adoption factors with regard to AI through the use of a qualitative interview approach. Importantly, research that focuses on the adoption of AI should not only consider its technological features but also acknowledge the organisational capabilities and external environmental factors that impact its adoption (Tarafdar et al., 2019). Therefore, we employ two grounded models: the technology–organisation–environment (TOE) framework, and the diffusion of innovation theory (DOI), to identify factors that influence the adoption of AI. Accordingly, we propose the following research questions: 1) What factors influence the decision to adopt AI? 2) How do different factors differ in their influence on AI adoption in organisations?

To answer our questions, we interviewed 18 experts from both user and provider organisations from within Australian industry, and provided supporting empirical that are integrated to expand the TOE framework. Thus, the primary contribution of this paper is to offer a framework for the adoption of AI which provides business leaders with a broad overview of AI-related conditions within organisations. Our study can help Australian industry to better plan for, and effectively implement, AI technologies. Moreover, our study contributes to IS research in the field of AI by illustrating how researchers can integrate the technological and organisational context into their explorations of the adoption of AI.

2 Theoretical Background

2.1 Artificial Intelligence Adoption in Organisation

The adoption of AI at the organisational level is rapidly becoming a ubiquitous topic in both research and practice, indicating the potential attributed to AI. However, only a few researchers have focused on best practices and AI technology scenarios by developing case studies and using anecdotal evidence IS (Alsheibani et al., 2018; Gentsch, 2019; Pumplun et al., 2019; Ransbotham et al., 2018; Thompson et al., 2019). In addition, most of the recent AI studies at the organisation level have tended to concentrate on a technological understanding of AI adoption (Popa, 2019) rather than attempting to identify the strategic and business challenges associated with its adoption. Similarly, Nascimento et al. (2018) identified some specific aspects of AI such as human requirements, but they did not incorporate their results into a theoretical context. Another common limitation noted in these studies is the focus on specific industries or technologies (Kruse et al., 2019). We argue that while these AI researchers address the perspectives of AI technological development and functionalities, there is a need for research into AI adoption and business aspects, along with a discussion on successful adoption.

AI faces many of the same issues and challenges faced by other innovations (Tarafdar et al., 2019). However, AI differs from previous technologies in several ways including uncertainty concerning AI capability and business value. These, inter alia, have distinguished it from the challenges facing other digital technologies (Ransbotham et al., 2018). Indeed, a study by Ransbotham et al. (2019) observed that the early adopters of AI technologies showed that such technologies are capable of producing unexpected results, and raise new challenges and concerns about the long-term impact of AI investment in organisations. Chui and Francisco (2017) emphasise that the implementation of AI, considered both powerful and scalable, is capable of exceeding human ability and understanding. One of the main challenges is still the low maturity level in terms of the understanding of leaders regarding what AI can do (Agrawal et al., 2019). A recent survey by the A O'Reilly shows that AI efforts are developing from prototype to production but that the business leaders' support and AI skills gap remain as snags (Magoulas & Swoyer, 2020). This is in line with Tarafdar et al. (2019), who point out that having the right AI experts and data skills is not sufficient for success.

In addition, gaining advantages from AI innovation involves not only the organisation-wide introduction of these innovations, but also a carefully-considered technology foundation and a comprehensive environmental policy (Yao et al., 2018). One of the concerns with regard to AI technology solutions is the use of untrained algorithms and the amount of effort required to arrive at AI. As Chui (2020) has pointed out, a number of keys features such as data structures and improvement of deep learning algorithms, make it necessary to collect comprehensive and up-to-date data. Owing to these observations of AI in terms of its values, resources, and technical knowledge, the unique characteristics of AI tend not to be sufficiently addressed. A comprehensive framework is therefore required that is based on prominent and relevant technology adoption theories that cover all the essential factors. Based on these findings, the present study aims to determine the key factors affecting Australian organisations' adoption of AI, and provide further insights that potentially deepen and extend the proposed TOE framework.

