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Applications of Artificial Intelligence for Strategic Management of Organisation

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Abstract

Artificial intelligence (AI) is a new tool for organisational and strategic development which has not much been investigated. Therefore, this research investigates perceptions of strategic management experts about the future of Artificial Intelligence and its usage in strategic management. To achieve the research objective, a survey of strategic management specialists, including organisational strategy managers, consultants and academics (n = 231) was conducted. The research used the modified unified theory of acceptance and use of technology (UTAUT) model to investigate the factors that could contribute to an adoption of AI in the strategic management process of organisation. Within this model, situational factors include technological capability and organisational culture. The study showed all relationships of variables within the model were significant. The strongest effect on adoption intention was from technological readiness, while the effect of performance expectancy and effort expectancy was fully mediated. Furthermore, organisational culture had a significant effect on the adoption intention. The implication of these findings is that there is a need to consider utility and ethics of AI implementation for strategic management. There were several limitations of the study, including geographic focus and inclusion of specific adoption factors. In addition, more research is needed to examine AI adoption for strategic management.

Keywords: organisational culture; technological readiness; UTAUT, artificial intelligence, strategic management

Introduction

Artificial intelligence (AI) has its roots in computation and intelligence and has been in research since 1950s and later, but for a long time, it remained a somewhat obscure area in the academia (Haenlein & Kaplan, 2019). In the past decades, this has gradually changed, with increasing interest in AI for practical applications and further development of artificial neural networks (ANNs) for the complex computing challenges that internet has been now creating the huge amount of data (Haenlein & Kaplan, 2019). Today, AI is viewed as having a high potential for digital transformation not just for data processing, but for work, organisations and industries (Dwivedi et al., 2019). According to a World Economic Forum (WEF) analysis reported by Dwivedi et al. (2019), up to 20% of UK jobs, and up to 26% of jobs in China and India, could be affected by the introduction of AI technologies. This does not mean a negative impact, as AI's introduction is likely to create new jobs, but simply that the nature of work in some industries (particularly knowledge and innovation-driven industries) is likely to change. However, AI does have its limits as a tool for transformation. Despite the popular belief, AI does not mimic human thought or consciousness; one conservative estimate suggests that this threshold may not be reached until 2075 at the earliest (Müller & Bostrom, 2016). Furthermore, Müller and Bostrom's (2016) survey of AI experts suggests that there may be both ethical and practical reasons for not attempting to achieve an AI that fully mimics human intelligence. Despite these limitations, AI as it exists today, using machine learning and ANNs to analyse big data, has some potential strategic advantages for firms that can implement it effectively (Dwivedi et al., 2019; Haenlein & Kaplan, 2019). For example, AI could be used for better processing and understanding of information and for creating model strategic possibilities using simulation tools to clearly identify customer segments and target markets more, and generate other strategic insights (Dwivedi et al., 2019).

The objective of this research is to investigate perceptions of strategic management experts for the future of AI and its usage in strategic management of organisation. The study uses a survey of strategic management consultants to investigate the issue and examine what factors would influence the adoption of AI in strategic management and to determine the conditions under which widespread adoption of AI for strategic evaluation and planning may take place, as well as the barriers to adoption. The significance of the study is that AI is a new tool for organisational and strategic development which has not been investigated much. Therefore, business executors could apply these findings to consider the utility and ethics of AI implementation for strategic management.

Literature Review

Organizations are scrambling to invest in, deploy and leverage AI tools in various functions of organizations to pursue its benefits, build competitive advantage, and accelerate performance (Venkatesh, 2022). AI is entailed the evolution and integration with many new and modern technologies, such as Internet of Things, and data, such as big data in various business sectors and industries (Wang et al., 2019) such as supply chain (Priore et al., 2019), biomedicine (Kocheturov et al., 2019), and smart healthcare (Pan et al., 2019). Some critical issues of AI that it is required human operation and adoption (Venkatesh, 2022). Based on this discussion, the unified theory of acceptance and use of technology (UTAUT) is used as a theoretical foundation to propose variables, which include performance expectancy, effort expectancy and social norms, attitude toward adoption, technological capability, organisational culture and adoption intention.

