Integration of AI Chatbots in MSMEs: Factors Affecting Adoption and Their Effects on Organizational Performance

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Abstract— **AI Chatbot is currently growing rapidly to be implemented by various large companies, but many MSMEs still do not have the readiness and feel the impact of using AI Chatbot. To support digital transformation in Indonesia, it is important to know, how the impact of AI chatbot on organizational performance. However, research that discusses AI chatbot factors and their impact on organizational performance is still limited. This study aims to identify Organizational readiness and Competitive pressure factors on AI Chatbot Adoption and evaluate the impact of the chatbot on Organization Performance with a quantitative approach. Data was collected from 250 MSME owners/managers in Bandung City through a survey and analyzed using PLS-SEM. The results of the analysis show that AI Chatbot Adoption has a negative impact on organizational performance. Then Organizational Readiness has a significant effect on AI Chatbot Adoption, but the direction of the effect is negative and Organizational Readiness and Competitive Pressure have no significant effect on Organization Performance. Additional variables such as digital literacy, organizational culture, AI governance, and maturity implementation, as well as the use of mixed method for deeper understanding can be used for future research.**

Keywords— AI Chatbot, MSMEs, Technology Adoption, Organizational Readiness, Organizational Performance

I. INTRODUCTION

MSMEs or Micro, Small, and Medium Enterprises have an important role as the backbone of the economy in Indonesia, which can be seen from their contribution to the national Gross Domestic Product (GDP) of more than 60%, and the number of MSMEs in Indonesia which touches more than 64 million business units to date [1]. This shows that MSMEs have great potential to actively contribute to developing the Indonesian economy [2]. Recent development in digital technology which is growing rapidly and has an impact on the emergence of innovations such as service provision, product development, and business process optimization [3]. Artificial Intelligence (AI) is one of the major contributors to this transformation [4]. Globally, the adoption rate of AI in the industrial sector has reached 56 percent. However, according to the Global AI Index 2023, Indonesia is still ranked 46th out of 62 countries, so digital infrastructure must be further improved to address the challenges of AI development [5]. A survey conducted by MIT Technology Review on the AI agenda in Asia revealed that the greatest challenge in AI adoption is the lack of internal talent within companies [6].

Amid the increasing intensity of business competition, organizations are increasingly required to every industry player is required to adopt advanced technologies, including AI. Adopting AI has transformed how various organizations manage their business operations [6]. One of the most widely implemented AI-based applications is the chatbot. The COVID-19 pandemic marked the peak of accelerated adoption of AI chatbot technology, which has assisted people across various parts of the world [7]. Today, chatbots play an important role in consumer life and serving multiple functions that span all levels of an organization [8]. The emergence of chatbot technology provides an opportunity for MSME actors to serve customers 24/7. Chatbots can respond to frequently asked questions, recommending appropriate products, and handling customer complaints instantly [9]. However, despite these anticipated advantages, according to the Minister of Communication and Information, Budi Arie, only 12% of MSMEs in Indonesia have effectively adopted digital technology [10]. Prior studies indicate that uncertainty about organizational benefits, especially in terms of performance, is one of the key obstacles faced by micro, small, and medium enterprises (MSMEs) in adopting artificial intelligence (AI) [11]. Therefore, this raises a significant research problem: even though AI chatbots have been widely used as a tool to improve MSME performance, empirical evidence on whether adoption can improve performance is still inconsistent, especially in developing countries.

Prior studies indicate that AI chatbot adoption contributes positively to customer satisfaction through the speed and efficiency of the responses provided, the availability of services 24/7, and the ability to resolve issues quickly [12]. Existing research suggests that AI chatbot adoption has extrinsic value for the consumer experience and subsequently affects customer satisfaction itself [13]. However, there are still limitations in systematically evaluating the results of chatbot adoption at the organizational performance level. In addition, most previous studies have focused almost entirely on technological features or user perceptions, with few discussing about organizational readiness and contextual constraints that influence adoption decisions and outcomes. To address this gap, this study proposes and empirically tests a research framework that influences the adoption of AI chatbots in MSMEs and evaluates the consequences of such adoption on organizational performance. The focus of this research includes three aspects: first, identifying internal and external factors that drive AI-based chatbot implementation among MSMEs; second, measuring the level of chatbot adoption in business operational practices; third, assessing the contribution of chatbot adoption to company performance. Through this approach, the study contributes to the MSME AI adoption literature by providing evidence-based insights that inform both academic research and managerial decision-making related to digital transformation.

