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Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry

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ABSTRACT

This research intends to investigate the technology acceptance of artificial intelligence (AI) among the heads of finance and accounting units in the shared service industry, using the Theory of Planned Behavior (TPB) and the Unified Theory of Acceptance and Use of Technology (UTAUT). A structured questionnaire was used to conduct a cross-sectional study of 75 heads or representatives of the Shared Service Industry in the Finance and Accounting departments. The findings show that performance expectancy, attitude, skill, and technical capability all have a major impact on AI technology acceptance. On the other hand, there is no link between AI technology acceptance and effort expectancy, social influence, or facilitating conditions. The findings provide insights on the important areas that need to be prioritized when businesses use AI, particularly in finance and accounting.

1. Introduction

Artificial Intelligence (AI) has unquestionably progressed alongside many other cutting-edge technologies. According to Habeeb (2017), AI is a branch of computer science concerned with the development of intelligent machines capable of doing human-like tasks. The advantages of artificial intelligence technology and its ability to address issues have been thoroughly established (Chen, 2019; Venkatesan and Sumathi, 2019; Chukwudi et al., 2018; and Satokangas, 2013). According to Satokangas (2013), AI can convert data into meaningful information, allowing for faster data storage and retrieval. Furthermore, the primary goal of AI is to accomplish complex problems using computers that replicate human intelligence. Creating and exploiting expert systems is part of the most well-developed accounting AI literature (Chukwudi et al., 2018). Expert systems are computer programs containing expert knowledge and simulating problem-solving reasoning (Vasarhelyi and Kogan, 1997). It's been used to solve complex problems (Chen, 2019). The expert system, for example, has been widely employed in decision-making and problem-solving (Liao, 2005). However, numerous experts believe the term “AI” should be used to characterise contemporary machine learning systems. Machine learning is artificial intelligence that allows a computer to learn from past data without being explicitly programmed (Economics, 2001). Machine learning and expert systems are used to construct AI systems and various other methodologies. According to Venkatesan and Sumathi (2019), AI is a technology discipline concerned with competing with modern-day computer systems' ability to solve issues using complicated human-like cognitive skills, knowledge acquisition, and self-correction.

AI is fast evolving and becoming smarter every day, allowing more modern sectors to utilise AI for various purposes. Various advanced technologies have been developed in recent years, and AI is applied in the e-commerce industry and other industries such as airlines, hotels, and telecoms companies (Mohd Noor and Mansor, 2019; Aisyah et al., 2017). Because AI is more convenient, it is frequently utilised in travel, such as when booking flights and in the fashion industry (Mohd Noor and Mansor, 2019). The e-commerce industry uses messaging software on their websites, such as Chatbots, in numerous lines of business, such as airlines, hotels, and telecoms companies. Intelligent digital assistants or voice assistants are terms used to describe chatbots that can respond to voice instructions. Aside from that, Apple's “Siri” is an excellent example of an intelligent chatbot and voice assistant (Aisyah et al., 2017).

AI is one of the key technologies featured in Malaysia's Industrial Revolution 4.0. Malaysia has announced the National AI Framework to help the country accomplish its AI goals (Kaur, 2019). According to research conducted in 2019 by Microsoft and the International Data Corporation (IDC) across Asia Pacific, Malaysia was not fully prepared for AI. According to the report, only 26 % of Malaysian businesses have

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begun their AI journey. Furthermore, according to K Raman, managing director of Microsoft Malaysia, 82 % of firms prioritise future skills and skills retraining (Bernama, n.d.; Microsoft – IDC, 2019). In Malaysian publicly traded enterprises, AI acceptability and usage are still low. He went on to say that only around 1 % of corporations, or about 20 organisations, had cited "artificial intelligence," "big data," and "machine learning" in their annual reports. These terms were largely used in the Chairman's Statement as well as their future strategic business strategy. This suggests that AI acceptability among Malaysian public-listed corporations is still in its early stages, or at least at the awareness stage (Aisyah et al., 2017).

Recently, AI has advanced significantly, particularly in the accounting industry, where it has shifted the focus away from paper and pencil entry and toward computer and software entry (Chukwudi et al., 2018). Accountants provide information services to their clients, according to Satokangas (2013), where an accountant employs other resources such as computers and software approaches to provide relevant information. Furthermore, AI is quick and can be linked to accounting processes that entirely automate data handling and processing (Jędrzejka, 2019; Madakam et al., 2019; Mendling et al., 2018). Automated data entry and data classification can assist accountants more effectively in evaluating broader financial patterns and providing better recommendations, resulting in better decision-making. Due to the rise of AI, accountants' use of paper and pencils to enter data will gradually fade away, becoming a thing of the past (Greenman, 2017). Accountants will need to specialise and use cutting-edge technology to survive in this modern era (Howieson, 2003). Most accountants need to improve their skills with the right training to meet the job market's needs.

