Re-thinking the Competitive Landscape of Artificial Intelligence

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Abstract

Artificial Intelligence (AI) has emerged from its traditional domain of computer science research to be a management reality. This can be seen in the remarkable increase in the adoption of AI technology in organizations resulting in increased revenue, reduced costs and improved business efficiency [19]. Despite this trend, there are still many organizations that are facing the decision whether to adopt AI. Thus, to evaluate the adoption of AI at organizational-level, we draw on two-grounded theories: Technology-Organizations-Environment (TOE) framework and Diffusion of Innovation theory (DOI) to identify factors that influence the adoption of AI. Survey data collected from 208 large, medium-sized and small organizations in Australia is used to test the proposed framework. We offer a method of how examining AI over a set of organizations. Besides offering several important recommendations for AI adoption future directions for research in this area are also included in this paper.

1. Introduction

Artificial intelligence (AI) is one of the most significant competitive trends in business today [13]. AI is defined as 'a set of tools and technologies that has the ability to augment and enhance organizational performance' [5, p3]. This achieved by creating "artificial" systems to solve complex environmental problems, with "intelligence" being the simulation of human-level intelligence. This intelligence plays a crucial role in strategic planning and has been used by organizations to gain a competitive advantage over their rivals [48]. It is popularly believed that AI will bring benefits such as human augmentation which should be taken into account when thinking about economic growth [41]. AI has been used and deployed at government, industrial and personal levels. This study is motivated by the exponential growth interest in the field of AI and its impact on organizations. AI has evolved from a process involving robotic-like game playing and knowledge representation to cognitive automation [32]. Within the corporate world, AI is having a growing impact on businesses themselves. According to Gartner [18, 19], AI is ranked in first place as a strategic technology for organizations. This is supported by Google, Amazon, IBM, Apple and others, all of which have leveraged AI to help deliver better customer experiences [11] and improve productivity [48] through easier collaboration [22]. The worldwide use of AI offers a substantial opportunity for Australian businesses [2]. The study also estimates that the Australian economy has the potential to gain 2.2 trillion USD by 2030 from AI and automation [41]. However, despite the successful testimonial of AI, a survey of business leaders by Alphabeta has indicated that only 9% of Australian organizations are making sustained investment in AI and automation compared with more than 25% in the US. Currently, Australian organizations are lagging behind global rival in embracing AI technology [26]. Indeed, a recent industry survey by Gartner [18] indicates that a majority of organizations are still gathering information about what and how to adapt AI. Many organizations appear to still be at the stage of deciding how to create a business case for AI implementation, and the necessary organizational skills needed to evaluate, build and deploy AI solutions, and are unclear what AI can be used for in a business context [41]. Thus, a holistic view of AI adoption and associated factors have not yet advanced within Australian context. Therefore, this research aims to develop an in-depth understanding of AI adoption among organizations in Australia. Consequently, the unit of analysis is the organization. In this research, we adopt a broad definition of adoption by [43] that focuses on how new ideas are adopter among the population of potential adopters [37]. To study AI adoption in organizations, this research employs two well-establish theories. First, we adopt innovation diffusion theories that explain how innovation is adopted and used within

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organizations [42, 43]. Second, we employ a general theory – the Technology-Organization-Environment (TOE) framework - to identify and theorize which factors influence the adoption of AI at the organization level in the Australian context. Therefore, this study proposes a comprehensive framework to evaluate AI adoption on the part of organizations, and secondly to verify the fitness of the proposed AI adoption framework with regard to how it affects the successful adoption of AI on the part of organizations. The following research questions are formulated to address this broad goal: *1) What are the factors specific to AI which impact an organization's aim to adopt AI? 2) To what extent do those factors influence the adoption of AI on the part of Australian organizations?* To answer these research questions, we offer a method of how examining AI over a set of organizations leads to identifying the factors which impact AI adoption.