II. Literature Review

A. Organizational Readiness

Organizational Readiness (OR) describes the availability of resources and governance structures owned by a business. In making AI Chatbot adoption decisions, business managers must be sure that this technology is suitable for the business conditions being faced and have considered the risks involved [14]. In addition, Organizational Readiness can also be the level of readiness of an organization to implement new technology, especially chatbots, as well as the availability of resources capable of managing information technology [15]. According to Crossan and Apaydin (2010) innovation is the process of creating or adopting or utilizing something new and can provide added value to an organization. This innovation includes the development and updating of systems and services. [16]. This perspective emphasizes that innovation adoption is not solely driven by technological availability, but also by organizational preparedness in terms of strategy, structure, and resources.

Prior studies suggest that organizational readiness has an important role in determining the company's relationship with consumers and improving organizational outcomes [17]. Based on research by Herzallah and Muriati (2015), it shows that organizational readiness has a positive relationship with the performance of MSMEs. A company with higher levels of readiness in adopting e-commerce technologies experience significant improvements in business performance. [18]. Accordingly, organizational that has resource readiness for the application of new technology is expected make a positive contribution to improving organizational performance.

B. Competitive Pressure

Competitive Pressure (CP) focuses on the influence of a company's level of competition in a particular market or sector. The company's competitive conditions can encourage businesses to improve strategies, services, and products [13]. The factors that affect the existence of competitive pressure include the emergence of new competitors, increasing consumer expectations, price fluctuations, and rapid technological advancements. Therefore, companies must be able to adapt in response to these pressures to maintain their market [19]. Ultimately, this competitive drive has led MSMEs to integrate AI to improve the consumer experience, or to help make decisions. Under such conditions, competitive pressure acts as an external force that accelerates organizational decisions to for adopting AI [20].

Every organization must face a dynamic and competitive environment; therefore, organizations need innovation, and adjustments in both internal and external aspects [21]. With the emergence of innovative strategies because of competitive pressure, companies can not only meet market demands but also directly contribute to competitive advantage and improve organizational performance [22].

C. AI Chatbot Adoption

Artificial Intelligence (AI) is a discipline within computer science that concentrates on creating intelligent systems capable of carrying out tasks that normally require human cognitive abilities [23]. These AI systems are built to process and interpret information, learn from prior experiences, make decisions, and resolve problems by applying reasoning processes like those used by humans. AI utilizes algorithms, data, and also uses machine learning techniques [24]. One well-known implementation of AI is the chatbot, a conversational interface designed to emulate human dialogue and engage users in real-time communication through text-based interactions [25]. In recent years, the use of chatbots has expanded to various industries. A study shows that chatbot-based systems integrated with immersive technology can support complex question-and-answer interactions with high performance accuracy, demonstrating the maturity of the technology and the reliability of chatbot solutions [26].

Numerous studies have identified a strong correlation between innovation and organizational performance. Innovative efforts within a company aimed at increasing productivity, all of which contribute to boosting sales [27]. The evolution of information technology, particularly with the rise of AI, has significantly reshaped business operations. AI contributes not only to marketing functions but also enables businesses to gain deeper insights into customer needs by delivering personalized services, redefining marketing strategies, and enhancing overall business performance [28].

D. Organization Performance

Organization performance (OP) has a broad context for evaluating the effectiveness and success of an entity in achieving its predetermined goals. In a business context, organizational performance is the ability to realize work programs efficiently and on target to get outputs that match economic and operational values [29]. The measurement can include customer satisfaction and service quality. This is in line with the theory according to Kaplan & Norton (1992) which assesses performance from finance, customers, internal processes, and learning and growth [30]. According to Ridhwan et al (2023) MSMEs that adopt technology get many benefits, such as being able to improve business performance and encourage innovation and efficiency [31]. This means organizational performance also influenced by the organization's ability to adapt to changes in technology and the external environment.