Although AI is recognised as a strong business enhancer, employees and management could decline the acceptance of AI in organisations for specific reasons. From the top management or directors' point of view, adopting AI would be expensive and high risk due to the high degree of uncertainty that can lead to adverse outcomes (Osoba and Welser, 2017). Therefore, the top management or directors may not consider accepting AI due to the inability to see the potential benefits of AI and prevent the cost-outweighed benefits situation (Aisyah et al., 2017). According to Ratnasingam et al. (2020), a significant challenge the Malaysian sector faces is the lack of awareness and skilled workers. Training costs would contribute to the enormous cost that the company would incur if the company decided to accept and adopt AI in the business operation. Moreover, Aisyah et al. (2017) found that the acceptance of AI among Malaysian public listed companies is still at an early stage or mainly at the awareness level. Even though most companies have raised awareness of AI in their business processes and management, they lack proper planning and approach to ensure the potential of acceptance and AI adoption.

From the employees' viewpoint, they are often reluctant to accept and learn AI due to a fear of job security and protection. Additionally, employees resist adapting and are unprepared to use AI in daily business operations (Aisyah et al., 2017). The Ernst & Young (EY) survey reveals that 31 % agreed that the lack of skilled workers is the biggest obstacle to AI acceptance and adoption (EY - Global, n.d.). On top of that, the Association of Chartered Certified Accountants (ACCA) is also concerned for the accountants' future. The skills and knowledge currently applied by accountants may no longer be considered relevant in the upcoming years (Economics, 2001; Satokangas, 2013). Essential accounting functions that require predictable collection and data processing tasks such as payroll, auditing, bank reconciliation, risk assessment, categorisation of invoices and payments tend to be automated with AI. This dispute increases the anxiety among employees as AI could affect and displace their work, creating a barrier to confidence and further slowing down adoption (James et al., 2017).

Today, the acceptance of AI in accounting and finance services is hardly known, especially in Malaysia. AI is still in the infancy stage and is an area that receives significant interest from various parties, such as accounting and finance professionals and academicians. However, it is now challenging to find studies on the acceptance of AI in Malaysia, where the existing research aims for AI awareness (Khatri et al., 2020). The current study is intended to fill the gap in the literature by investigating the technology acceptance of AI among Heads of Finance and Accounting Units in the Shared Service Industry in Malaysia. This industry-specific context presents unique challenges and opportunities in adopting AI technology. Based on these grounds, the current study is conducted to address the following research questions:

1. Does performance expectancy predict AI technology acceptance?
2. Does effort expectancy predict AI technology acceptance?
3. Does social influence predict AI technology acceptance?
4. Does facilitating condition predict AI technology acceptance?
5. Does attitude predict AI technology acceptance?
6. Does "skill and technical capabilities" predict AI technology acceptance?

The practical implications of the study are twofold. Firstly, it provides guidance to organisations in designing targeted strategies to effectively promote the AI technology adoption. This will unlock its full potential for streamlining financial operations and gaining a competitive edge. Secondly, findings of this study would assist the development of training and skill-building programs tailored to the specific needs of finance and accounting professionals, ensuring that they are well-equipped to leverage AI technologies. Besides, this study would help bridge the gap between theory and practice, offering valuable insights that can empower organisations in the Shared Service Industry to navigate the evolving landscape of AI technology adoption, and driving growth and innovation in organisations.

Section 2 reviews pertinent literature that has garnered theoretical and practical support, which resulted in developing a research framework and a series of testable hypotheses. The research methodology employed is explained in Section 3, and the results are discussed in Section 4. The recommendations are concluded in Section 5.

2. Literature review

Theory of Planned Behavior (TPB) and Unified Theory of Acceptance and Use of Technology (UTAUT) were used to measure AI's acceptance in Malaysia's shared services' finance and accounting units. These two theories have been applied in various researches relating to information technology (IT) adoption. As examples, the TPB and UTAUT have been utilised in the studies of intelligent games (Lim, 2013), intelligent healthcare systems (Fan et al., 2018), and intelligent based products (Sohn and Kwon, 2020). The TPB was developed simultaneously with the Technology Acceptance Model (TAM) to be used for the evaluation of the acceptance intention. Similarly, UTAUT was developed from an integrated perspective by redefining representative technology acceptance theories, such as TAM and TPB. Besides, these two theories are applicable to research at the individual level (Chen, 2019). Although UTAUT and TPB theories are considered matured theories in elucidating technology behaviors that could be argued to be no longer contributed to the novelty of the research, the contextual relevance of this study cannot be overstated. This study is novel in several ways:

i. Industry Specific Focus: This study narrows down the application of UTAUT and TPB theories to a specific industry, the Shared Service Industry. This sector's unique operational dynamics and technological demands make it an ideal context for exploring technology acceptance.
ii. AI Context: AI is at the forefront of technological advancement. The AI adoption carries distinct implications and challenges. This study pioneers the application of established theories to the AI technology adoption, a field with emerging complexities, opportunities and keep evolving

Considering the contextual relevance discussed above, this research aims to study technology acceptance of AI among the head of finance and accounting unit in the shared service industry in Malaysia, both TPB and UTAUT. As technology adoption in the Shared Service Industry, especially with AI, presents unique challenges and opportunities, this study integrates UTAUT and TPB and tailored the adaptation to the specific context, aligning the theories' constructs with the intricacies of AI adoption in this industry.

