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The Factors Analysis Shaping SMEs: Adoption Intention of Artificial Intelligence Technology

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Abstract

Artificial intelligence (AI) technology has become a significant trend today because of its ability to process and analyze data quickly and efficiently. Along with the popularity of artificial intelligence (AI) technology in the past ten years, the trend of research, publications, and patents related to AI has experienced rapid and significant growth. AI technology has offered new opportunities for SMEs to assist in market and consumer behavior analysis, enabling them to accurately identify customer trends and preferences. This study aims to determine factors shaping the interest in adopting SMEs towards AI technology. Based on pre-survey data using the FGD method for 10 SME business owners, 32 independent variables were collected to be examined. The population in this study were SMEs assisted by the Department of Cooperatives, SMEs and Trade of the City of Surabaya, and SMEs assisted by PT. Petrokimia within the 2022 period. The sample of the respondents in this study is set as many as 119 SME business owners of the population. The analytical tool used in this research is exploratory factor analysis. The results of this study indicate that six factors shape SMEs' intentions in adopting AI technology, namely the features of AI technology, the awareness of AI technology, the benefits of AI technology, the support of government and external organizations, the influence of social values, and the anthropomorphism factor.

Keywords: artificial intelligence technology, SMEs, exploratory factor analysis, technology acceptance model, adoption intention

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INTRODUCTION

Development is a planned effort to improve society's quality of life and well-being. Moreover, development is a gateway to science and technology and creates sustainable endeavors. One of the parameters for the success of national development is the increase in economic sector growth. Economic development is a government effort to enhance production and national income, create job opportunities, increase investment levels, improve infrastructure, enhance access to education and healthcare, and create an environment conducive to economic activities (Heinrich et al., 2020; Sehgal & Batool, 2024; William, 2023). If development only focuses on concentrated and uneven growth and disregards balance in social, political, and economic aspects of life, then such development will become unstable (Sarfiah et al., 2019; Selwyn, 2020). Therefore, the community must play a role in the development process.

Society plays a crucial role in economic development by implementing Micro, Small, and Medium Enterprises (SMEs) (Widjaja, 2024; Pandey & Chaudhary, 2024; Shaikh & Mandviwala, 2023). SMEs are a vital sector of Indonesia's economy. The role of SMEs is quite significant in the Indonesian economy due to their large numbers and diverse range of activities. The contribution of SMEs to the Gross Domestic Product (GDP) continues to rise; for example, based on data obtained from the Ministry of Cooperatives and Small and Medium Enterprises, the contribution of SMEs to the GDP in 2018 was 60.34%, an increase of 3.26% from 2017's 57.08%. Then, from 2019 to 2020, the contribution of SMEs to the GDP remained around 60%, precisely 60% in 2019 and 60.16% in 2020. SMEs' contribution to the GDP peaked in 2021, reaching 61.97%.

The momentum of the Covid-19 pandemic has made digitization almost unavoidable. Of the numerous SME units, the number of SMEs that had entered the digital ecosystem in 2021 reached 15.9 million, accounting for 24.83% of the total SME operators. The remaining 74.53% had yet to join the digital ecosystem. Although this number increased significantly during the COVID-19 pandemic from around 8 million before the pandemic, the Ministry of Cooperatives and SMEs targets that 30 million SMEs should be engaged in digital business by 2024. This means that 14.1 million business units will need support to enter the digital ecosystem in the coming year.

The challenging goal of reaching 14.1 million units within a year has prompted many parties to accelerate the advancement of SMEs through digital transformation. One catalyst for boosting the acceleration of SME digitalization is the implementation of artificial intelligence (AI) systems in its processes (Baabdullah et al., 2021). AI is the capability of a system to interpret and learn from data (Akter et al., 2021), resembling human intelligence (Rahman et al., 2021), and is part of the new generation of technology that introduces a fresh approach to the business world (Dwivedi et al., 2021). As an intelligent system, AI facilitates SMEs in creating, managing, and utilizing knowledge for various business decisions to enhance market share and revenue (Basri, 2020).