III. Methodology

This research uses quantitative techniques to examine the effects of Organizational Readiness and Competitive Pressure on MSMEs' decisions to adopt AI chatbots, as well as the subsequent impact of AI chatbot adoption on Organizational Performance. Measurements are also taken to see the relationship between Organizational Readiness and Competitive Pressure on Organization Performance. Based on theory and previous research, a research model is formed consisting of four variables, namely Organizational

Readiness, Competitive Pressure, AI Chatbot Adoption, and Organization Performance.

A. Research Instrument

In obtaining data, a questionnaire with a 5-point Likert scale was used (1 = strongly disagree, 5 = strongly agree). Each variable is tested using several indicators adjusted from previous research, such as Lokuge S, Sedera D, Grover V, Dongming X (2018), P Beneito (2015), R. Urbani et al (2024), Zimmerer et al (2008), Hoque (2004), and Chandler & Hanks (1994). Data analysis was conducted using SmartPLS 4, which is suitable for partial least squares structural equation modeling (PLS-SEM), particularly for predictive research models, complex causal relationships, and relatively small to medium sample sizes, based on Hair et al. (2019) [32].

B. Data Collection and Sample

Data was gathered through an online survey administered via Google Forms and was administered to MSME owners in Bandung City who had already implemented AI chatbot technology from various sectors to test the proposed hypotheses. Based on the research model MSME owners or managers were chosen as respondents. This sample provides sufficient statistical power to test the proposed hypotheses and evaluate the structural relationships within the research model with distribution of the questionnaire resulted in 250 respondents.

IV. RESULTS

A. Respondent Profile

TABLE I. RESPONDENT PROFILE

Category	Description	Frequency	%
Position	Owner	132	52.8%
	Manager	118	47.2%
Business Sector	Food & Beverages	77	30.8%
	Fashion	97	38.8%
	Services	16	6.4%
	Trade	8	3.2%
	Construction	6	2.4%
	Tourism	8	3.2%
	Information Technology (IT)	9	3.6%
	Interior Design	13	5.2%
	Craft	14	5.6%
	Other	2	0.8%
Business Age	Less than 1 year	35	14%
	1–3 years	90	36%
	4–6 years	95	38%
	More than 6 years	30	12%
Revenue	< IDR 300 million	59	23.6%
	> IDR 300 million – 2.5 billion	111	44.4%
	> IDR 2.5 billion – 50 billion	80	32%
Number of Employees	1–2 persons	42	16.8%
	3–5 persons	80	32%
	6–10 persons	83	33.2%
	More than 10 persons	45	18%
Marketing Platform	Offline store	110	44%
	Personal website	139	55.6%
	Marketplace	132	52.8%
	Social media	99	39.6%
	WhatsApp Business	99	39.6%
	Other	25	10%

Table I shows the number of MSMEs in each sector that have adopted AI chatbots. A total of 250 MSMEs participated in this study, with 38.8% in the fashion sector, 30.8% in the food and beverages sector, and 30.4% spread across other sectors. Based on the total number of respondents, 52.8% were business owners and the remaining 47.2% were business managers. Based on the respondents' data, 38% of the businesses had been established for 4–6 years, 36% for 1–3 years, 14% for less than 1 year, and 12% for more than 6 years. Based on the revenue category, it can be concluded that 44.4% of the total respondents were small enterprises, 32% as medium enterprises, and 23.6% as micro enterprises. Most of the businesses involved in this study had 3–5 employees, and marketing platforms used by MSMEs were personal websites and marketplaces.

B. Convergent Validity

Convergent validity is evaluated using several indicators, including factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's Alpha for reliability assessment [33]. Model is considered valid if it achieves a CR value of at least 0.7, each factor loading is equal to or above 0.5, and the AVE meets the minimum threshold of 0.5 or higher [34].