Related Theory

Unified Theory of Acceptance and Use of Technology (UTAUT)

The theoretical basis of the research is the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). The UTAUT framework was proposed as a theoretical explanation for the individual decision to use technology. It is developed from the technology acceptance model (TAM), which in turn is based on the theory of reasoned action (TRA), along with the theory of innovation diffusion (Im et al., 2011). In form, UTAUT is an attitude-behaviour theory, which is a general type of decision theory that explains actions through the formation of positive attitudes, which in turn influence intention to act (Fishbein & Ajzen, 2011). This study uses the modified UTAUT rather than the classical model. This model was derived from the modified UTAUT model of Dwivedi et al. (2019).The modified UTAUT argues for a mediating variable of attitude towards use, which in turn influences behavioural intention. This helps to improve the predictiveness of the UTAUT framework, which has been known to underperform its original predictions (Dwivedi et al., 2011; Khechine et al., 2016). Although this model is relatively new, a review of emerging literature indicates that it has been used in several instances and retains its predictive power (Dwivedi et al., 2020). In addition, the modified UTAUT is more appropriate than the original UTAUT for this research because it removes the emphasis on individual demographics and conditions, making it amenable to organisational adoption questions. This study investigates only behavioural intention to use AI since AI is not yet in wide use in strategic management. Furthermore, two specific facilitating conditions are included which are technological capability and organisational culture. While no studies could be identified that applied the modified UTAUT proposed by Dwivedi et al. (2019) in strategic management, there was evidence of the use of the earlier traditional UTAUT in other fields.

Related Terms and Relationships

Performance Expectancy, Effort Expectancy and Social Norms

The first three relationships investigated are direct relationships of performance expectancy, effort expectancy and social norms on the adoption intention for AI in strategic management domains. One of these studies examined the adoption of AI in human resources information systems (HRIS) (Hmoud & Várallyai, 2020). Venkatesh et al. (2003) has defined performance expectancy as the degree to which one believes that the job performance will improve by using innovative technologies and effort expectancy refers to how an individual feels he/she uses technology as easy. Social norm is defined as a normative social belief of an individual about the behaviors and evaluations of others in a social setting (Schultz et al., 2008). This study showed that performance expectancy was a significant factor in behavioural intention. A second study also investigated the use of AI in HR (Alam et al., 2020). This study demonstrated that there was a significant, positive effect of all three variables (performance expectancy, effort expectancy and social norms) on the behavioural intention to adopt AI in HR processes and systems. The expected performance and challenge of implementation (effort expectancy) have been found to be factors in small and medium enterprise (SME) adoption of AI in strategies and operations (Hansen & Bøgh, 2020). While evidence for social norms is somewhat weaker, it is well understood that AI is a controversial ethical domain and there are a lot of questions about what uses (if any) it should be put to, how it should be controlled and other aspects of use (Baum 2017; Belanche et al., 2019; Dwivedi et al., 2019; Haenlein & Kaplan, 2019; Wright & Schultz, 2018). Therefore, the pressure of social norms on the adoption intention for AI in a particular business domain cannot be ignored. Therefore, there is adequate evidence to support the first three core relationships of the UTAUT: those of performance expectancy, effort expectancy and social norms respectively to the behavioural intention. These relationships are formalised as the following hypotheses:

Hypothesis 1: Performance expectancy of AI for strategic management influences adoption intention.

Hypothesis 2: Effort expectancy of AI for strategic management influences adoption intention.

Hypothesis 3: Social norms surrounding use of AI for strategic management influence adoption intention.