The number of publications and patents on AI technology globally has significantly increased recently (Ruiz-Real et al., 2020). Over two decades, an enormous trend of a 1200% increase in AI technology publications has been discovered. Notably, there was a significant 20% increase from 2018 to 2020. Several AI technology applications, such as planning and forecasting, machine learning, and knowledge representation, also exhibit substantial upward trends. Planning and forecasting trends using AI technology is one of the most widely adopted applications by businesses (Ren et al., 2018). This is because AI usage results in fewer errors and often outperforms scientists and data experts. Comparisons between AI predictions and expert human predictions almost always favor artificial intelligence. Although current AI development has not entirely replaced human intelligence for the future, AI's ability to analyze large amounts of data will always remain a preferred choice for businesses.

SMEs face several challenges in adopting AI technology into their business systems (Hansen & Bogh, 2020). One fundamental challenge is accepting AI technology (Contessa et al., 2018). Low acceptance of AI technology can reduce usage, leading to suboptimal human resource utilization, a lack of AI-based hardware and software, and potential harmful technological innovation decline for consumers (Lee & See, 2004; Kirlidog & Kaynak, 2013). Moreover, several issues in Indonesia, such as inadequate digital infrastructure in certain areas, human resource limitations, digital illiteracy, difficulty in adapting to changes, and significant disparities in education and knowledge, make AI technology acceptance more challenging (Efendi & Wulandari, 2022).

Two theories that examine an individual's interest in adopting AI-based technology are the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM & UTAUT theories introduce perceived usefulness and ease of use, performance expectancy, social influence, effort expectancy, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003). These technology acceptance models were primarily developed to investigate the adoption of non-intelligent technology (Lee & Cranage, 2018). AI technology possesses human-like intelligence, and users are no longer taught how to operate it (Kelly et al., 2022). AI technology also involves physical performance and social and emotional aspects embedded within it, making the relevance of variables like ease of use and usefulness strong when supported by other variables consistent with AI technology characteristics (Doorn et al., 2017).

Based on the described data and considering SMEs' significant role in driving business, economic, and development growth, it becomes crucial to ascertain the factors that propel and the results that stem from integrating emerging technologies. The factors shaping SMEs' intention to adopt AI technology are also essential to ensure these entities' success and sustained competitiveness. The manifest variables are collected through an online Focused Group Discussion (FGD) identifying SMEs AI's adoption intention. The paper explains the exploratory factor analysis method to shape those variables into defined factors. Finally, the paper delves into examining the outcomes within the framework of existing literature, addressing the practical and theoretical implications of the discoveries, the limitations, and future research directions.

LITERATURE REVIEW

Hedonic Treadmill Theory

User acceptance of technology is the basis for successful device uptake (Davis, 1989). AI technology can benefit many people, but users must accept, embrace, and use it adequately. Low acceptance can reduce users' use of AI, resulting in wasted resources, redundant AI tools, and a potential reduction in technological innovation at the expense of consumers (Kirlidog & Kaynak, 2013; Lee & See, 2004; Parasuraman & Riley, 1997).

Acceptance is a predictive measure summarizing personal choices, such as purchasing a known AI device and, in other words, buying a technological device with the knowledge that it contains some form of AI. Alternatively, acceptance can be unintentional, such as using an AI chatbot that may exist as a non-AI agent. For example, an online banking AI chatbot can present itself as a customer service agent, evoking a customer's sense of talking to a human rather than an AI chatbot. Therefore, different levels of agencies are involved in user acceptance. Assessing user acceptance is critical for stakeholders to understand the variables required to maximize the use of technology in various circumstances. Several models have been used to evaluate user acceptance of AI, including the TAM by Davis (1985) and the UTAUT (Venkatesh et al., 2003).

A framework known as the TAM has been developed regarding individual attitudes toward accepting or rejecting the use of Information Technology. The TAM model is the output of research conducted by Davis (1989). TAM found two main variables that influence a person's behavior in adopting a technology system or computer system: the user's perception of usefulness and ease of use. Perceived usefulness is the extent to which a person believes using a specific system will increase productivity or efficiency in a professional or non-professional context. Meanwhile, Perceived Ease of Use reflects the level at which a person believes that using a new technology does not require effort (Davis, 1989). In the literature, it has been confirmed that there is a positive relationship between perceived ease of use and perceived usefulness (Lee et al., 2009; Lee, 2010). An example of how perceived ease of use affects perceived usefulness is that if someone feels the system is easy to use, the system benefits them. These two factors have been proven to strongly relate to adoption and purchase intention (Sutrisno, 2023; Gunawan et al., 2023).