2.2 The Technology–Organisation–Environment Framework (TOE) and Diffusion of Innovation Theory

To address the identified knowledge gaps in the literature, and thereby the issue of the adoption of AI, we have built on technology adoption research. In line with IS, researchers have considered the study of technology adoption at either an individual level (Rogers, 2010; Oliveira & Martins, 2011) or at an organisational level (Chen et al., 2015). To study AI in organisations, it is necessary to consider innovation diffusion theories that explain how innovations are adopted in organisations (Hsu et al., 2006; Zhu et al., 2006) are necessary. Among these, two of the most prominent theoretical frameworks for IT innovation adoption at the organisational level are the TOE framework introduced by Tornatzky and Fleischer (1990) and the DOI theory proposed by Rogers (2003). The TOE framework is one of the most popular theories in IS and one which has been applied to explain organisational technology adoption in a variety of settings (Oliveira & Martins, 2011; Zhu & Kraemer, 2005). TOE postulates that there are three specific perceptions that influence the adoption of technological innovations, namely the technological context, the organisational context, and the environmental context (Picoto et al., 2014). The technological context refers to what is available to an organisation, and reflects how the adoption process is affected by a particular technology. In an organisation, the organisational context investigates the structure that constrains or facilitates the adoption of innovations. Although DOI does not provide potential determinants in the environmental factors' category, the TOE framework suggests that critical environmental factors with regard to AI would include external pressure from competitors and business partners, and AI government regulations (Picoto et al., 2014). Therefore, the factors we have chosen to consider are assumptions based on past experience and practice from related research areas (Webster & Watson, 2002). The DOI theory focuses on how technology or innovative ideas progress from conception to adoption. This includes five innovation characteristics: relative advantage, compatibility, complexity, trialability, and observability. A considerable amount of empirical IS research has shown that the most common significant and relevant characteristics are relative advantage and compatibility (Picoto et al., 2014; Zhu & Kraemer, 2005; Tornatzky & Klein, 1982); accordingly, these two characteristics will be considered in this research. Relative advantage is the degree to which an organisation perceives an innovation to be better than its alternatives (Rogers, 2003) while compatibility refers to an innovation being consistent with existing practices and processes (Rogers, 2003). In the context of AI, compatibility could be seen as how existing processes are similar to the processes required to evaluate how AI technologies can improve them. Looking at the role of organisation-related factors in the IS adoption research (Alsheibani et al., 2020) we can postulate a positive influence on the part of business leaders, managerial obstacles, and organisational readiness. In the context of the environment (Ransbotham et al., 2018), the influence of competitive pressure as a positive driver for adoption as well as government regulations may have both negative and positive consequences with regard to the adoption of innovation.

Due to the novelty of AI adoption, we have combined these two models to form an integrated research framework for the adoption of AI, and have focused on a number of factors that have been identified as the most common antecedents in prior studies on AI, technology adoption, and AI adoption at the organisational level. Through empirical studies, it has been found that the combination of TOE and DOI better explains the adopted use of electronic commerce compared to the explanation provided by each one individually (Oliveira et al., 2014; Picoto et al., 2014; Zhu et al., 2006). Therefore, this study utilises DOI theory and the TOE framework as described above. This combination is employed as the conceptual starting point (Figure 1), which will be expanded in the course of the study.