2. Theoretical Background

2.1 AI from Science Fiction to Business Fact

The rise of digital transformation powered by AI has become an important driver for change in various industries. Investments in AI around the world have grown at a staggering rate over the last four years. AI has become one of the key technologies being considered by organizations worldwide [17]. This notion of AI is in itself nothing new. It was developed in the 1950s as a computer science discipline in the United States since its introduction by Professor John McCarthy at a conference held at Dartmouth in 1956, when he described AI as the '...science and engineering of making intelligent machines, especially intelligent computer programs'[31, p.423]. A range of terms such as "Machine Intelligence," "Intelligence Agents," "Intelligent Systems" and "Algorithms" also serve as labels for describing AI. Today, AI starting to become an essential feature of almost all industries [9] including education [22], healthcare [57], finance [3], transportation [11], agriculture [6], and manufacturing [32]. In these contexts, AI consists of a comprehensive set of training computers that aim to do tasks involving human intelligence. AI encompasses many different aspects, including machine learning, deep learning, expert systems, and robotics [41]. Although many researchers have focused on AI techniques from various perspectives, AI adoption at the organizational level faces several challenges because of its complexity [13]. According to a McKinsey Global report [31] the implementation of AI at the organizational-level poses crucial challenges that cut across developers, government, and employees [12]. In fact, the adoption of AI technologies at an early stage is challenging, as multiple aspects may need to be taken into consideration [41]. From this perspective, the Information system (IS) adoption theories are useful to underline and overcome the challenges to new technological innovation adoption, such as AI adoption at the organizational-level [60].

2.2 Technology Innovation and AI

A considerable number of empirical IS research has involved the study of technology adoption at either an individual level [34, 42] or at an organizational level [60]. Given the unique nature of AI regarding their values, resources, and technical knowledge, a theoretical structure for AI adoption needs to take into account the necessary capabilities to manage and adapt such innovation. AI technology and its techniques offered today are a result of several tools developed for very different tasks [41]. In line with IS innovation literature, researchers have suggested that there are also different forms of innovation. Swanson [45] identified three basic kinds of IS innovation: technical innovation (e.g., relational databases) that is restricted to the IS function, support innovation (e.g., payroll systems) that apply IS to support administrative tasks and complex innovation (e.g., e-business) that relates to innovation that has strategic relevance to the organization. We argue that AI is a complex innovation, in the sense that AI offers a new strategic approach towards business decision-making, resulting in new ways to create value which are not well understood [13]. It can be anticipated that the complex innovation associated with AI will trigger significant organizational change through the introduction of new technological processes and new organizational practices. Rogers argued that the adoption of complex innovation requires an advantages technology foundation as well as a carefully thought out organizational strategy and a comprehensive environmental policy. In line with these arguments, we employ the TOE framework and DOI theory to determine the factors that affect AI adoption. Both theories are similarly applied to adopting innovation at the organization level in terms of such innovations as electronic data interchange [23], and e-business [60], and SaaS [34]. This has received a great deal of empirical support from different technology innovations [35]. Recent developments in technology innovation with regard to IT adoption have suggested three dimensions in terms of related forces: the technological, organizational or environmental contexts [34]. According to Tornatzky and Fleischer [46], the TOE framework with regard to the adoption of innovation at the organization level is not only built on technological factors but is also influenced by organizational and environmental contexts. Therefore, we draw on the TOE framework to identify the AI adoption factors. The TOE framework becomes a powerful framework for understanding the adoption of technological innovation on the part of an organization [54]. Besides, unlike other adoption theories, the TOE framework does not specify a set of factors that affect innovation adoption [2]. The DOI theory [42] focuses on how new ideas are communicated through culture. According to the DOI theory, there are five characteristics of a new innovation that may be essential for its adoption: relative advantage, compatibility, complexity, trialability, and observability. In line with DOI theory, the organizational context and the innovation characteristics determine the likelihood of adoption [54]. Rogers [42] found a basic pattern that was almost universally present as innovation ideas diffuse through a culture. Therefore, the underlying AI dimensions that lead to organization adoption, as well as the adoption factors, deserve closer investigation.