Attitude Toward Adoption

The attitude toward adoption explains the cognitive process which depicts the prospective adopter's positive or negative feeling about adopting a new technology (Au & Enderwick, 2000). The next set of hypotheses concerns the effect of attitude toward adoption as a mediating variable between performance expectancy and effort expectancy and the adoption intention for AI in strategic management. This set of relationships is novel with the introduction of the modified UTAUT, and as the model is relatively new, it has only been tested in limited circumstances (Dwivedi et al., 2019; 2020). Therefore, there is no direct evidence for this relationship in the domain of strategic management. However, Dwivedi et al.'s (2020) evidence suggested that the inclusion of attitude toward adoption of a given technology can substantially improve the prediction of behavioural intention. Other studies have also shown that attitude toward AI is a significant influence in organisational adoption intentions (Hansen & Bøgh, 2020; Sheel & Nath, 2020). Therefore, this research tested this relationship to determine whether attitude toward adoption of AI in strategic management mediates the performance expectancy-adoption intention and effort expectancy-adoption intention relationships. In response to this set of relationships, the following experimental hypotheses are proposed:

Hypothesis 4: Attitude toward adoption influences adoption intention.

Hypothesis 5: Attitude toward adoption mediates the relationship of performance expectancy and adoption intention.

Hypothesis 6: Attitude toward adoption mediates the relationship of effort expectancy and adoption intention.

Technological Capability

The first facilitating condition that was investigated in this study is technological capability. Technological capability is the organisation's resources, skills and organisational learning and knowledge acquisition processes that enable it to implement or use a specific technology or approach (Figueiredo, 2002). While AI is an attractive tool for strategic business applications, it remains a cutting-edge technology that is challenging both technically and organisationally to implement and use effectively (Davenport, et al., 2020). As a result, even though organisations may be highly optimistic about the use of AI in strategic applications, the actual adoption or intent to adopt may be severely limited by the organisation's current technological capabilities. However, it is unclear whether strategic managers will recognise the technological challenges in implementation; as shown by Davenport et al. (2020), who investigated the application of AI to marketing. Poor understanding of the technologies involved can hamper implementation. Previous studies have also shown that AI implementation for strategic management can be a challenge, especially if the firm underestimates the technical challenges of implementation (Batra, 2017). However, the difficulty of this implementation varies widely, depending on whether the firm has the existing technological capabilities and resources to be effective. For example, SMEs may have low knowledge of AI applications and poor technological capability, limiting their adoption intention (Hansen & Bøgh, 2020). Technological readiness (a similar concept) was also a factor for AI adoption in HRIS (Hmoud & Várallyai, 2020). Thus, in addition to the modified UTAUT framework above, this research also argues that:

Hypothesis 7: The organisation's technological capability to implement AI for strategic management influences adoption intention.

Organisational Culture

The second facilitating condition is organisational culture, which can be broadly defined as the set of organisational beliefs, norms and practices that drive its activities and relationships (Hofstede, 1980). While organisational culture is often derived from the national or other group cultures to which its members belong, it is also distinct from national culture and in the case of international firms, it is shared across cultures within the firm (Hofstede, 1980). Here, organisational culture is considered not as a source of social norms (already investigated above), but as a factor in where and how decisions are made and what kinds of questions are important (Duan et al., 2019). For example, if organisational decisions are autocratically controlled by leaders, the role of AI in the strategic management practice may be far more limited. There is limited empirical evidence for the effect of culture (either organisational or national) on the adoption and use of AI. However, one study has examined the role of culture in implementation of AI in Chinese firms, finding that cultural norms surrounding relationships influenced its use (Liu et al., 2019).