This is in line with previous studies that have successfully integrated UTAUT and TPB to explore technology adoption in different contexts (Venkatesh and Davis, 2000; Legris et al., 2003). It is believed that this integration allowed a holistic understanding of the factors influencing AI adoption among Heads of Finance and Accounting Units in the Shared Service Industry in Malaysia. The integration of UTAUT and TPB was guided by their theoretical richness, empirical support, and the need to address the nuanced context of AI adoption in the Shared Service Industry. This approach enabled the researchers to comprehensively explore the determinants of technology acceptance in our specific research setting.

2.1. Performance expectancy and AI technology acceptance

Al-Htaybat and von Alberti-Alhtaybat (2017) stated that organisations search for efficiency to fulfil the client's expectations of getting the fastest results at the lowest price with the highest quality. Accordingly, by introducing advanced technologies like AI, accountants will concentrate on value-added activities such as figure analysis and advisory. By doing innovative and non-structured tasks, the accountant's work can be improved (Economics, 2001; Herbert and Dhayalan, 2016). With the integration of technology, the possibility of mathematical errors can be reduced and subsequently increase the quality of reporting (Herbert and Dhayalan, 2016; Lim, 2013). Users will accept AI if they believe it could provide fast, reliable, consistent, and accurate outcomes to improve their service's quality. Numerous studies suggest that performance expectancy is one of the determinants in AI usage (Chua et al., 2018; Gursoy et al., 2019; Hazen et al., 2014). According to the previous research that reported the benefits of AI, such as competency and high AI level, AI could influence the user's willingness to accept AI (Gursoy et al., 2019). In addition to that, Chen (2019) noted that AI's innovation attributes, high relative advantages, and compatibility causes significant effects on AI adoption. The following hypothesis is developed to test the relationship between performance expectancy and acceptance of AI:

Hypothesis 1. There is a significant relationship between Performance Expectancy and AI technology acceptance.

2.2. Effort expectancy and AI technology acceptance

Using an AI system, the communication barriers between the users and the AI complex system may require much effort to overcome. Therefore, if using AI takes too much effort, it will negatively affect the acceptance of AI. The prior studies suggested that effort expectancy is a crucial determinant that influenced the users' acceptance of AI (Gursoy et al., 2019). Additionally, perceived ‘ease of use’ directly affects a person's behavioural intent and may influence modern technologies' implementation (Damerji, 2019). The complexity of the AI system will contribute to the barriers or obstacles in implementing AI. The easier the technology is incorporated into company activities, the greater the chances of its acceptance and adoption (Oliveira et al., 2014). However, AI's difficulties come from lack of maturity and technical information technology expertise, time-consuming, and high cost. AI's characteristics suggested that its immaturity is the most significant barrier to AI adoption. Past studies have shown that the degree of information technology maturity greatly influenced companies' strategic decisions to procure and deploy an information technology or system. When a new product is mature, the organisations will become aware of its implementation. Businesses will be more likely to embrace the latest technology if they feel they can work efficiently with the vendors (Chen, 2019). As effort expectancy seemed to be the potential determinant of AI technology, a hypothesis will be tested as follows:

Hypothesis 2. There is a significant relationship between effort expectancy and AI technology acceptance.

2.3. Social influence and AI technology acceptance

One reason companies decided to invest in technology is whether they experience pressure from the clients or experience competitive pressure (Gursoy et al., 2019; Rather, 2018; Vives, 2008; and Kuan and Chau, 2001). The demand usually comes from young people who want to use the latest technologies when looking for a company that provides services. Nowadays, businesses should not neglect this demand to attract potential customers. Social impact refers to the degree to which a social community of customers, such as relatives, colleagues, and others, agree that AI is acceptable and in line with group norms. Past research showed that the social network's norms and behaviors are the critical factors influencing behavioural intention (Gursoy et al., 2019; Rather, 2018). Based on the social identity theory, the user may assume that using AI will enhance their social identity as other people within their social group are likely to support using AI. Consequently, this external support factor produces positive attitudes about AI usage (Gursoy et al., 2019). To test whether the social influence is one of the factors that contribute to AI acceptance, the following hypothesis was developed:

Hypothesis 3. There is a significant relationship between social influence and AI technology acceptance.

2.4. Facilitating condition and AI technology acceptance

Several researchers have discovered that good facilitating conditions from the management influenced the implementation of advanced systems and technology in an organisation (Chong et al., 2009; Müller and Jugdev, 2012; and Teo et al., 2006). This is where the organisation's top management facilitates allocating enough resources to adopt any technological advancements. In addition, Elbanna (2013) also commented that management support during project execution needs to be consistent and continuous; otherwise, the project will fail. Therefore, lacking managerial support could negatively impact a project (Wixom and Watson, 2008). An organisation with good organisational support and capability will overcome these obstacles and rapidly implement the new technologies. The high degree of managerial assistance and support raises the understanding and usefulness of the new technology and reduces the complexity of adopting new technology. Hence, the company will quickly implement AI technologies and applications, improve performance, and achieve competitive advantages (Chen, 2019). This suggests that AI acceptance could be influenced by the facilitating conditions, particularly by the organisation itself, resulting in the following hypothesis:

Hypothesis 4. There is a significant relationship between facilitating conditions and AI technology acceptance.