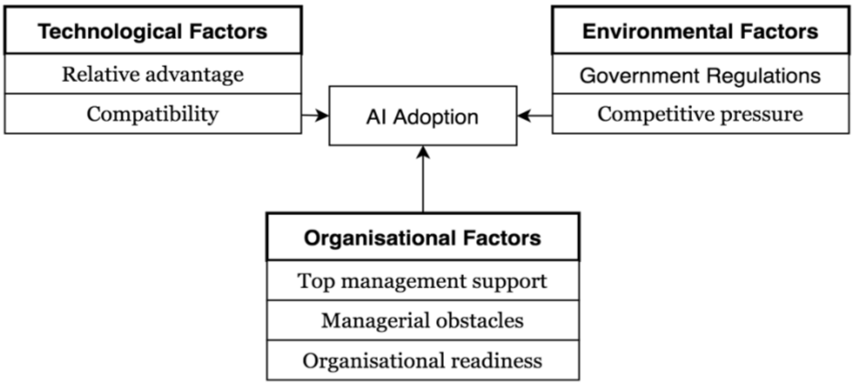

Figure 1. Research framework for AI adoption

3 Research Methodology

Given the existing gap in the literature, this study applied a case study approach involving in-depth interviews in order to increase the current understanding of AI technology (Yin, 2013). The design of the semi-structured qualitative interviews was based on a theoretical discussion of IS innovation, and on the findings from existing studies on AI (Alsheibani et al., 2020) adapted to fit the AI adoption context. This study aims to expand the current state of IS research concerning AI application in organisations by making use of face-to-face, semi-structured online interviews with organisations which currently make use of this technology. The objectives of this data collection round included; 1) to determine whether or not the qualitative data findings provide evidence that is consistent with the conceptual linkages defined in the theory; and 2) to enrich comprehension of the problem under review by providing rich, descriptive explanations. Thus, we are using a combination of focused and conventional analyses, where the focused approach uses theory-derived codes (the TOE framework) and the conventional analysis takes into consideration the data collected directly from the research participants (Hsieh and Shannon, 2005).

Given the nature of this study, the type of unit being analyzed is the organisation. The interviewees who made up the sample were identified using a purposeful sampling strategy involving selecting individuals representing different industries within Australia to increases the generalizability of the results (Yin, 2013). The LinkedIn business database (see https://www.linkedin.com) was used to identify organisations that implement AI for inclusion in the research. The list acted as a sample frame, and email invitations were sent to all list members. The use of this LinkedIn database provided this research with significant benefits. First, it is difficult to reach many respondents given the time restrictions associated with this study. Therefore, Linkedin.com provides a feasible option. Second, this list contains a high diversity of respondents within Australia in terms of their characteristics such as position, gender, educational level and geographical location; this gives the outcomes more generalizability. For the interviews, an invitation to participate and an explanatory statement were sent via LinkedIn and email in advance to all informants.

3.1 Data Collection and Analysis

Multiple data sources were used in this study. This included interview data (online interview transcripts and notes) that was supplemented by online documents (marketing reports, usage, etc.) provided by the interviewees and system providers. Due to the coronavirus pandemic, the data collected in this research was primarily gathered in the form of online face-to-face interviews, an adequate technique for exploratory research because it allows expansive discussions of various factors (Yin, 2017). In addition, one interview was conducted using telephone calls, and two participants replied in written form due to the coronavirus showdown. Prior to data primarily gathered in the online face-to-face interviews, the secondary information was gathered from internal and publicly-available sources including industry reports and business websites. The reasons for secondary information collection was to allow 'pre-understanding' of the in-depth case, and to overcome the online interview limitations (Yin, 2013). The interview protocol was pre-tested with a panel of experts to ensure that the questions to be asked were relevant to the research framework. The experts were also asked to identify any possible leading questions. Prior to each interview session, a plain language statement (PLS) explaining the confidentiality policy of the research was presented to the participants. During interviews, we kept our questions open to encourage participants to talk freely. Additional questions were used when new concepts and areas of potentially-valuable data appeared from the respondents' responses. The interview sessions with business leaders, AI seniors, and data scientists lasted 53 minutes on average.

In total, we conducted 18 interviews between February 2020 and June 2020. Three of the participants were at senior manager level or were company founders, eight were IT middle managers or heads of department, while the remaining respondents were either AI consultants or strategists. To achieve more generalizable research results, a representative sample made up of organisations across various industries and of differing sizes were selected (Flick, 2004). Table 1 provides an overview of the participants as well as the duration of the interviews. In choosing the participants, we used the rules of data triangulation (Flick, 2004). Consequently, we selected the interview partners such that both demand organisations (DO) and supplier organisations (SO) were surveyed. In order to reduce response bias, we chose the wording of the semi-structured open-ended questions with care, and were careful to interview individuals at different hierarchical levels. Due to the methodology used in the study, each interview was analysed prior to engaging in the next interview. The interview guide comprises two sections. The interviews started with questions aimed at obtaining demographic information from the respondents and understanding their previous experience in the field of AI. The second section dealt with the actual use of AI and the main factors in terms of the AI adoption framework, namely AI business case, business leaders, AI benefits, organization readiness, competitive pressure, and government regulatory frameworks. For example, we asked the interviewee 'What are the benefits expected from adopting AI in your organization' and 'Do you consider these benefits as a driver for adopting AI'. In addition, the ideas that emerged during the interview were documented as the interview was taking place, or directly after each interview. Most of the interviews were transcribed immediately after each session had been conducted. To ensure familiarity with the data, the preliminary data analysis began with a review of the interview transcript. We achieved our termination criterion in terms of theoretical saturation after 15 interviews (no. 8 in Table 1) after which no further codes were added. We conducted three additional interviews to confirm that the termination criterion had been achieved (nos. 9, 17,18). These three interviews with demand and supplier organisations helped validate our results, and do not develop much code as we have experience with all relevant actor groups.