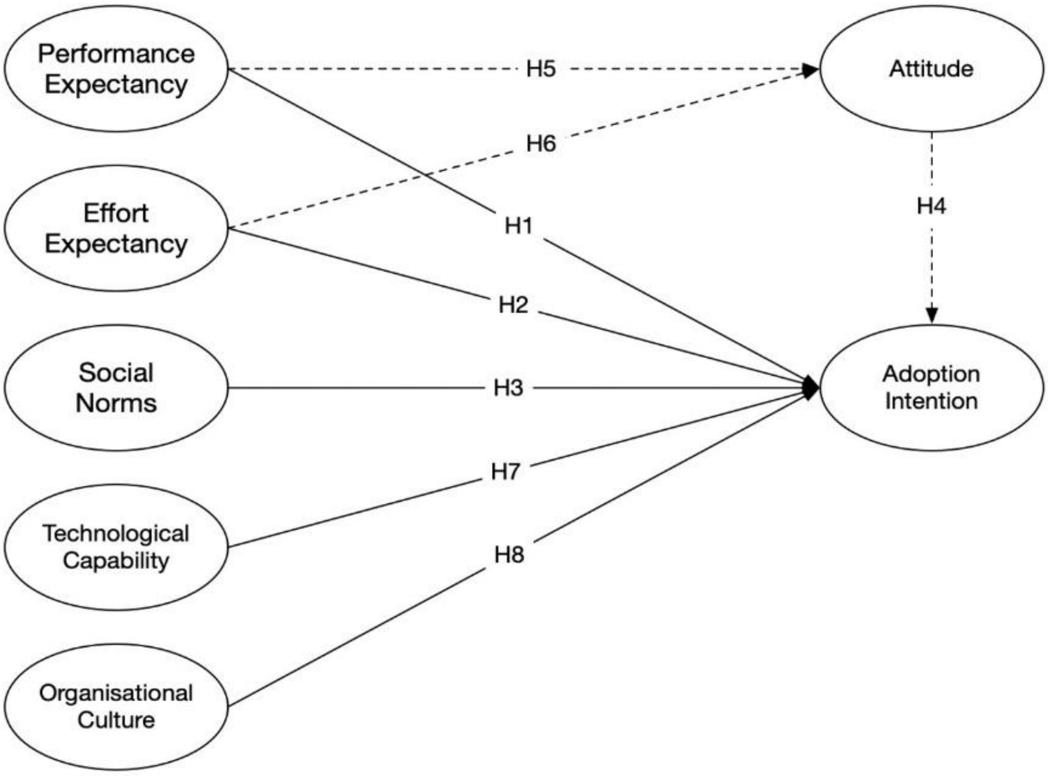
Hypothesis 8: Organisational culture surrounding use of AI for strategic management influences adoption intention.

Conceptual Framework

The conceptual framework was developed based on UTAUT model (Venkatesh, et al., 2003) incorporating performance expectancy (PE), effort expectancy (EE) and social norms (SN), attitude toward adoption (ATT), technological capability (TC), organisational culture (OC) and adoption intention (ADOPT). Seven variables and eight hypotheses were proposed. Consequently, the conceptual framework is proposed in Figure 1.

Figure 1

Conceptual Framework



Note. Constructed by the author (2022).

Research Methodology

Research Design

This study applied a quantitative approach, using online questionnaire to collect the data from organisational strategy managers, consultants and academics (n = 231). The sampling techniques include judgmental sampling, convenience sampling and snowball sampling. Prior to the data collection, item objective congruence (IOC) and Cronbach's Alpha coefficient test were conducted. Afterwards, scale and model reliability and validity test, Pearson correlation, confirmatory factor analysis (CFA) and structural equation modelling (SEM) were processed.

Research Instrument

The survey consisted of three parts which are screening questions, five-point Likert scale, ranging from 1 to 5 for strongly disagree to strongly agree and demographics questions. The theory is based on UTAUT model (Venkatesh et al., 2003) including performance expectancy (3 items), effort expectancy (3 items) and social norms (3 items), attitude toward adoption (3 items), technological capability (3 items), organisational culture (3 items) and adoption intention (3 items).