TABLE II. CONSTRUCT VALIDITY AND RELIABILITY

Variable	Cronbach 's Alpha	CR	AVE
AI Chatbot Adoption	0.899	0.931	0.660
Competitive Pressure	0.867	0.892	0.647
Organizational Performance	0.946	0.967	0.671
Organizational Readiness	0.906	0.911	0.679

Based on Table II and Fig. 1, overall, the constructs in the model demonstrated adequate convergent validity, as indicated by high and consistently strong, each latent construct has a high degree of association with its indicators. The CR values ranging from 0.892 to 0.967 indicate that the indicators were appropriate for measuring each respective latent construct. Based the AVE values were sufficiently high, and the Cronbach's Alpha values, it shows that each construct had strong indicators in measuring the intended concepts.

C. Discriminant Validity

Discriminant validity is needed to ensure that each indicator measures concepts that are different from each other and each variable has a strong relationship with its indicators when compared to other indicators [35]. According to Henseler et al (2015), HTMT has high specifications in detecting discriminant validity problems compared to the Fornell-Larcker method, so this study uses this approach. A good HTMT has a value below 0.85 and based on Table 3, all HTMT values between each pair of variables have a value below 0.15 [36].

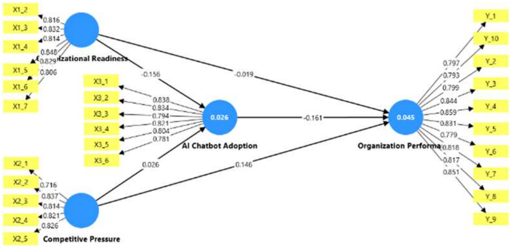
TABLE III. DISCRIMINANT VALIDITY: HETEROTRAIT-MONOTRAIT RATIO (HTMT)

	AIA	CP	OP	OR
AIA				
CP	0.089			
OP	0.139	0.133		
OR	0.164	0.104	0.064	

D. *Assessment of the Structural Model*

In PLS-SEM analysis, the model is evaluated by path coefficients, the R2 coefficient of determination, p-values, and the model's explanatory and predictive power regarding the relationships among variables [37].

Fig. 1. Structural Model



Based on Fig. 1, the path coefficient for H1 is β = -0.156, indicating a negative direction. H2 shows a very weak relationship with a coefficient of -0.019. H3 and H4 have coefficients of 0.026 and 0.146, respectively, suggesting a positive direction but with weak effect sizes. In contrast, H5 has a coefficient of β = -0.161. The R^2 value for the AI Chatbot Adoption construct is 0.026, while for Organizational Performance it is 0.045. According to Falk and Miller (2014), the R^2 value is relatively low, but this result is acceptable and expected in organizational and behavioral research conducted on MSMEs due to various factors. Previous studies have also shown that small businesses have low explanatory power when adopting new technologies. Therefore, the low R^2 value indicates that the adoption of chatbots and their performance results are not influenced by one dominant factor, but rather by a combination of organizational, managerial, and contextual conditions [38].

V. Discussion

The relationships among latent variables were analysed using the PLS-SEM technique to identify the factors affecting MSMEs' decisions to adopt AI chatbots and to assess the effect of such adoption on MSME performance. This study aimed to evaluate each variable affects AI chatbot adoption in the MSME sector and to what degree contributes to improving MSME business performance.

TABLE IV. Summary of Hypothesis Testing and Path Analysis

Hypothesis	Path Coefficient (β)	T-Statistic	P-Value	Result
H1	-0.156	2.526	0.012	**Supported**
H2	-0.019	0.239	0.811	Rejected
H3	0.026	0.237	0.813	Rejected
H4	0.146	1.854	0.064	Rejected
H5	-0.161	2.332	0.020	**Supported**