2.5. Attitude and AI technology acceptance

The accounting and finance firms prefer staff who are not afraid of using technology and searching for creative and broad-minded individuals who can work with technology (Al-Htaybat and von Alberti-Alhtaybat, 2017). In AI applications, users are likely to concentrate on whether the AI system can provide the same quality or better service than human employees (Gursoy et al., 2019). The biggest obstacle in embracing AI advancement is behavioural concerns such as resistance to changes and different acceptance levels for modern technology. Furthermore, the organisation's adoption could be rejected, which resulted in a diffusion rate of <100 % acceptance within the organisations. Moreover, individuals within the organisation may be comfortable with the existing system and hesitate to advance AI. Besides that, they may not be willing to accept the learning process within the organisation. The acceptance of AI technology is called organisational learning due to introducing the latest thing or advancement (Aisyah et al., 2017). The following hypothesis is developed to test the relationship between users' attitudes and acceptance of AI.

Hypothesis 5. There is a significant relationship between attitude and AI technology acceptance.

2.6. Skill and technical capability and AI technology acceptance

The lack of skill and technical capability in AI technology is another barrier to adopting AI. According to Ati 'ewell (1992), organisations delay implementing new technology in-house until they have adequate technical skills and expertise to introduce and manage it effectively. AI technology is still new to several businesses, and a lack of understanding of AI technologies is an issue (Chen, 2019). Equivalently, technical capability is a crucial factor affecting information technology adoption. Strong technological skills and capabilities will allow the Information Technology department to implement AI technology faster and more efficiently. On top of that, technical skill or capability includes tangible and intangible assets such as computer hardware, technical knowledge, strategies for developing information technology, and the implementation processes that can effectively use the latest technologies (Garrison et al., 2015). Adopting AI can be successful if an organisation efficiently provides the latest technologies and incorporates emerging AI technology into its current infrastructure. This leads to the following hypothesis.

Hypothesis 6. There is a significant relationship between "skill and technical capability" and AI technology acceptance.

Fig. 1 shows the research framework developed and depicts the six hypotheses to be tested in this study, which allows the variables to be investigated holistically, enabling more meaningful results. Section 3, next, discusses the methodology of the current study.

3. Methodology

The purposive sampling technique is used to obtain the desired information from a specific category of individuals. This choice of people is best positioned to provide information since they meet specific research criteria (Sekaran and Bougie, 2016). In this research setting, the main inclusion criteria are operating under the main Global Business Services (GBS) cluster, with its core activities being accounting and finance. Generally, sample sizes >30 and <500 are appropriate for most research according to the rule of thumb for determining the sample size, as Roscoe (1975) suggested. Within this limit, it is recommended that the minimum sample size needed should be around 30 participants (Space, 2014).

The closed-ended online questionnaire is developed by adapting several questionnaires from the previous studies from Chen (2019), Gursoy et al. (2019); and Sohn and Kwon (2020) as the reference. The survey instrument consists of two parts: demographic information and key questions. The demographic information section asks about gender, age, marital status, education, income, and working experience in the shared services. The main questions consist of several items to measure the six independent variables and one dependent variable. Items were measured using a 6-point Likert scale (1 – strongly disagree; 6 – strongly agree) as it mitigates "neutral" responses and encourages respondence to take a stance, thus reducing midpoint bias.

The data collected from the online survey were systematically compiled using Microsoft Excel. The data gathered was cleaned, sorted, categorised, coded, reversed coded and analysed using the Statistical Package for Social Science (SPSS). A normality test was carried out to determine whether the obtained data fit the standard normal distribution.

Table 1 shows a slightly skewed negative with a skewness value of −0.341. This negative value indicates high scores. Z-score distribution is calculated by dividing the skewness by the standard error, z-score = −1.196 > −1.96. While the Kurtosis value is 0.120, which indicates a pointy distribution, and the data distribution is the central tendency. The Z-score when we divide the kurtosis with the standard error is 0.213 < 1.96. Hence, the data is normally distributed based on the skewness and the kurtosis. Furthermore, the Kolmogorov-Smirnov statistic test of normality, as shown in Table 2, indicates non-significant results (p = .200 > 0.05), which indicates normality. Under the Shapiro-Wilk test,

