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ANALYSIS OF THE USE OF ARTIFICIAL INTELLIGENCE IN THE FORM OF A CHATBOT AS AN INFORMATION SEARCH ENGINE

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ABSTRACT
The quick development of artificial intelligence has contributed to the use of chatbots as alternative methods for collecting information within organizations. However, empirical studies that combine technology acceptance and system success perspectives to clarify chatbot usage remain lacking. This study analyzes the adoption of chatbots as information search engines by integrating the Technology Acceptance Model (TAM) and the DeLone and McLean Information Systems Success Model (ISSM) through a quantitative approach involving the distribution of questionnaires to 400 employees who have experience interacting with chatbots. The research model includes Information Quality, System Quality, Service Quality, Perceived Ease of Use, Perceived Usefulness, Intention to Use, and Actual Use, and the data were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results indicate that System Quality and Service Quality substantially impact Perceived Ease of Use and Perceived Usefulness. Perceived Ease of Use significantly influences Perceived Usefulness, which eventually impacts Intention to Use and Actual Use. However, Information Quality doesn't significantly impact Perceived Ease of Use or Perceived Usefulness. These results provide theoretical and practical insights for improving chatbot adoption for employees.
Keywords: *Artificial Intelligence, Chatbots, Search Engine, Technology Acceptance Model*

1. Introduction

Technological developments have quickly changed the operations of people and businesses across multiple industries. The majority of individuals are acquainted with the concept of artificial intelligence. Artificial Intelligence (AI) is defined as a collection of algorithmic process that are designed to produce texts and images, and also emulate human intelligence and capabilities by enabling forecasts, suggestions, or logical choices (Cox & Mazumdar, 2024; Gil de Zúñiga et al., 2024; Zhang et al., 2023).

Chatbots can be defined as computer programs that utilize natural dialogue such as text-based or voice-based to analyze and progress human discussion via digital devices (Alazzam et al., 2023; Hannigan et al., 2024). In industrial environments, employees from different positions frequently use chatbots to get details about daily operations, ongoing tasks, and business strategies. Chatbots can facilitate marketing and customer engagement, in addition to addressing internal informational requirements. They also present a better variant of search systems, as they are capable of providing users with responses that are both composed and locally relevant. This indicates that users are not required to manually sift through various information sources. Consequently, chatbots can transform information-seeking behaviors by providing superior and more user-friendly tools compared to conventional search engines.

Previous research focused on the setup and utilization of chatbots, focusing on the factors that influence of user satisfaction and the impact of chatbots on users, using known theoretical frameworks such as the Technology Acceptance Model (TAM) and the Information System Success Model (ISSM). These studies indicate that perceived usefulness, perceived ease of use, and system quality significantly impact users' behavioural intentions about chatbot usage. Furthermore, previous research was performed in diverse areas, such as art and design, e-commerce, fashion, and customer service.

Previous research has focused on user satisfaction or usage intention, excluding the influence of information quality on user trust and satisfaction with chatbot systems. Additionally, empirical evidence regarding the effect of information quality on chatbot usage effects is inconsistent across different contexts. Additionally, current research mainly highlights educational or customer service situations, resulting in a significant gap within the business. These limitations underscore the necessity for additional research regarding the implementation of chatbots in industry.

This study is designed at analysing the factors influencing chatbot usage in industries by integrating components from the Technology Acceptance Model and the Information Systems Success Model. This research investigates the effects of perceived usefulness, perceived ease of use, system quality, and information quality on users' intention and the actual use with chatbot systems. By focusing on employees, this study seeks to provide empirical evidence on chatbot usage within an industry.

This study contributes to existing research like expands on previous research on chatbot adoption by including information quality as a key determinant in an integrated acceptance and success framework, also provides empirical evidence from an industrial context which is still underrepresented in existing studies. These results offer insights for employees seeking to utilize chatbot systems to access information.

2. Literature Review

Artificial Intelligence has been widely recognized as a technology that allows computers to do operations that normally require human insight. Artificial Intelligence (AI) refers to a system's ability to learn from external data in order to achieve specific objectives by emulating human cognitive processes, thereby enabling computers to perform tasks efficiently, thereby enhances decision-making and problem-solving skills (Bahoo et al., 2023; Z. Chen, 2023; Helo & Hao, 2022; Pantano & Scarpi, 2022; Spring et al., 2022; Zhao & Gómez Fariñas, 2023).