The UTAUT theory is based on eight theoretical acceptance models, including TAM (Venkatesh et al., 2003). UTAUT suggests that performance expectations, social influence, effort expectations, and facilitating conditions predict behavioral intention, which informs usage behavior (Venkatesh et al., 2003). Performance expectation is the degree to which the user believes the device will help them achieve their task. Social influence can be defined as the perception that essential people will approve or disapprove of the behavior. A facilitating condition is the support available for using the technology.

Furthermore, this model also proposes that gender, age, voluntary use, and prior experience moderate the effects of these predictors on intention and behavior (Venkatesh et al., 2003). The role of social influence in the decision to accept technology is complex and depends on various aspects. Social influences impact individual behavior through three factors: adherence, internalization, and identification (Venkatesh & Davis, 2000; Warshaw, 1980).

Artificial Intelligence Technology

Artificial intelligence (AI) is a computational discipline focusing on solutions to cognitive challenges often related to human intellectual abilities, such as developing learning abilities, problem-solving, and pattern recognition. (McCarthy, 2014). AI technology was first created and is here to shake the world. The principles of AI began in 1950 when Alan Turing, a computer scientist and pioneer of computer technology, proposed a human test for machine intelligence. It was created by John McCarthy, a computer and cognitive scientist, in 1954, who defined AI as the science and technique of making intelligent machines.

The main goal of AI technology is to solve real-world problems. Meanwhile, the scientific goal of Artificial Intelligence is to explain various types of intelligence. The application of artificial intelligence should be judged based on whether there is a well-defined task, an implemented program, and an identifiable set of principles. Artificial intelligence can help us create new opportunities in business, engineering, and many other application fields (Winston, 1993). The development and utilization of artificial intelligence (AI) tools have gained momentum over the past few years (Duan et al., 2019). Today, these technological aids enhance people's daily lives through various sectors, including health care (Becker, 2018) and customer service (Murphy et al., 2021). education (Kashive et al., 2021), and transportation (Kaye et al., 2020), to name a few.

Wirtz et al. (2018) proposed that AI software that works autonomously and learns over time can be differentiated from service robots depending on manifestation (virtual or physical), degree of anthropomorphism (from none to high), and task orientation. From robots used on assembly lines by the automotive industry to clinical decision support systems used by hospitals, AI technology has become a critical component of business in several sectors. Tasks previously only performed by humans, such as driving a vehicle, processing human language, recognizing faces in photos, analyzing big data, or conducting online searches, can now be performed easily by AI technology (Anthes, 2017).

The research has two main goals: to promote the publication of Artificial Intelligence (AI) research and to emphasize its significance for the global economy. Recent data shows a significant surge in AI research, with over 0.6 million publications in 2018 (Shoham et al., 2019), reflecting a more than seven-fold increase since the early 2000s. Alongside this growth, numerous literature reviews on AI's applications in various fields have emerged, totaling 1544 systematic reviews. This review focuses on empirical AI studies, including machine learning, robotics, and intelligent agents, covering methods, applications, adoption patterns, business impact, and, to a lesser extent, societal implications.

Technology adoption hinges on perceived benefits and ease of use, influencing behavior and interest in new technology (Bahmanziari et al., 2003). Perceived usefulness and ease of use are critical factors in this decision-making process. Nevertheless, certain factors can deter individuals from adopting AI technology, such as concerns about data privacy and security, a lack of understanding about AI, or discomfort with its use (Hu et al., 2021). To boost AI adoption interest, it's essential to highlight the benefits, address privacy and security worries, and enhance understanding (Wijaya et al., 2023).

Various reports underscore AI's potential value to the global economy, predicting a substantial increase in GDP and significant contributions to economic growth (McKinsey Global Institute, 2018; PWC, 2019). Digitalization is a gateway for AI, particularly for Micro, Small, and Medium Enterprises (SMEs), aiding their recovery from the COVID-19 pandemic. Governments actively support SMEs' digital transformation by improving connectivity and digital skills. This preparation considers the potential recession in 2023, which could impact Southeast Asian countries, including Indonesia. The growing impact of AI is raising awareness among SME stakeholders, even though Indonesia boasts the largest economy in Southeast Asia and possesses a diverse SME ecosystem. Successful AI adoption examples include the e-commerce platform Tokopedia, which has shown remarkable growth after implementing AI-based product suggestions, and Jakarta's efforts to address urban challenges through AI-driven solutions.