3. Framework and Hypotheses Development

The identification and development of AI factors were based on the procedure proposed by [60] and the two-procedure approach developed by [49]. These two procedural methods helped us to determine a set of factors that are theoretically related to the context of AI adoption. ***Procedure 1: factor identification*** In line with this step, first, we consider those factors that are significant for IT innovation adoption at the organizational level from the existing literature [37]. Therefore, we review factors from the related IT adoption innovation literature at the organization level, that draw on the TOE framework and on DOI theory and prior AI research [4]. Based on the outcomes, we have identified five factors that have been noted as being significant determinants of organization IT innovation adoption: relative advantage, top management support, firm size, government regulations, and competitive pressures. ***Procedure 2: AI dimensions*** In the second step, review the theoretical relevance of the TOE factors identified in procedure 1 and assesses them with prior AI research to understand the characteristics of AI adoption. In line with this argument, [60] suggests the initial model dimension or domain can be justified based on existing literature or expert knowledge. Therefore, we identify a new factor for AI that were not mentioned in prior studies. Increasingly, a considerable amount of studies has underlined a number of AI dimensions. McKinsey and Global Institute Company has suggested a number of key dimensions of AI adoption [25]. The first dimension is the level of digital maturity of the organization. AI's dependence on a digital foundation develops as each new generation of innovation builds on the previous one [41]. The organization's digital maturity is defined as the availability of the essential organizational resources for AI adoption [25]. In this study, we refer to digital maturity as the availability of the essential organizational resources for AI adoption. Thus, the implementation of AI requires not only the technical factors of IT but also human resources. In the context of this research, we argue that the availability of AI skills and data capability is critical for AI adoption. Due to the confusion that may be caused by the term digital maturity we adopt the concept of organizational readiness that we believe is much more accurate in terms of representing the AI factors. Wright [54] define organization readiness as "organization capability to support these innovations and existing technology" (p.515). In the context of this research, organization readiness refers to both human and capital resources such as computer hardware, data, and networking, all of which are essential in terms of AI adopting innovations. As a result, we combined organizational readiness, which is an organizational factor, into our framework as a key determinant of AI adoption.

The second dimension is the management awareness of AI. Strong top management support goes hand in hand with AI adoption [25]. Regardless of how advanced organizations are in terms of technology deployment, many barriers must be faced with regard to the adoption of AI. Such adoption at an early stage is challenging, as multiple aspects may need to be taken into consideration. AI offers a new strategic approach towards business decision-making, resulting in new ways to create value, which are not well understood [13]. According to a McKinsey Global report [19], the implementation of AI within organizations poses crucial challenges that cut across developers, government, and employees [25]. Organizations worldwide are facing substantial challenges as a result of the economic and technological developments in AI [40]. Prior studies have identified numerous barriers and enablers that affect AI adoption which we have used to frame our survey [9]. There is currently a need however, for further exploration of the main barriers that are important with regard to the adoption of AI in organizations in Australia. To address these challenge to AI adoption, we propose to examine the effects of the managerial obstacles. These obstacles refer to the lack of managerial skills associated with managing organizational adaptations to AI. We suggest, when organizations come up against obstacles when organizational changes, there is a need to develop a business case for AI implementation. This would incorporate limitations on the technology capabilities, the lack of clarity in terms of what AI can be used for the organizations, and the lack of access to new skills to evaluate, build and deploy AI solutions that lead to difficulties in achieving smooth AI adoption. To date, this has not been empirically tested.

The third dimension of AI is that organizations need to align AI to their core business. Consequently, AI transformations require a solid AI business case that should be aligned with existing strategies. Building on DOI theory [34], we assess the AI compatibility of an organization to its existing culture and current processes. Compatibility has been noted as one of the most commonly cited factors with regard to technology innovation [60]. Picoto [38] argue that the most common significant characteristics are relative advantage and compatibility, both of which are going to be applied in this study. Therefore, decision-makers will be willing to adopt AI if the organization's role, responsibilities and accountability are clearly defined within each AI project, and these are compatible with its internal processes and culture. From this perspective, we suggest that an organization with a high level of technology compatibility will be in a better position to adopt AI. After reviewing the literature dealing with IT diffusion innovation, and considering previous AI research in order to understand the characteristics of AI, we propose an AI adoption framework as shown in Figure 1, in which the three functional areas of technology, organization, and environment are measured in terms of relative advantage, compatibility, top management support, managerial obstacles, organization size, organizational readiness, competition pressure, and government regulatory.