Chatbot have emerged as the most noticeable and common example of Artificial Intelligence among a variety of technology-related systems. Chatbots can be defined as an interactive computer programs or conversational agents that use Artificial Intelligence (AI) and Natural Language Processing (NLP) to create answers based on specified inputs and implemented through websites and mobile apps for simulating and maintain personified discussions with complete various functions (Belda-Medina & Kokošková, 2023; Castagna et al., 2024; Guan et al., 2025; Wang et al., 2023). In an industrial context, chatbots serve as a tool to find company information rapidly and effectively to minimize time and effort.

Technology of Acceptance Model (TAM) is a theoretical framework to investigate the adoption of recent electronic technologies and individual acceptance that developed by Fred Davis in 1989 and predicated in the Ajzen and Fishbein's theory of Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) (Chen et al., 2025; Zheng et al., 2026). Information System Success Model (ISSM) is a model established by DeLone and McLean to influence user behavior through System Quality, Service Quality, Information Quality, and Intention to Use (Chen et al., 2025; Ebnehoseini et al., 2022). The model that shown is the result of the Technology of Acceptance Model (TAM) that combined with Information Systems Success Model (ISSM), which has been adapted to the research. Additional variables have been added into the model, including:

1. Information Quality refers to the importance or quality of information that produced by the systems that measured by its importance, precision, completeness, and punctuality. The information that received must be concise, precise, and immediate, with straightforward arguments (Kala et al., 2024; Tri Wibowo & Mariani, 2026).
2. System Quality indicates a system which in the expected attributes of mobile devices and web browsing are presumed to be accessible by users which includes accuracy, availability, response time, and adaptability (Cheng et al., 2024). When a system provides prompt and accurate responses, users' expectations are generally met or exceeded. This rapid confirmation increases their confidence in the chatbot's abilities
3. Service Quality refers to the results of an assessment process where customers connect their expectancies against the service received that should be valuable, dependability, responsiveness, assurance, and compassion (Abu-Taieh et al., 2022). Users would sense the superior service when it's built to comprehend their worries and provide timely, tailored

solutions. The prompt, dependable, and tailored response can cut down the time and users' effort for spend looking the information.

4. Perceived Ease of Use denotes the extent to which an individual anticipates that utilizing a new technological system will require minimal effort (Lv et al., 2025; Sulaiman et al., 2023). Based on the chatbots, PEOU is a term that refers to the users' idea that using chatbots would be easy and the interactions should be straightforward and understandable.
5. Perceived Usefulness refers to an individual's belief that adopting a certain system or product would improve their performance (Vidarshika et al., 2025). In the context of chatbots, PU see the utility of technologies of AI in improving the users' performance, productivity, and efficiency in certain tasks because PU evaluates the perks and advantages of an AI system.
6. Intention to use is a person's determination to employ a specific technology that is heavily impacted by PU and PEOU and also a predictor of actual use activity (Alshurideh et al., 2024). This indicates that if people believe that a technology is beneficial and simple to operate which means believe in perceived ease of use and perceived usefulness, they have a greater probability to be entrusted about utilizing it and intend to use it.

3. Research Methods

This study employs quantitative research techniques, which necessitate processing respondent data. Quantitative research is an approach that used to perform statistical tests to analyze the data and explore the cause-effect relationship between two or more entities or variables (Chan et al., 2025; Kittur, 2023). Employees of businesses that use chatbots as an instrument to locate information and assist with their tasks as a population will be given a questionnaire by the author in order to collect this data. The model below is a model that modified by DeLone and McLean and combined with the Technology Acceptance Model (TAM).