Participants (DO): Participants of organisations that are predominantly users of AI technology and services.				**Participants (SO): Participants of organisations that are predominantly providers of AI products and services.**			
ID	Position/employment	Interview Method	Length	ID	Position/employment	Interview Method	Length
1	Head of Data Engineering and AI	Online interview	0:57	10	Senior Vice President	Phone	1:04
2	Manager	Online interview	0:45	11	National Lead Higher Education Technology	Online interview	1:05
3	Head of Data Science and AI	Online interview	0:49	12	Senior Front-end Developer	Online interview	0:59
4	Principal Consultant	Online interview	1:04	13	Funder	Online interview	0:55
5	IT Manager	Online interview	0:58	14	Principal Consultant	Online interview	1:05
6	Manager	Online interview	0:45	15	Manager	Online interview	1:03
7	AI specialist	Online interview	0:59	16	Funder	Online interview	0:38
8	Data Scientist	Online interview	0:51	17	Manager	Written	-
9	Manager	Phone	0:55	18	AI specialist	Online interview	1:06

Table 1. Participant Overview

Most of the interviews were transcribed immediately after each session had been conducted. To ensure familiarity with the data, the preliminary data analysis began with a review of the interview transcript. We achieved our termination criterion in terms of theoretical saturation after 15 interviews (no. 8 in Table 1) after which no further codes were added. We conducted three additional interviews to confirm that the termination criterion had been achieved (no. 9, 17,18). These three interviews with demand and supplier organisations help validate our results and do not develop much code as we have experience with all relevant actor groups. For our analysis of the interview transcripts, a thematic analysis using two cycles of coding was applied as recommended in Saldaña (2016). The first coding cycle was conducted using a mixture of descriptive coding and hypothesis coding, followed by the second coding cycle using pattern coding. In the first cycle, descriptive coding was used to identify the key concepts in each document, and to break down the captured data line-by-line. In addition, hypothesis coding was performed to assess the factors conceptualized from the AI adoption framework (see Figure 1). Hypothesis coding has been chosen because it can be particularly useful where prior research is available to inform the initial generation of codes and themes (Saldaña, 2009). In the second cycle, the pattern cycle involved the process of systematically relating the identified factors based on their relevance to the research themes. This coding method is primarily developed to extract patterns by combining first-cycle codes into a smaller number of categories (Miles and Huberman, 1994). Finally, the list of codes, factors and themes was explored in detail with two researchers and experts to validate and ensure validity and objectivity.

4 Results and Discussion

The AI adoption framework presented in this paper includes factors that are based on a theoretical explanation, and empirical findings from related research areas (Webster & Watson, 2002). In the following sections the statements were divided into two major categories: predefined factors based on the context for the AI adoption framework, and evolving sub-categories. It consists of three main categories - technology, organisation, and the environment - and their associated 7 sub-categories (Figure 2). Therefore, the emergent factors were investigated, grouped, categorized and incorporated as discussed in more detail below.