3.1 Framework Development

A theoretical model with regard to AI adoption needs to take into account factors that affect the propensity of an organization to adopt AI, which is rooted in the specific technological, organizational, and environmental conditions of that organization. This framework extends our previous study on the AI adoption at the organizational-level [4, 5]. ***The role of technology-related factors.*** The technological factors are measured by relative advantage and by the degree of compatibility, both of which can positively influence new technology adoption. First, Relative

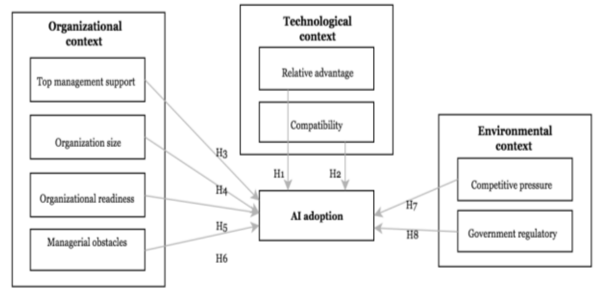

Figure 1. Research framework for AI adoption

advantage refers to the perceived advantage of adopting AI at the organizational-level. Any organization must carefully consider the relative benefits and challenges associated with adopting new technology. AI allows an organization to gain a competitive advantage, reduce costs [11, 19] and generate opportunities in terms of transferring into new business situations [41, 48], raise top-line profits [31], and increase efficiency and amplify human intelligence [26]. The use of technology such as deep learning (DL), and machine learning (ML) allows firms to develop a competitive advantage [13] when adopting AI, which leads to the following hypothesis *H1: The relative advantage of AI technology positively influences AI adoption.* As we have mentioned, ***compatibility*** is a close associate attribute of AI adoption. In the current study, compatibility refers to the extent to which the innovation fits with the current technological situation and its ability to provide value and experience, while addressing the needs of the expected adopters [32]. Zhu [60] found that a greater match between the adoption process and the diffusion of technology innovation leads to an easier adoption. This study argue that successful AI adoption require a solid AI business case, and should align with existing business strategies and organizational values. Thus, we hypothesize *H2: Compatibility between the AI business case and an organization's existing strategies positively influences AI adoption*. ***The role of organization-related factors*** In the IS adoption research, ***top management support*** is one of most commonly-cited factors in terms of innovation adoption. This refers to the degree of engagement of top-level management with regard to appreciating the value of new IS/IT implementation. Previous research has suggested that top management have a positive influence on the adoption of new technology by allocating resources and providing capital funds to support the adoption of such a system. Thus, we argue that top management is a key driving force in terms of AI adoption. Therefore, the following hypothesis is proposed *H3: Top management support positively influences AI* *adoption.* ***Organization size*** is an important factor that affects the adoption of new innovation. Several studies have found that large companies tend to invest in AI faster at a scale more readily than other types of investments. We suggest that organization size relates to the organizational context that will directly affect the adoption of AI. Thus we hypothesize *H4: organizations size positively influences AI adoption.* ***Organizational readiness*** also play a critical role with regard to adopting AI [29]. A report from Narrative Science indicates that 59% of organizations that are skilled in big data also use AI technology [38]. As we described earlier, AI adoption implementations not only relates to the organization's technical readiness but also to the skill of its human resources. Thus, we suggest 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. Thus we hypothesize *H5: Organizational readiness positively influence AI adoption.* ***Managerial obstacles*** have been cited as some of the most critical factors for technology adoption decisions. Due to the novelty of AI adoption, investigating the barriers to such adoption at an early stage is challenging. Organizations in Australia continue to face many challenges in terms of the adoption and utilization of AI [26]. It has been argued that investigating the factors that obstruct the adoption of IS innovation is a central concern, because such an investigation can explain why an innovation that appears advantageous is not adopted [11]. This paper suggests that overcoming barriers of AI will lead to increased AI adoption, which in turn, leads to a higher degree of practice involving the use of AI. To address these barriers to AI, we hypothesize the need to test the effect of managerial obstacles to AI adoption: *H6 Managerial obstacles are negatively related to AI adoption.* ***The role of environment-related factors*** For the adoption of AI, ***Competitive pressure*** is defined as "the degree to which a company is affected by competitors in the market" p 69. In the current study, competitive pressure refers to the threat of losing a competitive advantage with regard to the external environment, which motivates an organization to adopt a new innovation [2]. We suggest that the risk of losing a competitive advantage is one of the key drivers of AI adoption. Thus we hypothesize *H7: Competitive pressure has a positive influence on AI adoption.* Within the environmental context, ***government regulatory*** issue factor has been recognized as one of the factors that organizations need to consider [22] when adopting new innovation. Government regulatory issue activity is the assistance provided by a government for AI adoption. Organizations can be persuaded to engage in AI adoption when a government provides an appropriate environment for such developments. According to our review of the literature, eighteen countries have been recognized as AI competitors and have established "AI strategies" at the government level. Therefore, this study enhances to the growing evidence of the importance of government regulations in guiding and supporting AI adoption. Thus we hypothesize *H8: Government regulations can have a positive influence on AI adoption.*