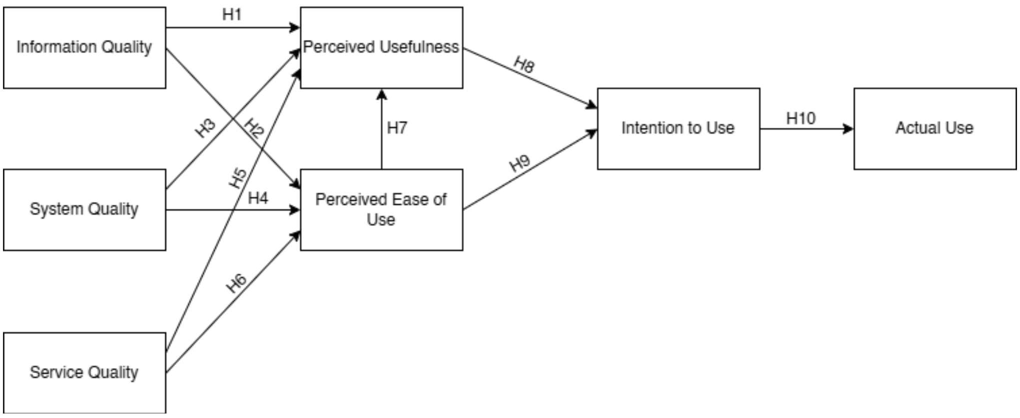

Fig. 1. Framework of Research Methodology

In order to support the hypotheses that have been created based on the study model, data from samples will be collected using a questionnaire and then assessed for validity and reliability. The questionnaire will consist of 30 questions in total, broken down into 7 categories. In addition, there will be 4 questions on their occupation, present employment, whether or not they have used chatbots, and which chatbot they have used. The purpose of the questions is to learn how staff members are aware of chatbots and how they are used in the workplace. Based on the variables mentioned above, it can be inferred that there are 10 hypotheses to be examined as follows:

H1: Information Quality has a positive influence on Perceived Usefulness
H2: Information Quality has a positive influence on Perceived Ease of Use
H3: System Quality has a positive impact on Perceived Usefulness
H4: System Quality has a positive impact on Perceived Ease of Use
H5: Service Quality has a positive impact on Perceived Usefulness
H6: Service Quality has a positive impact on Perceived Ease of Use
H7: Perceived Ease of Use positively influences Perceived Usefulness
H8: Perceived Usefulness positively influences Intention to Use

H9: Perceived Ease of Use positively influences Intention to Use
H10: Intention to Use positively impacts Actual Use

To make it simpler for respondents to react in accordance with their own evaluations, questionnaire data will be gathered and measured using a Likert scale. The Likert scale, developed by Rensis Likert in 1932, is a method for assessing individuals' levels of agreement regarding specific issues, allowing respondents to evaluate the significance of topic attributes on a scale from one to five, without pressing them to adopt a definitive position on an issue (Heo et al., 2022; Schrum et al., 2023). Lemeshow formula will be utilized to determine the minimum number of respondents. Lemeshow formula is a formula in quantitative research to estimate sample size due to undetermined total population size (Rio et al., 2026).

$$n = \frac{z^2 \cdot P \cdot (1 - P)}{d^2} \tag{1}$$

This Lemeshow's formula has the following explanation:
n= Sample size
z = Confidence score (95% = 1,96)
P = Maximum estimate (0,5)
d = Error rate (5% = 0,05)

$$n = \frac{1{,}96^2 \cdot 0{,}5 \cdot 0{,}5}{0{,}05^2}$$

$$n = \frac{3{,}8416 \cdot 0{,}5 \cdot 0{,}5}{0{,}0025}$$

$$n = \frac{0{,}9604}{0{,}0025}$$

$$n = 384{,}16$$

From the results of the calculation above, the minimum number of respondents that will be used is 384 respondents.

4. Results and Discussions

Below is a summary of the respondents' demographics according to their responses, with following results:

Table 1 – Respondent Demographics

Description	Detail	Total Answer	Percentage
Gender	Male	223	55,75%
	Female	177	44,25%
Age of Respondents	18 – 25 years old	93	23,25%
	26 – 35 years old	80	20,00%
	36 – 45 years old	77	19,25%
	46 – 55 years old	75	18,75%
	>56 years old	75	18,75%

Table 1 indicates the respondent demographics that answered the questionnaire. From the 400 respondents above, the majority of respondents who answered were aged between 18 and 25 years old. This indicates that the sample represents users that familiar with digital technology.