Validity and Reliability of the Instrument

Before the data collection, item objective congruence (IOC) was conducted to examine all measuring items which all results are validated from three experts at the acceptable value of 0.60 or above. The pilot test was used to verify 50 participants by using Cronbach's Alpha coefficient test. All measuring items were reserved at coefficient value above 0.7 (Nunnally & Bernstein, 1994).

Research Population and Sample

Because the research was designed to provide an expert view of AI in strategic management, the population of interest was strategic management professionals. This population included independent consultants, academics and strategic analysts and planners in companies and organisations in Thailand. The sample was selected using snowball sampling (Babbie, 2008). While this does not guarantee a random sample, it does increase sample randomness and therefore reduce bias. Initial participants were selected from LinkedIn and professional communities and they were asked to refer one to three additional participants to the survey. A minimum sample size of 200 members was identified as appropriate given the model structure and observed variables (Soper, 2020). The actual sample size was n = 231.

Data Collection

Data collection was conducted using an online sampling site (SurveyMonkey). The survey (summarised in Table 1) was partially adapted from previous quantitative surveys addressing the item variables (Dwivedi et al., 2019; Hmoud & Várallyai, 2020; Liu et al., 2019). Organisational culture and adoption intention items were designed by the researcher.

Table 1

Summary of Questionnaire Items, Alpha Coefficient and Factor Loadings

Scale	Item	Factor Loading	alpha
Performance Expectancy	PE1. AI would be useful for strategic planning and management. PE2. AI would improve efficiency of strategic management. PE3. AI would improve effectiveness of strategic management.	.794 .891 .799	.857
Effort Expectancy	EE1. AI would be easy to learn to use. EE2. AI would be simple to implement for strategic management. EE3. An AI system for strategic management would be easy to design.	.803 .820 .794	.811
Social Norms	SN1. Upper management would support use of AI for strategic management. SN2. Upper management would be helpful for implementing AI for strategic management. SN3. Thought leaders in the organisation would support use of AI for strategic management.	.800 .794 .694	.792
Technological Capability	TC1. The organisation has the resources to implement AI for strategic management. TC2. The organisation has the knowledge to implement AI for strategic management. TC3. The organisation has the connections to implement AI for strategic management.	.750 .792 .802	.766
Organisational Culture	OC1. The organisational culture supports use of innovative technologies. OC2. The organisation has ethical concerns about use of AI and big data. OC3. The organisation's strategy is based on intensive technology adoption.	.850 .833 .810	.848
Attitude	ATT1. In general, AI would be beneficial for strategic management. ATT2. Strategic management could be improved through the use of AI tools. ATT3. There is a role for AI in strategic planning and management activities.	.700 .822 .776	.773
Adoption Intention	ADOPT1. I would recommend that the organisation employ AI in its strategic planning process. ADOPT2. There are plans to implement AI in strategic planning. ADOPT3. The company is evaluating AI for its strategic planning process.	.711 .810 .853	.792
Acceptance cut-off		**≥.70**	**≥.70**

Note. Constructed by the author (2021).

Data Analysis

Data analysis conducted in preliminary analysis included scale and model reliability and validity checks, Pearson correlation, and a confirmatory factor analysis (CFA) process to validate the scale structure and items for the latent variables. Alpha coefficients (minimum value ≥.70) and factor loadings (minimum value ≥.60) (Hair et al., 2016) were calculated to determine the reliability and validity of the observed scales and, if necessary, remove any poorly fitted items.

The analysis then continued to the structural equation modelling (SEM) process (Kline, 2016). Goodness of fit checks were conducted using the criteria summarised in Table 2 (Hu & Bentler, 1999; Kline, 2016; Schumacker & Lomax, 2010). Following this process, hypotheses were tested using the regression outcomes (for direct relationships) and the direct and indirect standardised effects (for the mediation relationship in H6).

Results and Discussion

Preliminary analysis

Initial Scale Evaluation

Alpha coefficients (Table 1) were all above the established cut-off of .70, which offered an initial check on the model quality. The CFA process generated factor loadings (Table 1), which were assessed for potential model reduction. All items were above the minimum factor value of .70. Therefore, the initial scale validation and measurement model testing was met.