4. Research Methodology

4.1 Measurement and data collection

To empirically test the proposed framework, we first conducted a comprehensive review of the literature, followed by a quantitative approach using a survey to collect data. A rigorous literature analysis of scholarly articles on technology readiness and AI was conducted. To assist cumulative research, items adopted and tested by previous research were used [23,35,49]. For managerial obstacles and organizational readiness factors items were designed specifically for this study by considering prior research [38, 54]. However, to the best of our knowledge, although the TOE has been applied in numerous IT adoptions at the firm level, none of the constructs used in these studies were focused on AI adoption. Therefore, a pre-test survey was performed to ensure the suitability of the items for measuring framework dimensions in the context of this study. Next, an online questionnaire using the survey software Qualtrics was used in this study to reach a large number of potential participants. Eight constructs (relative advantage, compatibility, top management support, organization size, organizational readiness, managerial obstacles, competitive pressure, and government regulatory) were operationalized as reflective of a total of 34 indicator items. A 5-point Likert scale, ranging from "I strongly agree" (5 points) to "I strongly disagree" (1 point) is used to measure these items and to collect most responses. The target participants are senior managers, particularly those who are immediately in charge of information systems in both private and public organizations in Australia. The online questionnaire was distributed by sending the survey link to potential respondents via the LinkedIn network using the snowball sampling technique. The aim was to attract a representative sample of Australian industry from various levels, backgrounds, gender and age groups, and from a wide geographical area. The use of the LinkedIn.com database provides benefits such as the potential to reach a large number respondent who are highly diverse in terms of their characteristics such as position, educational level and geographical location within Australia, thus enabling the outcomes to be more generalizable. In total, 1,150 invitations targeting all Australian industries were sent between 28 August 2018 and 28 October 2018. The number of responses collected from LinkedIn was 228 of which 20 included missing data. Eliminating these responses reduced the number of valid responses to 208, which is still acceptable as a valid sample in terms of informing the quantitative analysis [24].

The sample represented a variety of industry backgrounds. The respondents worked primarily in large organizations, and (47%) worked in an organization with over 1000 employee, while 37.8% worked for companies with fewer than 200 employees. The respondents were from Information, Media and Telecommunications (37%), Education (8%), Health Care (8%), Financial and Insurance (8%), Manufacturing (6%), Public Administration and Safety (2%), and 26% were from other industries. Among the respondents, the majority held a position of middle-level AI specialist and IT manager (50%), 35.6% were IT executives (CIO, CEO), and the remainder were IT technical. These findings indicate that the respondents had sufficient knowledge to provide valid responses to survey questions. The organizations in the sample had different AI adoption status.