METHODS

This study employed a quantitative approach using the Exploratory Factor Analysis (EFA) method to condense manifest variables into new factors. This research contributes to initiating AI-based digital product development by technology startup companies. The study's population involves Micro, Small, and Medium Enterprises (SMEs) that have been intervened by the Department of Cooperatives, SMEs, and Trade of Surabaya City, selected due to their high level of digital literacy, and SMEs community trained by PT. Petrokimia, Gresik, East Java. The sampling method used is purposive sampling, with a sample size of 119 small and medium-scale business owners in Surabaya City. Primary data is collected through questionnaires distributed by the researcher to respondents, utilizing both a pre-survey (focused group discussion) and a survey phase with questionnaires adopting the Likert scale technique. Table 1 provides 32 manifest variables or indicators that are hypothetically classified into certain factors collected from February to April 2023. The results from questionnaires will be assessed using SPSS 2.0.

Table 1. Variables and Operational Definitions

Variables	Indicators	Source
Technology Awareness	1. Awareness of the importance of AI technology for business (X_1 & X_3) 2. Familiarity with the concept of AI technology and its applications. (X_2) 3. Curiosity about AI (X_5)	Bamberg & Möser, 2007; Abubakar, 2013; Ilesanmi, 2012.
Perceived of Usefulness	1. Business digitalisation acceleration (X_4) 2. Improve employee productivity (X_7) 3. Time saving for business operational process (X_8)	Davis, 1989; Chau, 1996, 2005; Fishbein & Ajzen, 1975.
Perceived of Ease of Use	1. Easy to operate (X_{11}) 2. Easy to learn for a newbie or non-technical employee (X_{12}) 3. Good experience in the use of technology (X_{14})	Davis, 1989; Chau, 1996; Fishbein & Ajzen, 1975.
AI System Features	1. Has solutive features for company problems (X_{15}) 2. Has a market trend prediction feature (X_6) 3. Has an automation system (X_9) 4. System functions are kept up to date (X_{16}) 5. The system is capable of surviving in the long term (X_{10}) 6. The system is capable of surviving in the long term (X_{17}) 7. The system can guarantee the security of business data (X_{13}) 8. The system has a high level of accuracy in data analysis results (X_{18}) 9. The system has a shallow system error rate (X_{19})	Venkatesh et al. 2003 p. 447); Ameen *et al.*, 2021 ; Almaiah, M.A., *et al.*, 2022.
Social Influence	1. Has added value for business (X_{20}) 2. Establish social status in business networks (X_{21}) 3. Create a high-profile image (X_{22})	Venkatesh et al. 2003 p. 451
Facilitating Condition	1. Clear operational instructions (X_{23}) 2. Support from AI provider (X_{24})	Venkatesh et al. 2003 p. 453
Anthropomorphism	1. Has analytical abilities that resemble humans (X_{25}) 2. Has emotional awareness that resembles that of a human (X_{26})	Kim & McGill, 2018
AI Anxiety	1. Anxiety about the emergence of reductions in employees (X_{27}) 2. Concern about data security and business privacy (X_{28}) 3. Worried about rising unemployment (X_{29})	Li & Huang 2020; Yukdowski, 2008; Johnson *et al.*, 2017; Carsten *et al.*, 2018.
Organizational Support	1. Government support (X_{30}) 2. Infrastructure readiness (X_{31}) 3. External support from independent businesses/organizations (X_{32})	Chatzoglou, *et al.*,2010; Igbaria, *et al.*, 1997; Kim, *et al.*, 2007 ; Raffat, 2003.

RESULT

Respondents' Demographic Characteristic

Table 2 shows full descriptive details of the respondents' characteristics. Business owners dominated respondents in this study with an age range of 23-30 years (65.5%) and 31-40 years (27.7%). Most respondents or business owners in this study are male (60.5%). Regarding industry, most of the participating SMEs were from the service and creative sectors (45.3%) and culinary sectors (26%). There is even a distribution of respondents across different business ages ranging from more than five years.