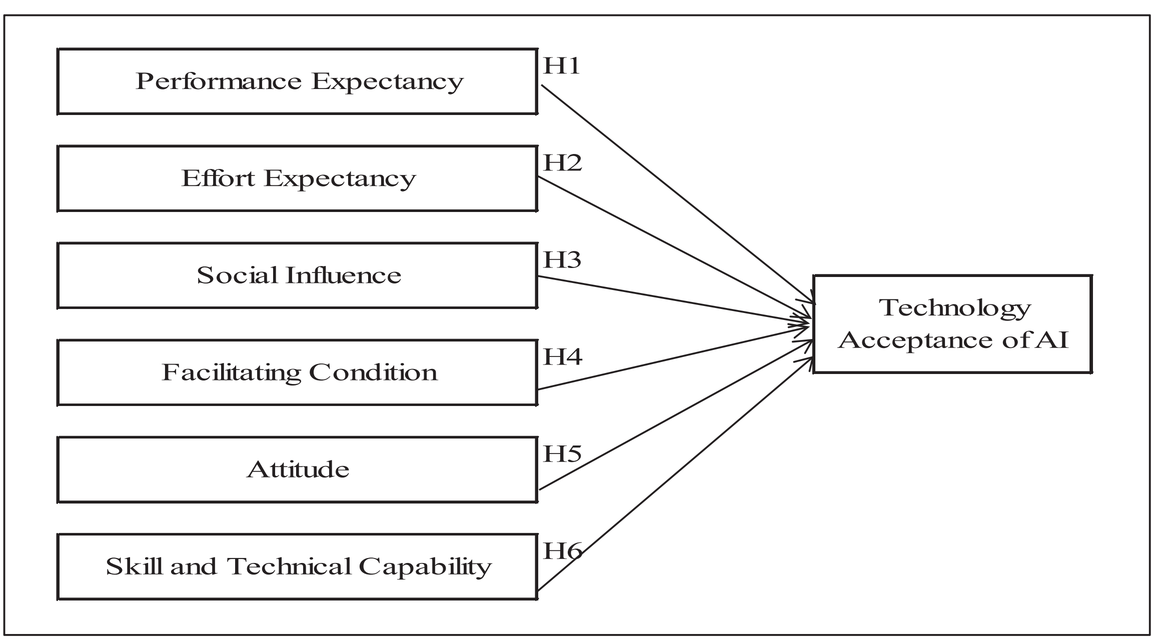

Fig. 1. Research framework and hypotheses of the study.

Table 1
Descriptive statistics.

			Statistic	Std. error
Technology acceptance of AI	Mean		211.338	3.11283
	95 % confidence interval for mean	Lower bound	205.1297	
		Upper bound	217.5464	
	5 % trimmed mean		211.8067	
	Median		212	
	Variance		687.97	
	Std. deviation		26.22918	
	Minimum		154	
	Maximum		270	
	Range		116	
	Interquartile range		32	
	Skewness		−0.341	0.285
	Kurtosis		0.12	0.563

Table 2
Tests of normality.

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Technology acceptance of AI	0.067	71	0.200*	0.969	71	0.08

* This is a lower bound of true significance.
[a] Lilliefors Significance Correction.

the p-value is 0.080 > 0.05, indicating that the data is normally distributed.

Also, a reliability analysis was performed in this study to test whether all the items used to measure the research variables are reliable and can be used to achieve the study's objectives. Cronbach's Alpha is a reliability coefficient that indicates how well the items in a set are positively correlated to one another. Cronbach's Alpha is computed in terms of the average intercorrelations among the items measuring the concept. According to George and Mallery (2003), the reliability coefficient for scale should range from 0.7 or higher to be considered reliable. Table 3 shows the Cronbach's Alpha for the overall scale is 0.920. Therefore, the internal consistency for reliability for all 47 scaled items is excellent.

71 responses were received out of 93 target respondents from the 93-target sample of companies. Hence, the response rate of this study is 76.34 %. The response rate was calculated using a simple mathematical formula by dividing the total responses received (71) by the number of online survey links sent out (93). According to Uma Sekaran and Bougie (2016), a 30 % response rate is acceptable. Even though the online survey distribution is easy and fast, the rate of online survey responses can be extremely low.

Table 4 displays the respondents' demographic and background. The number of female respondents is much greater than that of male respondents. Most of the respondents' age range is from the 25 to 35 ages of category. This age category reflects the shared service industry, where younger professionals are prevalent in finance and accounting roles related to technological advancement. The shared service industry is characterised by its emphasis on efficiency, automation and technological advancement that attracts a younger workforce due to the demand for digital skills and adaptability. Most respondents had a bachelor's degree in education analysis, with 55 % of total respondents.

Table 3
Reliability statistics.

Cronbach's Alpha	Cronbach's Alpha based on standardised items	N of items
0.936	0.942	47

Table 4
Demographic profile.

Item	Particular	Frequency	Percentage
Gender	Female	48	67.6
	Male	23	32.4
	Total	71	100
Age	Under 25	2	2.8
	25–35	47	66.2
	36–45	19	26.8
	46–55	3	4.2
	Total	71	100
Level of education	Up to SPM	1	1.4
	Diploma	6	8.5
	Undergraduate/bachelor's degree	39	54.9
	Professional (i.e., ACCA)	15	21.1
	Postgraduate/master's degree	9	12.7
	Doctorate (PhD)	1	1.4
	Total	71	100
Marital status	Single	33	46.5
	Married	33	46.5
	Divorced	5	7
	Total	71	100
Average monthly income	Below RM2,500	1	1.4
	RM 2500–RM 5000	30	42.3
	RM 5001–RM 10,000	33	46.5
	Above RM10,000	7	9.9
	Total	71	100
Working experience	<1 year	2	2.8
	2–5 years	25	35.2
	6–10 years	28	39.4
	>10 years	16	22.5
	Total	71	100

The single and married respondents have the same percentage from the analysis, 47 %. While the rest of the respondents are identified as divorced. Nearly half of the respondents earned RM 5001 to RM 10,000, representing 47 % of respondents. The second-highest range in monthly income is RM 2500 to RM 5000 with 42 %. Regarding working experience, most respondents (39 %) have six to ten years of experience, 35 % have two to five years of experience, and 23 % have more than ten years of experience respectively.