4.2 Assessing the Measurement Model

In order to examine and validate the measurement model, indicator reliability, composite reliability, convergent validity, and discriminant validity were assessed. Indicator reliability represents how much of the variance can be extracted from an item. To ensure indicator reliability, the factor loadings of all 35 measurement items were checked to ensure a value above 0.7 [24]. In this research, only three items (OS3, R4, and CP4) in the outer factors loading were below 0.7. Therefore, these items were omitted from the analysis. All the other items in Table 4 have a factor loading greater than 0.7, and satisfy the indicator reliability threshold. Composite Reliability (CR) and Cronbach's Alpha (CA) were estimated to assess the internal consistency reliability of the measurement model. The reliability of CR and CA are acceptable if their values are 0.7 or higher [24]. Both the reliability for CR and CA for all critical factors greatly exceeded the minimum acceptable values as shown in Table 4. Hence, all constructs have shown high levels of internal consistency reliability. Convergent validity is used to determine the correlation between a measure and alternate measures of the same construct. In terms of all average variance extracted (AVE), as shown in Table 3, the value for all constructs is higher than 0.5 [17]. Thus, the discriminant validity of the square root of AVE should be greater than the correlations between the constructs [24]. Fornell and Larcker [16] suggest that the square root of the average variance must be more significant than its correlation with other constructs of AVE and should exceed the inter-construct correlations, indicating that all of the constructs satisfy the discriminant validity requirements.

Table 3. Latent Variable Correlations

	C	*CP*	*GR*	*RA*	*OR*	*TM*	*MO*	*OS*
C	0.826							
CP	0.648	0.784						
GR	0.544	0.457	0.764					
RA	0.608	0.482	0.488	0.901				
OR	0.657	0.626	0.322	0.434	0.872			
TM	0.726	0.611	0.474	0.445	0.631	0.914		
MO	0.722	0.655	0.466	0.493	0.602	0.631	0.809	
OS	0.456	0.499	0.437	0.358	0.338	0.584	0.496	0.854

Notes: C; Compatibility, CP; Competitive pressure, GR; Government regulatory, RA; Relative advantage, OR; Organizational readiness, TM; Top management support, MO; Managerial obstacles, OS; Organization size.

Table 4. Result of Measurement Model

Construct	CA	AVE	CR	Items	Loading
RA	0.923	0.814	0.946	RA1	0.932
				RA2	0.921
				RA3	0.837
				RA4	0.915
C	0.843	0.684	0.868	C1	0.803
				C2	0.831
				C3	0.868
				C4	0.805
TM	0.950	0.833	0.961	TM1	0.929
				TM2	0.951
				TM3	0.879
				TM4	0.894
				TM5	0.908
OS	0.762	0.723	0.769	OS1	0.820
				OS2	0.880
OR	0.723	0.723	0.821	OR1	0.793
				OR2	0.887
				OR3	0.917
MO	0.744	0.722	0.801	MO1	0.844
				MO2	0.752
				MO3	0.756
				MO4	0.801
				MO5	0.716
CP	0.793	0.614	0.790	CP1	0.728
				CP2	0.798
				CP3	0.810
				CP5	0.797
GR	0.825	0.584	0.75	GR1	0.764
				GR2	0.833
				GR3	0.709
				GR4	0.786
				GR5	0.722

Note: Insignificant factors were dropped (OS3, R4, CP4)

4.5 Assessing the Structural Model

An assessment of the structural model evaluation was conducted to test the hypothesized relationships. The structural equation model SEM-PLS was then used to assess the structural model. In order to examine and validate the measurement model, path coefficients, the coefficient of determination, and predictive relevance were assessed. The path coefficients method represents the relationships between the constructs. As shown in Table 5, the outcome for the path analysis shows that five hypotheses (H1, H2, H3, H5, H6,H8) constructs have significant paths leading to the endogenous variable while two hypotheses (H4 and H7) were rejected (path coefficients < 0.20). The value of R2 represents the coefficient of determination (R2) and the effect size (f2) indicates the amount of variance in the endogenous construct as explained by all exogenous constructs. According to [16], results with a value greater than 0.67 are “substantial”, 0.33 are “moderate” and 0.19 are “weak”. Our finding shows that R square value is = 0.893, which can be considered as indicating substantial predictive accuracy. Finally, [16] describes f2 values above 0.35 as “large”, those from 0.15 to 0.35 as “medium”, those from 0.02 to 0.15 as “small” and those less than 0.02 as “weak”. The f2 of (TM, RA, and C) on the endogenous construct is large and the f2 of OS is small (less than 0.02), while the f2 of CP and GR on the endogenous construct is less than 0.02 (no effect size), [24].