Table 2. Respondents' Descriptive Characteristics

Characteristic	Category	Number of respondents (n=119)	Percentage (%)
Gender	Male	72	60.5
	Female	47	39.5
Age	17-22	5	4.2
	23-30	78	65.5
	31-40	33	27.7
	41-50	3	2.5
Business Industry	Tour Travel	2	1.68
	Technology	3	2.5
	Retails	25	21
	Manufacturing	3	2.5
	Construction & Development	1	0.8
	Culinary	31	26
	Service & Creative	54	45.3
Age of Business	1-3	42	35.2
	3-5	36	30.3
	>5	41	34.5

Construct Validity and Reliability

The validity test in factor analysis research aims to measure the extent to which research instruments can accurately measure the concepts or variables studied. The validity test in this study used the Pearson correlation method by correlating the item scores with the total score. Then, the significance test (*sig*) was carried out using Table R at a significance level of 5% with a 2-tailed test (Priyatno, 2014). According to the R table, for a total of 119 respondents at a significance level of 5%, the Pearson correlation value must be greater than 0.176. Based on the validity test results, as many as 29 out of 32 variables had a Pearson correlation value more significant than the R-value (0.176), with a significance value below 0.05. However, three variables with red labels have a Pearson correlation value below the R-value (0.170) and have a significance value above 0.05, namely variables X_{27}, $X_{28,}$ and X_{29}. Thus, these three variables must be eliminated from the factor analysis process before being tested for reliability.

Kuncoro (2013) states that the reliability of a study shows the stability and consistency of a score or measurement scale. The reliability test uses the Cronbach's Alpha formula, where a variable is declared reliable if Cronbach's Alpha (CR) > 0.600. Based on the internal consistency test results, it can be explained that the 29 variables have a Cronbach's Alpha coefficient value greater than 0.9, so the 29 variables are declared valid. However, not all variables have a corrected item-total correlation value above 0.4; there are four variables marked in red with a value less than 0.4, namely X_1, X_{13}, $X_{22,}$ and X_{28}, so these four variables will be eliminated from the following process. These 25 variables were then retested and proven to have the consistency of validity and reliability.

The CMB test was carried out using the single-factor method. According to Aguirre-Urreta et al. (2019), the Harman Single Factor method is a statistical approach used to identify the potential for

CMB in research data. Data is valid when it has a variance value below 50%. The result of the CMB test with the Harman Single factor is the score of cumulative variances. The value was found to be 36.14% for the first factor, so the current data has no issue with common method bias. This research uses the method of EFA. According to Hair (2010), EFA is a method that can reduce a set of original variables into several new variables called factors or dimensions.

Tests used to evaluate which factors shape interest in adopting AI technology can be identified through the results of the KMO test and Bartlett's test. The results of this test aim to determine the feasibility of a variable and whether it can be processed further using this factor analysis technique. If the KMO MSA value exceeds 0.5, then the factor analysis technique can be continued. Meanwhile, so that the factor analysis test can be continued, the value of Sig. The Bartlett test must be <0.05. This shows that the correlation between variables is quite significant for factor analysis. The KMO and Bartlett's results show the KMO value of 0.834 and Bartlett's Test of 0.000. The KMO test results show a value greater than 0.5 and Bartlett's value below 0.05, so all the factors in this study could continue for further analysis using factor analysis.

In EFA, an anti-image matrix is used to evaluate the fit between the original data and the resulting factor model. Anti-image metrics are used to check the adequacy of sample size in factor analysis (Schmiedek et al., 2015). This is done by estimating the anti-image matrix containing the anti-image correlation coefficient for each variable and factor. Based on the test results, it can be concluded that all variables have an anti-image correlation coefficient of more than 0.5, which indicates that the sample size used is large enough to explain the relationship between these variables. In this case, the process of EFA can be continued in the next stage.

According to Field (2009), factor extraction is a method used to reduce data from several indicators to produce fewer factors that can explain the correlation between the observed indicators. Variables undergoing the extraction process will produce extraction factors and Eigenvalues. Hair (2010) explains that the factor extraction value >0.50 compared to the initial factor value indicates that this factor can explain the variable under study, and the eigenvalue can also be used to determine the number of factors that can be formed from independent variables based on the factor explanatory variant value. According to Kaiser (1960), the eigenvalue of a factor that is more significant than one can be maintained in the analysis process. The results of the commonality test show a value range of 0.566 to 0.790 (> 0.5), so it can be concluded that these variables significantly contribute to explaining the extracted factors. The Extraction Sums of the Squared Loadings table provide information about the variation explained by each factor extracted in the factor analysis. Based on the results in Table 5.5, the eigenvalue for factor or component 1 is 9.037, then for component 2 is 2.340, up to component 6, which has a value of 1.064. This shows that six factors can be formed.