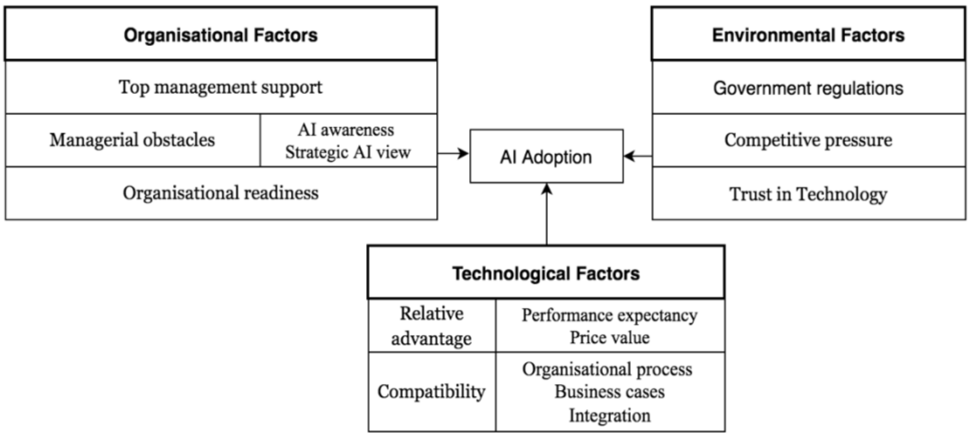

Figure 2 Extended Framework for AI Adoption

4.1 Technological Factors

The technological factors are measured in terms of relative advantage and by the degree of compatibility, both of which have the ability to positively influence new technology adoption. The relative benefits include preparing for the organisation-wide effects associated with AI technologies. Our analysis indicates that such technologies can deliver no results, or uncertain or unpredictable ones, and raise new challenges and questions about the long-term effects of AI investments in organisations. For example, it is possible to learn from the data over time. However, AI is not a panacea but should be compared to the use of robust conventional systems for the specific application, as demonstrated by the following quote:

"Often, AI is being attributed to lots of mystical type of things. Basically, there's this almost magical piece of technology, who can do everything you just basically let it do, without really clear understanding." [P-4].

Moreover, we derived that relative benefits on the basis of expert interviews, and grouped them into sub-categories: performance expectancy, price value, and effort expectancy. Performance expectancy refers to the degree to which the organisation believes that using AI technology provides functional benefits. Our analysis reveals that there are many organisations that have introduced new services relating to conventional products to enhance customer service and to not lose market share. Moreover, relative benefits include planning for the overall organisational impact resulting from the introduction of AI technologies as demonstrated by the following quote:

"The extent to which some of these things can be implemented, and the extent to which you can really centrally draw upon that innovation. " [P-3].

The second subcategory can be seen as the difference between the cost of using AI technology and its benefits. Similar to other innovations, the perceived trade-off between the cost of using the technology and the benefits obtained from the use of AI is an important aspect that generally determines the implementation of new technologies within companies.

"I think that at the point at which the quality of the outcome that is performed by AI is better than that provided by a human, then that's the point at which they will seriously consider it from a cost reduction perspective." [P-10]. "And so to me, that's the real opportunity. It's this reinvention of the way in which we go about our business rather than this trying to just chuck the existing problem method" [P-11].

In the context of AI, however, it is important for organisations to understand the technologies that perform what kinds of tasks before they embark on an AI adoption.

Our data also reveals that AI compatibility not only relates to the technical skills required to create AI technology, but also employing a business expert who knows the operations, the reasoning behind current business processes, and the ability to evaluate how AI technologies can improve them. AI compatibility is represented by three subcategories on the basis of expert interviews: organisational process changes, business cases and integration. After evaluating the interviews, AI technologies require organisations to undertake extensive organisational process changes in order to maximize product development performance and to enhance quality outcomes.

"That's one of the key messages that I'm saying. AI doesn't mean business as usual. AI usually means that you need to restructure the organisation, need to change the processes too." [P-2].

In addition, the analysis of the interviews identifies how organisations invest significantly in the change process and how these processes will have to be reimagined or reengineered. In the context of AI, organisations need to re-organize, or re-engineer, their business processes to achieve that level of quality resulting from the implementation of AI. This is made clear by the following statements:

“Absolutely, that's one of the key messages that I'm saying,[...]usually means that you need to restructure the organisation, need to change the process in that, too. In terms of that AI by itself, without organisational and business process change, means very little.” [P-7]. "To a degree you might have to make the organisation adapt to certain changes, but I think when you show them the benefit or the loss, they are happy to do it...it's a real poster story, almost, in terms of the fact that AI by itself, without organisational and business process change, means very little." [P-8].

In addition, to the business process change, another very frequently-mentioned aspect is the formulation of a concrete business case. A business case offers a clear problem description of what AI technology can do and demonstrates how its algorithms can improve the execution and outcomes of a business process or group of processes (Alsheibani et al. 2020). The process of building a AI business case should align with existing strategies.