Table 5. Results of Direct Effects

Hypothesis	Std. Beta	t Values	p Values	Decision
H1:RA -> AI	0.283	7.269	0.00	Supported***
H2:C -> AI	0.361	8.406	0.00	Supported***
H3:TM -> AI	0.481	15.893	0.00	Supported***
H4:OS -> AI	-0.046	1.586	0.368	Not Supported
H5:OR -> AI	0.144	7.014	0.010	Supported*
H6:MO - > AI	0.244	8.235	0.001	Supported***
H7:CP -> AI	-0.013	0.486	0.749	Not Supported
H8:GR -> AI	0.218	9.463	0.000	Supported***

Note: *p<0.10 **p<0.05 ***p<0.01

5. Discussion

Given that AI adoption is still at the early stages in term of theoretical foundations, one purpose of this study was to study AI adoption from an organizational perspective. With regard to organizational context, the findings indicate that top management support has emerged as one of the strongest determinants of AI adoption. The outcomes obtained in this study parallel those of the studies conducted by [24, 60], which indicate that top management commitment has a significant positive influence on new technology adoption. In addition, our findings show further evidence of role that individuals play when it comes to AI adoption. The significance of organizational readiness suggests that technological capabilities such as technology infrastructure, data structure and human capital, are critical for determining whether or not an organization adopts AI. The results indicate that an organization with a higher level of readiness tends to achieve a greater degree of AI adoption. As we mentioned, there are organizations that have initiated to building their human resources such as Google, Amazon, IBM, Apple and others that are capable of working in sync with AI technologies [11]. Consistent with [38] organizations that have already adopted technology such as the use of big data, and have more IT resources, have a higher level of AI adoption. Thus, trying to build hybrid capable skills to supplement the Artificial Intelligence technologies is also one of the characteristics of AI adopters. This could be explained in the case of Australian organizations by suggesting that they may have possessed sufficient related knowledge to overcome AI barriers. Future research could investigate how organizations leverage related knowledge to further AI implementation. Remarkably, this research found that the influence of organization size on AI adoption has not been supported at a statistically significant level. These results are inconsistent with those of [24] who found that organization size had a positive effect on AI and on the adoption of new innovations. Our results reveal that to understand AI adoption better is not sufficient to used organization size as an influential factor. This could be explained by the emergence of smaller technology-inspired start-up companies. Also, large organization s may be burdened by structural inertia, possibility due to having multiple levels of bureaucracy. This study indicates that AI adoption is not a phenomenon dominated by large organization. These findings is especially important for SMEs who think organization size limits them in terms of benefitting from AI.

With regard to the technological context, the findings show that both technological components (relative advantage and compatibility) directly influence AI adoption. Relative advantage was found to be the second most significant determinant influencing an organization’s AI adoption. As theorized earlier, a relative advantage for AI technology positively influences AI adoption. It allows organizations to recognize the various ways that AI will improve work performance and be advantageous as a result. The relative advantage provided by AI leads to advantageous organizational features such as improved work performance, increased productivity, and increased work effectiveness. Second, the results in terms of compatibility show a positive relationship with regard to AI adoption. This result is in line with other studies with regard to technology adoption [29, 60]. This indicates that Australian organizations have the necessary resources and clear strategies when it comes to handling AI, which indicates that their processes are compatible with AI advantages.