The factor extraction process has produced six factors that can be used to classify variables into the six factors by utilizing the factor loading values. According to Hair et al. (2010), factor loading is the correlation value between the original variable and the factor score formed during the factor extraction process. The factor rotation method used in this study is the varimax rotation method. The result of the factor rotation process gives the combination of variables into a classified factor, so it is essential to provide a new name that can represent the entire combination of these variables according to the characteristics of the variable (Widardjono, 2015). According to Ferguson & Cox (1993), naming new factors is a method used to interpret the construct variables that make up these factors. There are two types of naming methods: the recaptured item technique and research judgment. The naming technique used in this research combines the two approaches, which will be explained in the discussion section. The naming of these factors is presented in the following Table 3.

Table 3. New Factor

Factor Name	Variable Code	Variable	Variance
AI Technology Features	X_{12}	Ease of understanding AI technology	361.48
	X_{14}	Good experience when using AI technology	
	X_{15}	Solution features for business	
	X_{18}	High data accuracy	
	X_{19}	Low error rate	
	X_{23}	Clear system operating instructions	
	X_{24}	Assistance in the adaptation process	
AI Technology Awareness	X_{2}	Awareness of the importance of AI technology for their business	93.58
	X_{3}	Familiarity with AI technology in general	
	X_{4}	Familiarity with the implementation of AI technology	
	X_{5}	Curiosity about AI technology	
	X_{6}	Accelerate digitalization acceleration	
	X_{11}	Ease to operate AI technology.	
AI Technology Usefulness	X_{8}	Save business operational time	6.806
	X_{9}	Improving operational processes through automation	
	X_{10}	Reliable system	
	X_{17}	Help adaptation to dynamic technological changes.	
Government and External Organizational Support	X_{24}	Government support	56.41
	X_{25}	External organization support	
Social Influence	X_{16}	The system is always up to date	46.11
	X_{20}	AI technology provides social added value to businesses.	
	X_{21}	AI technology describes the social status of a business.	
Anthropomorphism	X_{25}	The similarity of the way of thinking with humans	42.57
	X_{26}	The similarity of emotions with humans	

DISCUSSION

A system feature is a functional unit in software that adheres to standards, embodying the software design and offering configuration choices. AI technology features represent innovations with broad applications in business. When grouping variables into the first factor, it becomes apparent that this factor, marked by a 36,148% variance, significantly outweighs the other five factors. This underscores the significance of five technical indicators within this factor, encompassing ease of use, problem-solving capabilities, enhanced data accuracy, and low error rates – all of which significantly influence business owners' interest in adopting AI technology. This aligns with previous research (Baabdullah et al., 2019; Lee & Chen, 2022; Zhou et al., 2010). User convenience, such as clear instructions and support assistance, also contributes to this factor, corroborated by a study by Kuberkar et al. (2020). This convergence of variables and prior research forms a robust foundation for naming this factor "AI technology features." These features indicate respondents' expectations for a practical and efficient system. With most respondents aged 23-30 and primarily hailing from service, culinary (F&B), and retail sectors (92%), sectors heavily impacted by COVID-19, digitalization has enriched their understanding of technology features. This drives their interest in AI technology adoption. However, the complexity of specific industries like manufacturing, logistics, or construction may influence the adoption of technologically advanced features, potentially resulting in higher implementation costs. This accounts for the relatively low number of respondents from these sectors in this study.

In this study, we identified a second factor with the second-highest variance after the "AI technology features" factor, accounting for 9.358%. We call this second factor the "AI technology awareness factor" because it reflects participants' awareness of AI technology, which plays a pivotal role in shaping their interest in adoption, especially in the context of digital acceleration. One of the factors contributing to technology awareness is "familiarity," indicating how well individuals know a particular technology. Increased familiarity tends to boost adoption interest and confidence among business owners in the technology itself, as noted in prior research (Sun et al., 2006). "Curiosity" also plays a role in technological awareness, as it represents an individual's intrinsic drive to explore new knowledge, a finding supported by Flavian et al. (2021). These findings align with previous studies, lending credence to the term "AI technology awareness" for this factor. The data from respondents further reinforces the concept of AI technology awareness, with approximately 70.5% of respondents aged 17-30. This data suggests that business actors in this age group are highly familiar with the latest technology and are highly curious about technological advancements.