This finding is based on 71 finance and accounting unit heads or representatives from shared service organisations. Malaysia's shared services perform various transactional activities within and in other countries. Finance and accounting may not be the primary core services provided for several shared service centres in Malaysia. The finance and accounting unit's actual head or chief mostly are not based in Malaysia's office. Therefore, the team leader or representative of Malaysia's office finance and accounting team can be considered a target respondent.

Table 5 shows that the respondents support most of all the variables proposed in this study to influence AI acceptance. As such, the data can be applied for further analyses. Section 4 shows the results of the six hypotheses tested in this study.

4. Results

Table 6 shows Pearson's correlation between the dependent and independent variables at a significant 0.05 (2-tailed) level. The Pearson

Table 5
Mean and SD scores of the constructs.

Constructs	Mean	Std. deviation
Technology acceptance of AI	5.01	0.75
Performance expectancy	4.97	0.66
Effort expectancy	3.86	0.71
Social influence	4.11	0.92
Facilitating condition	4.96	0.87
Attitude	4.85	0.89
Skill and technical capability	3.86	0.70

Table 6
Pearson's correlation coefficient.

		Technology acceptance of AI	Performance expectancy	Effort expectancy	Social influence	Facilitating condition	Attitude	Skill and technical capability
Technology acceptance of AI	Pearson correlation	1	0.639**	0.259*	0.329**	0.472**	0.644**	0.340**
	Sig. (2-tailed)		0	0.029	0.005	0	0	0.004
	N	71	71	71	71	71	71	71
Performance expectancy	Pearson correlation	0.639**	1	0.357**	0.573**	0.539**	0.604**	0.201
	Sig. (2-tailed)	0		0.002	0	0	0	0.093
	N	71	71	71	71	71	71	71
Effort expectancy	Pearson correlation	0.259*	0.357**	1	0.346**	0.290*	0.369**	0.388**
	Sig. (2-tailed)	0.029	0.002		0.003	0.014	0.002	0.001
	N	71	71	71	71	71	71	71
Social influence	Pearson correlation	0.329**	0.573**	0.346**	1	0.513**	0.509**	0.247*
	Sig. (2-tailed)	0.005	0	0.003		0	0	0.038
	N	71	71	71	71	71	71	71
Facilitating condition	Pearson correlation	0.472**	0.539**	0.290*	0.513**	1	0.631**	0.229
	Sig. (2-tailed)	0	0	0.014	0		0	0.054
	N	71	71	71	71	71	71	71
Attitude	Pearson correlation	0.644**	0.604**	0.369**	0.509**	0.631**	1	0.241*
	Sig. (2-tailed)	0	0	0.002	0	0		0.043
	N	71	71	71	71	71	71	71
Skill and technical capability	Pearson correlation	0.340**	0.201	0.388**	0.247*	0.229	0.241*	1
	Sig. (2-tailed)	0.004	0.093	0.001	0.038	0.054	0.043	
	N	71	71	71	71	71	71	71

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

correlation coefficient shows a significant positive correlation between AI performance expectancy and technology acceptance ($r = 0.639$, $p < .01$). Besides, there is a significant positive correlation between effort expectancy and technology acceptance ($r = 0.259$, $p < .05$). The correlation between social influence and technology acceptance also shows a significant positive correlation ($r = 0.329$, $p < .05$). Nevertheless, the fourth independent variable facilitating condition provides a significant low positive correlation with technology acceptance of AI ($r = 0.472$, $p < .05$). The Pearson correlation coefficient between the fifth independent variable, attitude, and technology acceptance, shows a significant moderate positive correlation ($r = 0.644$, $p < .05$). Finally, the correlation coefficient shows a significant low positive correlation between skill and technical capability with the AI technology acceptance ($r = 0.340$, $p < .05$).

Table 7 shows that the multiple regression analysis emphasises the R-square for this research model on the technology acceptance of AI, R-square = 0.571. This value indicates that 57.1 % of the variation in technology acceptance of AI can be predicted from independent variables: performance expectancy, effort expectancy, social influence, facilitating condition, attitude, and skill and technical capability. At the same time, the adjusted R squared is 0.531. The adjusted R-square value is 53.1 %, indicating the tendency to describe the technology acceptance of AI by performance expectancy, effort expectancy, social influence, facilitating condition, attitude, skill, and technical capability, considering the sample size and number of independent variables. This approximates the degree of correlation and does not reflect the degree to which the dependent variable is correlated with any independent variable.

The ANOVA Table 8 shows that the independent variables statistically significantly predict the dependent variable, $F(6,64) = 14.202$, $p = .000$. Therefore, the overall regression model fits the data well.

Based on the outcome shown in Table 9, the unstandardised coefficient, $\beta 1 = 0.380$ for performance expectancy, indicates that the score of technology acceptance of AI is predicted to increase on average by 0.380 when the performance expectancy variable goes up by one. On the other hand, the coefficient of effort expectancy, $\beta 2 = -0.069$, predicts the score of technology acceptance of AI to decrease on average by 0.069 when the effort expectancy variable goes up by one. The same goes with the unstandardised beta coefficient of social influence, a negative coefficient, $\beta 3 = -0.110$. It would indicate that the score of technology acceptance of AI is predicted to decrease on average by 0.110 when the social influence variable's score goes up by one. While the facilitating condition variable's beta coefficient is positive, $\beta 4 = 0.017$, which predicts the score of technology acceptance of AI to decrease on average by 0.017 when the facilitating condition variable goes up by one. Next, the attitude factor's coefficient is also positive at $\beta 5 = 0.255$, indicating that the score of technology acceptance of AI is predicted to increase on average by 0.255 when the attitude variable's score goes up by one.