"During all stages of this process, you will need to develop a business case that ties back to your strategic objectives. " [P-5]". “ working *with adopter organisations to clearly understand the business needs, the AI business case, and data management needs" [P-18].*

The third subcategory – integration – indicates that AI is complex and, as organisational integration continues, certain areas will have an impact on the business. Most organisations are now going the way of enforcing old, inhibiting mechanisms by building up a facility or a centre within the organisation. However, problems may also arise as a result of this procedure, as demonstrated in the following statement by an expert.

"I think that at the moment, we might all have a good idea with regard to what an AI workload could lead to We might also have a good idea as to what a human workload would be. But do we understand how they would integrate?" [P-17].

It could include establishing a clear strategy and putting it in place to provide the data that allows AI to function effectively, and to recruit or employ the best AI expertise. Developing AI is primarily the responsibility of domain experts, and data scientists and IT experts assess the need for AI integration with other applications, and identify any additional support the application might require.

4.2 Organisational Factors

The role of organisation-related factors with regard to the adoption of AI, must also be taken into account in such a way that they reflect the organisation's overall ability to implement AI. It is presented here in terms of three aspects: top management support, obstacles to AI implementation, and organisational readiness. In the current study, fifteen out of eighteen of the interviewees believed that top management support is the most vital aspect with regard to the adoption of AI. In its pursuit of the implementation of AI technology, top management cannot leave it to the technical experts alone; there is a need for collaboration between AI experts and senior management, as illustrated by one interviewee as follows:

"The top management support really is aiming to enable the staff, people that are involved in the whole process, and support them in their role. Consequently, the leadership role becomes distributed across a number of stakeholders who are enabled and who are supported in their basically joint quest, to incorporate certain new aspects of the innovation in the organisation."[P-3].

These developments demand that organisations plan and implement their strategies differently than what is occurring at present. Thus, the support of top management become has emerged as one of the strongest determinants of AI adoption. However, a certain understanding of the degree of policy-making skills of business executives is required.

In addition to top management support, addressing AI obstacles leads to greater AI usage, which, in effect, leads to a higher level of operation concerning the use of AI. Due to the novelty of AI adoption, its introduction in a specific organisational context can generate unexpected barriers (Yao et al., 2018). Our analysis reveals that organisations that have overcome managerial obstacles have a higher incidence of AI adoption. This could be explained in the case of Australian organisations by suggesting that they may possess sufficient related knowledge to overcome AI barriers.

"There's definitely a challenge because people misunderstand AI at times. AI is not just a blanket thing that works for everything. So you have for instance, or what we are doing for AI… "[P-7].

Also, our analysis reveals two sub-categories of managerial obstacles that contribute to preventing AI adoption. First, a lack of understanding of AI can delay the adoption of AI in some cases. There is a need to develop a better understanding of what AI entails, and to create a shared sense of, in particular, the extent of the purpose of AI within the organisation, and the organisation's related goals and ambitions. This is demonstrated by one interviewee:

"So when you think about artificial intelligence, there's a fair bit of fear, combined with a lack of understanding, et cetera. And so significant education will be required with regard to the general public and the workforce to achieve significant adoption of AI in corporate Australia for example."[P-9].

Second, accessing AI skills and identifying a clear strategy for sourcing the data that enables AI to work, also plays an important role. Successful AI adoption relies on a large volume of data from which organisations can obtain insights, and which provides information on the best possible response to any situation (Gartner, 2019). As one interviewee explains:

"For you to start getting a little bit more mature with regard to AI, and to really leverage AI, you need to first of all mature your data journey." [P-15].

This is consistent with the literature on organisational adoption (e.g., Chui and Francisco, 2017) who argue that the lack of clarity in terms of what AI can be used for in organisations, and the lack of access to new skills to evaluate, build and deploy AI solutions, can lead to difficulties in achieving a smooth AI adoption.

In addition, organisational capability also plays a crucial role in the adoption of AI. Our analysis shows that the availability of AI expertise, data required to train staff in the use of AI, and technical knowledge, lead to the promotion of the diffusion of AI.