Furthermore, the data reveals that the dominant sectors are services & creative, culinary, and retail, with an average business age of over three years. Businesses in these sectors, which have operated for more than three years, tend to have more industry experience. This period allows them to witness technology evolution and better understand its role in their operations, particularly post-COVID-19. Businesses with over three years of experience also boast extensive industry networks, including partners, suppliers, and business associations. Business owners gain access to resources and information about the latest technological developments through these networks, further enhancing their technology awareness. Consequently, it can be concluded that higher awareness of AI technology among business owners corresponds to a greater interest in integrating AI systems into their operations, supported by research (Abubakar, 2013; Ilesanmi, 2012).

The perception of the benefits of adopting AI technology in the TAM theory is also defined as the degree to which a person believes using a particular system can improve his performance (Davis, 1989). The concept of the benefits of AI technology is one of the factors found in the results of the analysis, with a variance of 6.8%. This factor, which was later named the “benefit factor of AI technology,” has several factor-forming indicators such as how AI technology can save business operational time, increase the efficiency of operational processes through an automation system, have a reliable system, and be able to adapt to rapid technological developments. These indicators are aligned and, at the same time, confirm the results of research conducted by Koufaris (2002), which describes that the perceived ease of technology consists of four indicators, namely improving performance, productivity, effectiveness, and business benefits.

The usefulness of AI technology is a crucial factor that respondents expect because of its ability to lighten the workload of business actors further than what non-AI technology has. This is not only limited to the respondent's age but also specific to the type of business sector. Data states that as many as 45.3% of business owners are engaged in the service and creative sectors, and saving operational time to produce more products is very important for them. Then, indicators of the benefits of operational process efficiency will undoubtedly be highly expected from business actors engaged in the culinary, retail, manufacturing, and technology sectors. However, some businesses that are over five years old and run by business owners in the age range of 30 years and over are financially stable and have continuity. This can make business owners who are very conservative and conventional reluctant to change how they work and adopt new features offered by technology. They may be more inclined to stick to methods they are familiar with and trust, so AI technologies must address the specific needs of potential users in these circles. If AI technology can be seen as valuable because of its helpful features for every business sector, especially for conventional business owners, then the chances of AI technology being adopted will be even higher.

The fourth factor is named the support factor from the government and external organizations, with a variance of 5.6%. Respondents agreed that two indicators formed this factor: support from the Indonesian government and support for local and international non-profit organizations. Even though this factor only has two indicators, these two indicators are proven to have the highest factor loading values among the 25 other variables (> 0.81). This indicates that this factor is significant in helping businesses adopt AI technology. This is consistent with previous research (Hwang et al., 2016; Lin et al., 2018; Osakwe, Chovancová & Agu, 2016; Pillai et al., 2021), which explains that government support and external organizations have a significant influence on the interest in technology adoption by the business owner. In 2018, the Government of Indonesia launched "Making Indonesia 4.0" as a national strategy to encourage digital transformation in the industrial sector. This includes using AI and other artificial intelligence technologies in production and business processes. As many as 30% of respondents are between 31 and 50 years old. At that age, business owners had been running a business for more than five years; of course, they had good knowledge about this government program. Thus, business owners' interest in adopting AI technology in this age range is very likely influenced by government support in the form of programs.

However, in this age range, business owners are very aware of the dynamic political and economic situation of the government, so the interest in adoption is also influenced by political dynamics in Indonesia for business actors at that age. This may contrast with business actors aged 17-30 years by 70% who have only been running a business for 1-3 years. In this age range, businesses will be very vulnerable to failure without good support for their business development. Based on the explanation above, government support and external non-profit organizations have a vital role in adopting AI technology for all age groups and all business sectors. This support is not limited to education & training support to increase technology awareness. Still, it can also be in the form of providing easy access to resources and infrastructure for financial support.