Table 7
Regression model summary.

Model summary[b]				
Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.756[a]	0.571	0.531	2.56363

[a] Predictors: (Constant), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Attitude, Skill, and Technical Capability.
[b] Dependent Variable: Technology Acceptance of AI.

Table 8
ANOVA.

ANOVA[a]						
Model		Sum of squares	df	Mean Square	F	Sig.
1	Regression	560.026	6	93.338	14.202	0.000[b]
	Residual	420.622	64	6.572		
	Total	980.648	70			

[a] Dependent Variable: Technology Acceptance of AI.
[b] Predictors: (Constant), Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Condition, Attitude, Skill, and Technical Capability.

Table 9
Regression coefficient.

Coefficients									
Model		Unstandardised coefficients		Standardised coefficients	*t*	Sig.	95.0 % confidence interval for B	
		B	Std. error	Beta			Lower bound	Upper bound
1	(Constant)[a]	3.093	2.752		1.124	0.265	−2.405	8.592
	Performance expectancy	0.38	0.093	0.466	4.098	0	0.195	0.565
	Effort expectancy	−0.069	0.072	−0.092	−0.963	0.339	−0.214	0.075
	Social influence	−0.11	0.062	−0.189	−1.771	0.081	−0.235	0.014
	Facilitating condition	0.017	0.069	0.027	0.242	0.81	−0.12	0.154
	Attitude	0.255	0.071	0.423	3.588	0.001	0.113	0.397
	Skill and technical capability	0.169	0.069	0.22	2.449	0.017	0.031	0.307

[a] Dependent Variable: Technology Acceptance of AI.

Lastly, the positive beta coefficient at β6 = 0.169 for skill and technical capability variables indicates that technology acceptance of AI is predicted to increase on average by 0.169 when the skill and technical capability score increases by one.

Furthermore, Table 10 shows that the technology acceptance of AI is strongly predicted by performance expectancy (β = 0.466), followed by attitude (β = 0.423), skill and technical capability (β = 0.22), social influences (β = −0.189), effort expectancy (β = −0.092), facilitating condition (β = 0.027). The R square value shown in Table 7 indicates that the six mentioned independent variables can explain 57.1 % of the variation in technology acceptance of AI.

Performance expectancy significantly influences the technology acceptance of AI, $p < .01$. The standardised beta value of 0.466 indicates that every increase of one standard deviation in the performance expectancy results in 0.466 standard deviation increases in the technology acceptance of AI. This assumes that the other variables are held constant. Therefore, H1 is accepted, where the performance expectancy has a significant positive relationship with the technology acceptance of AI.

Effort expectancy and technology acceptance of AI have no significant positive influence, $p > .05$. The standardised beta coefficient, β = −0.092, indicates that every increase of one standard deviation in the effort expectancy results in 0.092 standard deviation decreases in the technology acceptance of AI. In this study, this factor does not significantly impact the acceptance of AI because of the weak negative relationship between the effort expectancy and technology acceptance of AI. Hence, H2 is rejected.

Social influence and technology acceptance of AI have no significant positive influence (β = − 0.189, $p > .05$). The standardised regression coefficient indicates that when social influence increases by one standard deviation, it results in a 0.189 standard deviation decrease in the technology acceptance of AI. The regression coefficient and p-value indicated a weak negative relationship between AI's social influence and technology acceptance. Therefore, H3 is rejected as well.

Facilitating condition and technology acceptance of AI has no significant influence (β = 0.027, $p > .05$). The standardised regression coefficient indicates that when facilitating condition increases by one standard deviation, it results in a 0.027 standard deviation increase in the technology acceptance of AI. The regression coefficient and p-value indicate a weak positive relationship between the facilitating condition and AI technology acceptance. Therefore, H4 is rejected.

Attitude significantly influences the technology acceptance of AI, $p < .05$. The standardised beta value of 0.423 indicates that every increase of one standard deviation in the attitude variable results in a 0.423 standard deviation increase in the technology acceptance of AI. This assumes that the other variables are held constant. This study shows that attitude has a significant positive relationship with the technology acceptance of AI. Hence, H5 is accepted.

Skill and technical capability have a significant positive influence on the technology acceptance of AI (β = 0.22, $p < .05$). The standardised regression coefficient indicates that when skill and technical capability increase by one standard deviation, it results in 0.22 standard deviations increases in the technology acceptance of AI. This assumes that the other variables are held constant. Therefore, H6 is accepted, where the skill and technical capability have a significant positive relationship with AI technology acceptance.

Table 10
Summary of coefficient for regression.