"*And more digitally and tech-savvy boards will be required to get that AI capability established, but also really to understand fully the opportunity of it" [P-10].*

As we observe from the analysis, every organisation's AI driver is unique, as is its application of AI. The higher the level of AI adoption at the level of the organisation, the more organisational capability will be involved in the process. This involves identifying parameters in terms of conditions such as the degree of AI involvement, which is a form of autonomous decision-making and scalability. For example, chatbots or computer vision, machines that can think like humans can reason and can make decisions. In this context, AI benefits can be achieved in different forms, with differing degrees of human involvement.

4.3 Environmental Factors

Within the environmental context, government regulations and laws are one of the key components of new development within organisations (Meyer & Rowan, 1977). Accordingly, in the interviews we observed several experts describing the managing of the new legal situation as a challenge when it comes to accessing personal data to train their intelligent system.

"There was lots of uncertainty, like what that would entail, what exactly that means, how institutions are going to comply in terms of many of these elements. " [P-6].

Failures with regard to the adoption of AI are often due to a lack of government regulations to encourage organisations to adopt e-government (Ransbotham et al. 2020). Findings from this study indicate that government regulation is a strong factor when it comes to influencing the adoption of AI. In this respect, one interviewee shared his opinion about the lack of regulation in terms of government policies as follows:

"And this is why you've got these two things going on at the same time and there's a lot of issues between what governments want to regulate, what this techfin how they want to innovate I, and how they want to penetrate days, lives, companies, governments". [P-12].

Trust in technology emerged as another factor with regard to the adoption of AI. In this respect, trust is defined as an "...organisation's willingness to depend on another party because of the characteristics of the other party" (McKnight et al., 2018). The organisation faces the decision whether or not to implement AI, information, and the acceptance of the potential customer base, must also be taken into account."

There's a fair bit of work there to gain public trust in organisations, and the use of AI. "[P-11]. At the same time, there were some experts how commented on a lack of trust in providers in protecting their personal data: *"...but I think that often it's not really even AI. It's more clever use of data, algorithmic use of data that is not necessarily simulated intelligence."[P-10].*

As we mentioned, AI innovation involves top management involvement, a high level of technical, recourses, and organisational uncertainty, which can lead to unpredictable developments. Thus, if the level of barriers is too high to entry organisations will not feel competitive pressures. In addition, providers are frequently unable to train and adapt intelligent algorithms efficiently, as access to data and adequate computational resources are limited.

5 Conclusion, Limitations, and Future Research

This study makes several significant contributions and has implications for theory building and management practice. Using qualitative data obtained from Australian organisations, we developed a framework that explains the adoption of AI technology. The findings suggest that TOE factors are applicable to the adoption of AI. The use of the TOE framework is extended by incorporating variables established from DOI theory, and critical factors that are relevant to the adoption of AI in Australia. This will help organizations to perform a structured analysis of their status, and recognise areas for enhancement, in order to successfully adopt AI. However, the research also suggests some categories that are partially contradictory and need further evaluation before being used unilaterally in organization-level studies (e.g. trust in technology). The results of the qualitative data analysis comprise three main categories and 7 sub-themes. Their relationships are visualised in Figure 2. These considerations arise primarily from the challenges associated with the on-going digital transformation of all business processes and organizational change on the part of established businesses. In terms of the role of technology-related factors, the study participants suggest compatibility with regard to implementation, business process change, and defining a business case, as the major obstacles preventing organizations from further applying AI in their organizations. This will become even more relevant in future since it is important to continuously evaluate the progress of projects, since the feasibility of ideas in this area cannot be proven from the outset. In terms of the role of organization-related factors, the study results show a lack of strategic AI view, AI related skills, and top management support. The evaluation of the interviews found that government regulations and trust concerns are slowing down the pace of AI adoption from an environmental perspective. Meanwhile, in terms of practice, our results suggest a number of implications. The study offers relevant suggestions for organisations with regard to how the adoption of AI can be improved. It can also serve as a guideline for organisational AI adoption, and as a pointer for the competencies needed when rethinking their current AI innovation strategy. Our work is subject to some limitations that offer opportunities for further research. First, IS adoption theory other than TOE might be applied to better reflect the specific requirements of AI (e.g., the Affordance–Actualisation (A–A) theory of Gibson (1994)). Furthermore, future research could investigate the adoption of AI and other AI-enabled systems in different project settings and different types of organization, such as start-ups or large multinational corporations..

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