Based on the results in Table 4, Hypothesis 1 shows that the variable Organizational Readiness and AI Chatbot Adoption has no effect, as it is statistically significant but in a negative direction (β = -0.156, p = 0.012). The negative and significant relationship between Organizational Readiness and AI Chatbot Adoption suggests that higher levels of readiness does not necessarily mean that the technology can be implemented effectively. Organizations that have a higher-level of readiness concerning resources, infrastructure, etc. tend to become more conscious of implementing AI Chatbots; however, this same level of awareness may deter the organization from proceeding with adoption due to perceived implementation risks and costs associated with using AI Chatbots. This finding highlights that organizational readiness alone is insufficient without complementary managerial capability and AI-specific knowledge [39][40][11]. In Hypothesis 2. Organizational Readiness and Organization Performance do not have a significant effect (β = -0.019, p = 0.811). This indicates that internal readiness will not affect organizational performance if it is not accompanied by appropriate strategies and innovations. According to a study by Aboelmaged, M.G. (2014), it is also stated that an organization's internal readiness for technology does not guarantee the adoption of new technologies that have a direct impact on performance improvement. In most cases, organizational readiness only serves as an initial supporting factor, but it does not ensure the successful adoption of technology to enhance organizational performance [41]. In Hypothesis 3, the variable Competitive Pressure was found to have no significant effect on AI Chatbot Adoption (β = 0.026, p = 0.813). This means that in this study, the level of market competition was not a primary factor for MSMEs in Bandung City to adopt chatbots. This finding is consistent with the study by S. Lada et al. (2023), which reported similar results, namely that Competitive Pressure did not have a significant impact on SMEs in Malaysia in adopting AI technology. In the study by S. Lada et al. (2023), it was stated that Competitive Pressure did not affect AI adoption because businesses experience their own internal pressures when implementing this technology. Adopting AI requires substantial investment in data management, infrastructure, expert personnel, and maintenance, so the benefits obtained from AI adoption may not be highly significant[37]. In Hypothesis 4, the variable Competitive Pressure on Organizational Performance shows a positive but not significant relationship (β = 0.146, p = 0.064). The p-value is close to 0.05, indicating that this hypothesis requires further investigation. In Hypothesis 5, the variable AI Chatbot Adoption has a significantly negative effect on Organizational Performance (β = -0.161, p = 0.020 < 0.05) and this represents an important contribution of this study. The result indicates that the adoption of chatbots alone will not add to an organisation's performance, and that it is possible that by implementing chatbots, organisations will initially experience a drop in their performance levels. This is due to both the costs of adopting chatbots and difficulties that will inevitably arise during integration, along with limited knowledge/experience with AI among employees and any misalignment of the chatbot with the organisation's existing business processes. Additionally, this outcome supports the position that any AI or technology adoption without appropriate strategy alignment and operational integration will create initial inefficiencies that will need to be overcome before any benefits can be realised by the organisation. Overall, the results emphasize that contextual readiness, managerial capability, and implementation quality play a more critical role than adoption itself in determining performance outcomes.

VI. Conclusion and Future Research

From a theoretical perspective, this study contributes to the AI adoption literature by providing empirical evidence that challenges the assumption that AI chatbot adoption inherently enhances MSME performance. In response to the main research question, "Does AI Chatbot Adoption affect the organizational performance of MSMEs?" it can be concluded that chatbot adoption does have an effect, but the effect may be negative if the implementation process is not carried out optimally. From a practical standpoint, the findings imply that MSMEs should prioritize implementation quality, managerial capability, and organizational learning rather than focusing solely on technology adoption. Simply possessing internal readiness or responding to competitive pressure is insufficient to guarantee positive performance outcomes. For future researchers, the results of this study open opportunities to explore other factors that affect chatbot adoption and its impact on business performance, such as digital literacy, organizational culture, AI governance, and implementation maturity. In addition, mixed-method approaches could provide deeper insights into how MSMEs integrate AI chatbots into their daily operations and decision-making processes.

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Data Avaibility

Data supporting this study are openly available at DOI: 10.17632/x47h2kz4n3.1

Authorship Statement

Author Contribution:

1. Gabriella Kristiani Sandhya Dewanto: Formal Analysis, Resources, Writing, Editing.
2. Okky Rizkia Yustian: Conceptualization, Methodology, Investigation, and Review.

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