Correlations

Pearson correlations (Table 2) indicate that the relationships were mainly as expected. Although many of the variables did have some significant correlations, most of these correlations were consistent with the research model. None of the correlations were above r = .600. Therefore, the correlations did not identify any serious problems.

Table 2

Correlations

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Performance Expectancy	1					
(2) Effort Expectancy	.564***	1				
(3) Social Norms	.203	.234	1			
(4) Technological Capability	.599***	.390**	.289	1		
(5) Organisational Culture	.350**	.275*	.420**	.318*	1	
(6) Attitude	.455***	.397***	.360**	.349*	.477***	1

Note. Constructed by the author (2021).

Reliability and Validity

Reliability and validity measures for the variables are summarised in Table 3, along with typical cut-offs for acceptance (Hair et al., 2016). Composite reliability (CR > .70) was observed for all variables. Convergent validity (AVE > .50) was observed for all variables. Attitude had Average Variance Extracted (AVE) less than 0.5 but Composite Reliability (CR) was higher than 0.7, the convergent validity of the construct is still adequate (Fornell & Larcker, 1981). Discriminant validity (MSV < AVE) was also observed in all cases. Therefore, the variables were adequately reliable and valid based on the initial assessment.

Table 3

Scale Reliability and Validity Measures

Variables	CR	AVE	MSV
Performance Expectancy	.762	.565	.505
Effort Expectancy	.770	.506	.498
Social Norms	.701	.532	.477
Technological Capability	.803	.676	.630
Organisational Culture	.795	.680	.591
Attitude	.698	.497	.444
Adoption Intention	.724	.582	.501
Cut-off for acceptance	≥.70	≥.50	<AVE

Note. Constructed by the author (2021).

Structural Equation Modeling (SEM)

Goodness of fit was assessed using several criteria, all of which were above or below recommended cut-offs as summarised in Table 4. Based on these values, the SEM research model can be considered adequately fitted.

Table 4

Summary of Model Fit Measures

Measure	Recommended Cut-off	Observed Value
Chi-square	p > .05	p = .898
RMSEA	< .06	.048
SRMR	< .06	.048
CFI	> .90	.96
AGFI	> .95	.96

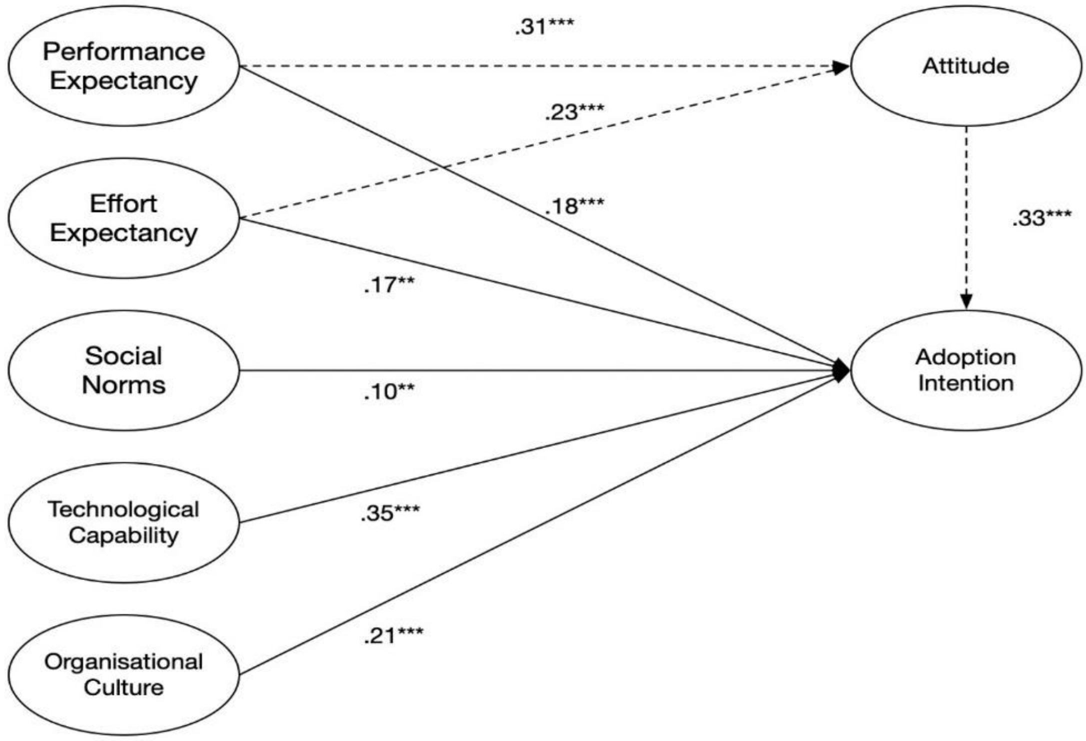
Note. Constructed by the author (2021).