Hypotheses	Model	Standardised coefficients (β)	p-Value	Result
H1	Performance Expectancy -> Technology Acceptance of AI	0.466	0	Accept
H2	Effort Expectancy -> Technology Acceptance of AI	−0.092	0.339	Reject
H3	Social influence -> Technology Acceptance of AI	−0.189	0.081	Reject
H4	Facilitating condition -> Technology Acceptance of AI	0.027	0.81	Reject
H5	Attitude -> Technology Acceptance of AI	0.423	0.001	Accept
H6	Skill and Technical Capability - > Technology Acceptance of AI	0.22	0.017	Accept

5. Discussion and implications

The findings of this study could guide organisations in developing plans and strategies to adopt AI in business services, especially shared services organisations in Malaysia. The findings align with prior studies, enabling the generalisation of the results obtained. Corroborating many prior studies provides further empirical support that performance expectancy has a significant positive relationship with AI acceptance. The potential users are willing to accept and adopt AI if they perceive AI could simplify their daily tasks. The result is consistent with previous literature that convinced the users to accept AI's use if they believe the attributes of AI could bring the expected benefits and subsequently affect AI adoption significantly (Chen, 2019; Damerji, 2019; and Gursoy et al., 2019).

This study suggests that the negative relationship between effort expectancy and technology acceptance of AI is weak. Even though the effort needed will influence their AI acceptance, this factor is not a significant determinant of their willingness to accept AI. Previous research is convinced that the chance of AI acceptance would be greater if AI is easy to use and less effort is required (Chen, 2019; Damerji, 2019; Gursoy et al., 2019; and Oliveira et al., 2014). If the users think that AI technology would take much effort, AI may not be accepted and adopted. AI technology can lead to barriers to effective communication with its users. The amount of effort needed may increase to understand AI's complex characteristics, and AI needs more attention.

The hypothesis testing result also shows a non-significant negative relationship between social influence and AI acceptance. This result indicates that increased social influence could decrease the technology acceptance of AI. This means that the employees are less likely to be influenced by other individuals. Wong et al. (2018) also found that social influence is not positively associated with accepting new technologies. The pressure from society to use AI is not a contributing factor to the acceptance of AI technology. Workplaces may have a culture of empowering employees to be competent and free-thinking. Therefore, employees are also less likely to be influenced by other individuals.

This study also found a non-significant positive relationship between the facilitating condition and the acceptance of AI. The prior studies also found that facilitating condition is a factor in AI acceptance (Chong et al., 2009; Nah et al., 2001; Müller and Jugdev, 2012; Teo et al., 2006). The organisation and government support, such as training and resource allocation, could influence AI acceptance. This study indicates that the increase in facilitating conditions could increase the technology acceptance of AI. However, the significant level is >0.05. Hence, the result does not support Hypothesis 4.

As expected, the result shows a significant positive relationship between attitude and the acceptance of AI. A positive attitude, such as wanting to use or interact with AI and learn new advanced technology, could improve AI acceptance. The previous research also induced potential users to accept AI if they have a positive attitude toward AI usage (Wong et al., 2018; Aisyah et al., 2017).

The result also shows a significant positive relationship between the skill and technical capabilities and the acceptance of AI. This finding is also consistent with the prior studies where skill and technical capability are key factors that affect the acceptance of AI and contribute to the effective integration of new technology like AI (Chen, 2019; Garrison et al., 2015). IT development strategies will effectively integrate AI technology into business or service activities with sufficient skills and technical knowledge. Otherwise, the lack of skill and technical ability will influence the potential users to reject AI, which becomes an obstacle to the organisation's successful adoption. Therefore, future accounting and finance professionals are expected to have diverse skills and learn continuously.

6. Conclusions

This study has met all primary and specific research objectives on the acceptance of AI in Malaysia's Shared Services. Based on the results obtained from the study, it seems that effort expectancy, social influence and facilitating conditions are not the crucial factors in predicting the technology acceptance of AI. Therefore, the organisation should focus on the three factors: performance expectancy, attitude, and skill and technical capability to ensure future technology like AI can be embedded smoothly within the organisation. AI can reduce routine tasks, streamline processes, and increase cost savings and efficiency. This will increase the organisation's Return on Investment (ROI). The individuals should also overcome their anxiety or fear toward AI and positively view AI's capabilities. AI technology has the potential to change society and significantly impact the quality of life by automating repetitive and time-consuming tasks. AI frees employees to focus on higher-value activities that can lead to job satisfaction, reduced stress and improved work-life balance. This study may also provide insight into the shared service organisations in Malaysia on what to focus on when deciding to adopt AI. Besides, it could provide some ideas and evidence for future studies on AI acceptance.

The study focuses on the six independent variables (performance expectancy, effort expectancy, social influence, facilitating condition, attitude, and skill and technical capability) to conclude the technology acceptance of AI among the heads of finance and accounting units in the shared service industry. While the findings offer valuable insights into the factors influencing technology acceptance in the Shared Service industry, the researchers acknowledge that the small sample size of 71 may limit the broader generalizability of the results. Future research in this area could consider increasing the sample size to enhance the robustness and external validity of findings. Besides, future study is also suggested to investigate other relevant determinants or variables that may influence AI technology acceptance. It is also interesting for future studies to examine the relationship between demographic profiles such as education levels or socioeconomic status and the acceptance of AI technology. Future research may also consider other factors that might have moderating effects on the relationships. Cross-industry and cross-country research can enhance the results' generalizability of the study.

Data availability

Data will be made available on request.

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