In addition, with regard to the environmental context, the results of this study confirm that government regulatory issues have a positive influence on AI adoption. Government regulatory activity is the assistance provided by the government with regard to AI adoption. Organizations can be persuaded to engage in AI adoption when the government provides an appropriate environment for such a development. Although AI has been used and deployed at government, industrial and personal levels, it is argued that this involves complex issues in relation to government regulations [41]. Finally, despite competitive pressure being recognized in the traditional innovation literature as a driver of technology adoption [37], this research found that the influence of competitive pressures on AI adoption has not been supported at a statistical level. Competitive pressure represents the threat of losing a competitive advantage to adopt AI as a result of not adopting AI. Unlike other IT/IS technologies, AI is both a relatively ‘old’ technology and a relatively ‘new’ one with emerging trends and applications and presents organizations with significant challenges. As we mentioned, AI innovation involves a high level of technical, recourses, top management involvement, and organizational uncertainty, which can lead to unpredictable developments. Thus, if the level of barriers is too high to entry organizations will not feel competitive pressures. Another explanation, Australia organizations may face immediate limitations and may perhaps wrongly assume that time is on their side or they may face capability issues that prevent them from joining the AI race. Organizations face regulatory requirements and reputational concerns behind every decision they make. Clearly, with AI, the rules of the game are changing their past reputation in terms of success rates and higher risks may mean that organizations are not that worried about losing competitive advantage in this aspect [11]. Furthermore, Australian organizations will still need to understand what AI does and create a strategy for its adoption. This outcome in line with parallel MIT Sloan Management report stated that 80 % of top management ware not sure what to expect from AI or how it fits into their business model [41]. These findings show that AI presents many of the same issues and challenges as other innovations; however other challenges such as uncertainty of AI capability and business value have distinguished it from other digital technologies. Therefore, future research could also collect more data in this respect to provide an even richer understanding of this phenomenon.

6. Limitation and Future Work

There are limitations to this study as follows. First, due to the multi-disciplinary knowledge required for this research, a trans-disciplinary research approach is suggested. Thus, we draw in DOI and TOE to describe the relationships in the AI adoption framework. However, the theories we employ do not fully allow organizational conclusions in terms of causality. Future research could explore the hypotheses and revisit them using a qualitative approach to gain a deeper insight into the problem. A qualitative study (e.g. case-based) might provide more insight into how the TOE factors influence AI adoption, and also how these factors interact with each other. This will enable the problem to be examined from various perspectives, as well as providing a more in-depth understanding of the problem. Second, our study focuses on AI adoption in an Australian context. For example, previous research has shown North America to be more open to AI than other parts of the world. Future research is thus required to investigate what causes these differences. Furthermore, as AI technology is currently in the early stage of adoption on the part of organizations, future research could examine the AI implementation (post-adoption) stage, when this phenomenon has become more mature.

Despite its limitations, our study makes key contributions in terms of both theoretical and practical points of view as well as opening interesting future research opportunities. The current study provides novel insights into the underlying factors that explain the factors specific to AI which impact an organization’s aim to adopt AI. This contribution starts with a definition of AI from the discipline of IS and organizational perspective. Furthermore, this research contributes to the existing body of knowledge with regard to technology adoption. This study combines established theories and in-depth research literature in AI to provide an extended framework. As we have shown in the literature review, little research has been done to understand what factors influence organizations to adopt AI. This study, therefore, supports the organizational context and innovation characteristics that determine AI adoption. The findings confirm that IS theories (TOE and DOI) as a theoretical foundation, as embedded in the AI adoption framework, can bring deeper understanding of successful adoption of AI at the organizational-level. Combining these theories could be useful to researchers when it comes to studying new innovations at the organizational- level. Second, we have discovered and validated three new factors (digital maturity, managerial obstructions and business cases) which influence the adoption of AI at the organizational-level. Although we adapted these factors from previous research [24, 34], we hypothesized and operationalized them from a process standards point of view [53]. The result of these factors is statistically significant in terms of both the path coefficient and t-value effect on AI adoption. Besides, the combination of those two perspectives – the theoretical aspects of IS innovation and the AI dimensions - allows a structured demonstration of the fields for further potential research. Our results provide a number of implications for practice. First, the present study proposes that the AI adoption framework can be appropriately used to help Australian organizations to prepare to adopt AI, and may use to overcome the issues and challenges associated with such a process. Second, we provide support that would help overcome the managerial obstacles to the adoption of AI that directly influence such adoption. As we have stated, although the significant benefits of AI are recognized and acknowledged by organization s, the concerns associated with having lack of leadership support and a lack of clarity as to which aspects of AI can be used, have hindered AI adoption on a widespread basis.

7. Conclusion

This research represents an early investigate of AI adoption at the organization level using well-establish theories into a new innovation. Our study offers a starting point for future research on why and how organizations implement AI. It can be used as a starting point for future research in different directions with regard to AI adoption. This contribution has shown the need for providing guidance and tools with which to examine the concept of AI adoption. Using the limitations identified the level of abstraction offers an overview of the potential directions for such research.

8. References

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