The attention now turns to the path coefficients (or regression estimates) generated for the research model (summarised in Figure 2). All regression estimates were significant. For the direct effects on Adoption Intention, the strongest effect came from Technological Capability (.35), followed by Organisational Culture (.21), Performance Expectancy (.18), Effort Expectancy (.17), and Social Norms (.11).

There was also a strong significant effect from Attitude (.33) which convergent validity was observed. This effect fully mediated the indirect effects of Performance Expectancy and Effort Expectancy. Thus, these results do support the modified UTAUT's argument for a mediator comprising Attitude.

Figure 2

Path Model and Regression Coefficients



(Note: ** $p < .01$ *** $p < .001$)

Hypothesis Outcomes

Table 5 summarises the hypothesis tests and outcomes. This shows that all hypotheses were supported, including both direct effects and mediation effects.

Table 5

Summary of Hypothesis Tests

Hypothesis	Relationship	Supported
1	Performance Expectancy → Adoption Intention	Yes
2	Effort Expectancy → Adoption Intention	Yes
3	Social Norms → Adoption Intention	Yes
4	Attitude → Adoption Intention	Yes
5	Performance Expectancy → Attitude → Adoption Intention	Yes
6	Performance Expectancy → Attitude → Adoption Intention	Yes
7	Technological Capability → Adoption Intention	Yes
8	Organisational Culture → Adoption Intention	Yes

Note. Constructed by the author (2021).

Discussion

The findings of this study indicate that according to strategic management experts, the strongest direct influence on adoption intention for AI in strategic management planning is technological capability, followed by attitudes to adopting AI. This suggests that the organisation's own capabilities, rather than the technology characteristics of AI implementation itself, drives implementation goals. This finding is consistent with earlier studies, which have shown that technological capabilities may be one of the highest barriers to implementation of AI for activities like business analytics (Hansen & Bøgh, 2020). Even for firms that have high technological capabilities, implementation of AI-based tools for activities like strategic management is a challenge (Batra, 2017). In particular, it is a complex process that must be designed specifically for the organisation, with few off-the-shelf tools available that make use of ANNs in a targeted way. Instead, such tools are typically structured into an existing organisational analytics system like HRIS, which may or may not be available depending on the firm's existing technologies (Alam et al., 2020; Hmoud & Várallyai, 2020). Thus, rather than the technological characteristics of AI itself, this may be the biggest problem for implementation of AI in the organisation as a strategic management tool.