The fifth factor is the social value influence factor, which has a variance of 4.6%. This factor is formed from three indicators: how AI technology can provide socially added value to business, how AI technology describes social status in business, and how AI technology always provides up-to-date systems. This confirms social influence in the UTAUT theory, where social influence factors are formed from these three variables. Also, according to UTAUT, the social value influence factor is defined as the extent to which an individual feels that other people believe he should use new technology

(Venkatesh et al., 2003). The perception and reputation of technology among businesses can influence the adoption of AI technology between businesses and their consumers. This is also the main result of a study conducted by Kuberkar et al. (2020), which found that if AI technology is perceived as innovative, effective, or efficient by other business owners, other businesses may feel interested in and motivated to adopt it. In fact, adopting AI technology will give consumers an excellent image. The discovery of this factor is confirmed by its fundamentals, with most respondents in the 23–30-year range and having a business in the service & creative sector. This age group comprises millennials and productive young entrepreneurs, where flexing and hedonism are part of their lifestyle. Also, in the post-Covid-19 pandemic era, sophisticated business branding has become one of the capitals for business promotions. So, even though the variance of this factor is not too high, it is essential to pay attention to aspects related to how the adoption of AI technology in business can provide social-added value and social status to business entities and the business actors themselves.

The sixth factor has the most minor variance of the other factors, namely 4.25%. This factor is then named the anthropomorphism factor because it has two forming indicators: the similarity of AI technology to human thinking and the emotional similarity of AI technology to humans. According to Kim and McGill (2018), anthropomorphism refers to the level of human-like characteristics of an object, such as human appearance, self-awareness, and emotions. This study's respondents have high technology awareness and high hopes and expectations for AI technology. The concept of AI is undoubtedly different from existing technology because AI technology carries the idea of artificial intelligence, where users are no longer taught how to operate. AI technology then does not only involve physical performance, but the social and emotional aspects that are embedded in the technology encourage researchers to find other appropriate and more relevant supporting variables such as anthropomorphism factors (Kelly et al., 2022; Doorn et al., 2017).

The anthropomorphism factor found from the results of this factor analysis then confirmed the results of studies from Lee & Chen (2022), Lu et al. (2019), and Doorn et al. (2017), which states that anthropomorphism is an important supporting factor for increasing the level of interest in adopting AI technology. Since 2018, through the government program "Making Indonesia 4.0", awareness of the potential of AI technology has increased among companies, governments, and the public. The development of technology startups in Indonesia also plays a vital role in driving the adoption of AI. Several Indonesian startups have focused on developing and implementing AI technology in various sectors, including e-commerce, fintech, transportation, and health. So, all age groups exposed to this business are indirectly exposed to AI technology and feel the benefits. Some of the business owners can see that the character of AI has an anthropomorphism factor where its mindset resembles that of humans. This is undoubtedly felt by young business owners aged 17-30 years in the creative business sector. Even though this factor is sometimes visible, it makes AI technology unique and has character. Thus, it is essential to raise potential users' awareness of the uniqueness of AI technology. The higher the implementation of the similarity of AI technology with human thinking systems, the greater the chance these business actors will adopt AI technology.

CONCLUSION

This paper aims to shape the factors that might attract business owners to adopt AI technology. The previous work found that demographic and social conditions in a specific city or country could form different factors that shape the intention and attitude toward adopting AI technology. The UTAUT model was adopted in this research to determine hypothetical factors, and the EFA method was proposed as the analysis tool. The result of this research concluded six factors that shape the interest in adopting SMEs towards Artificial Intelligence (AI) technology, namely the features of AI technology, the awareness factor of AI technology, the benefits of AI technology, the government support factor, and external organization, social value influence factors, and anthropomorphism factors.

The factors of AI technology features and AI technology awareness are the main factors that form a total combined variance of 45.5%. Meanwhile, the other factors have a total combined variance of twenty-one point three hundred and fifteen percent, forming the supporting factors. In the data analysis process, three variables were eliminated because the variables did not pass the validity test: anxiety about employee reductions, anxiety about data security, and anxiety about rising unemployment rates. Then, four factors were eliminated because the variables did not pass the reliability test, namely awareness of the importance of digitalization, the importance of data security, and digital infrastructure support.

LIMITATION

This study only uses a sample size of 1.2% of the total population, so many populations still need to be covered. This causes the data variation in this study to be relatively high. The sample in this study was dominated by males with higher technology acceptance than females. Technology acceptance by men is higher than that of women, so a more equal number of sexes is needed to get more representative results. Lastly, researchers collected data in this study through an online personal approach method due to distance limitations and time zones that are different from the Indonesian country's time zone, so more optimal data will be collected, and more SMEs will be covered.

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