While ANNs and other analytical tools have entered the market, it is expected to be a long time before there is what may be called a 'true' AI (Müller & Bostrom, 2016). However, given that there are tools that could be considered to be AI-driven already in use, and some that could be developed by firms, it is time for companies to begin thinking about incorporation of AI into their strategic planning activities. This does include not only the technological characteristics and social norms that the modified UTAUT (Dwivedi, et al., 2019) has exhibited, but also the ethical questions and dilemmas that AI proposes (Baum, 2017; Belanche et al., 2019; Dwivedi et al., 2019; Haenlein & Kaplan, 2019; Wright & Schultz, 2018). These ethical questions need to be addressed before strategic managers can make effective use of AI or integrate it into the organisational systems and processes, those related to strategic management or otherwise. Thus, this research does call for an evaluation of the potential role of AI in strategic management, focusing not just on the operational needs and technological capabilities needed to justify tools but also the strategic and ethical questions of their use.

The hypothesis results disclosed that there was a significant influence among performance expectancy, effort expectancy, social norms, attitude, technological capability and organisational culture on the adoption intention for AI in strategic management (Hmoud & Várallyai, 2020; Venkatesh et al., 2003). When one believes that the job performance will improve and it is easy to use and innovative technologies, users have intention to use it. Social norm explained individuals' belief about the behaviours and evaluations of others in a social setting, so a person is more likely to have an intention to use a technology (Schultz et al., 2008). Technological capability as the organisation's resources can equip a user to adopt a specific technology (Figueiredo, 2002). Furthermore, organizational culture can facilitate the adoption intention of users to use a system technology. Attitude was also found to have a moderating effect between performance expectancy and effort expectancy, and adoption intention for AI in strategic management. Previous studies suggested that the benefits and ease of use would affect the attitude toward the adoption intention for AI in strategic management (Au & Enderwick, 2000; Dwivedi et al., 2019; 2020; Hansen & Bøgh, 2020; Sheel & Nath, 2020).

Conclusion

This study has investigated expert views on AI and its role in strategic management, in order to understand what organisational and technological factors are most likely to influence adoption in the future. The study showed all relationships of variables within the model were significant. The strongest effect on adoption intention was from technological readiness, which is not surprising given the current complexity and technical demands of AI implementation. The effect of performance expectancy and effort expectancy was fully mediated. The organisation's general social norms and management acceptance also played a role in AI adoption intentions. However, the organisational culture surrounding innovation and perceived ethical challenges had a somewhat stronger effect.

Recommendations

The recommendations were implied from theories into practices for strategic management specialists, including organisational strategy managers, consultants and academics to promote applications of artificial intelligence for strategic management. Based on the findings, the adoption of AI for strategic management activities is likely to be driven more by the organisation's own technological capabilities and cultural norms than by the technology's characteristics. Of course, it is possible that this is because the role of AI in strategic management is not yet fully understood. Thus, this may be something that changes over time, especially as off-the-shelf AI-based applications begin to make their way into the strategic planning environment. In conclusion, strategic management experts are recommended to adapt the findings to carefully look through significant factor impacting adoption intention for AI in strategic management including performance expectancy, effort expectancy, social norms, attitude toward adoption, technological capability, and organisational culture. Besides, they need to consider utility and ethics of AI implementation for strategic management.

Limitations and Further Study

This research has some limitations as it only investigated the views of strategic management specialists in Thailand, who operate under a specific cultural and technological context. Thus, the views of experts from other countries may be different, for example being more (or less) concerned with technological readiness. The study also did not address questions like cost of implementation or perceived availability of existing tools for successful adoption which can realistically improve organizational performance. In practice, these issues are likely to influence the organisation's decision to implement AI in its strategic management activities. It is difficult to predict this, however, because of the limited literature in this area. The application of AI in management and planning is relatively new, with tools only being introduced within the past several years (Duan et al., 2019; Dwivedi et al., 2019; Haenlein & Kaplan, 2019). Thus, it is not surprising that these gaps are present. The gaps in understanding of organisational and strategic use of AI for planning and management (including both actual and potential) offer opportunities to develop and improve both academic understanding of AI in organisations and management and practical use of such tools. Thus, more of this type of research is needed.

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