Table 2 – Chatbot Usage Profile

Description	Detail	Total Answer	Percentage
Have you ever used a chatbot?	Yes	399	99,75%
	No	1	0,25%

Which chatbot have you used?	ChatGPT	147	36,84%
	Gemini AI	127	31,83%
	Grok AI	125	31,33%

Table 2 indicates chatbot usage profile that respondents have used or frequently use with the chatbots that the respondents used. This indicates that respondents have used or are currently using chatbots, with ChatGPT being the most frequently used chatbot among respondents.

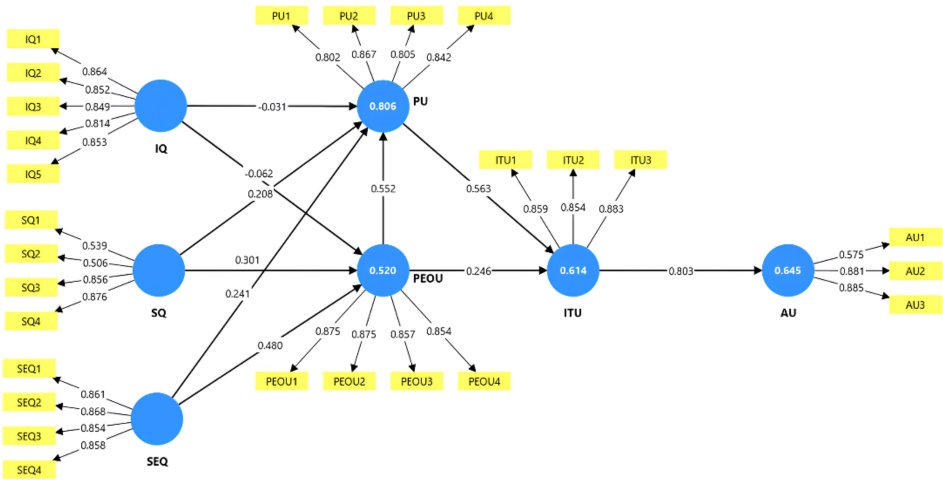

Fig. 2. The result of PLS-SEM Algorithm Calculation

Figures 2 explains the results of data analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM) to know the relationship between each variable in the model. PLS-SEM is particularly beneficial when the user's structural model purpose is to anticipate and clarify the target results as determined by the in-sample and out-of-sample metrics. It also produces answers with fewer sample sizes than CB-SEM. PLS-SEM goes back and forth numerous times, maximizing firstly the measurement framework and then the structural model, then back to the measurement model, next towards the structure model, and so on, until the ultimate goal of improving prediction rather than model fit is met (Hair & Alamer, 2022).

Table 3 – Outer Loadings

Variables	Indicators	Outer Loadings	Validity
Actual Use (AU)	AU1	0.575	Invalid
	AU2	0.881	Valid
	AU3	0.885	Valid
Information Quality (IQ)	IQ1	0.864	Valid
	IQ2	0.852	Valid
	IQ3	0.849	Valid
	IQ4	0.814	Valid
	IQ5	0.853	Valid
Intention to Use (ITU)	ITU1	0.859	Valid
	ITU2	0.854	Valid
	ITU3	0.883	Valid
Perceived Ease of Use (PEOU)	PEOU1	0.875	Valid
	PEOU2	0.875	Valid
	PEOU3	0.857	Valid
	PEOU4	0.854	Valid
Perceived Usefulness (PU)	PU1	0.802	Valid
	PU2	0.867	Valid
	PU3	0.805	Valid
	PU4	0.842	Valid
Service Quality (SEQ)	SEQ1	0.861	Valid
	SEQ2	0.868	Valid
	SEQ3	0.854	Valid
	SEQ4	0.858	Valid

System Quality (SQ)	SQ1	0.539	Invalid
	SQ2	0.506	Invalid
	SQ3	0.856	Valid
	SQ4	0.876	Valid

Table 3 summarizes the findings obtained from the outer loading calculations of every variable. The outer loading numbers indicate how strong of each item's association with its fundamental concept with higher outer loadings suggest higher correlations between items and their corresponding concepts. Outer loading is acceptable when indicators that available from each variable exceeds the approved level of 0.7 (Musyaffi et al., 2023). Table 3 presents the outcomes of the outer loading test, revealing that the majority of indicators exhibit outer loading values of > 0.70, while 3 indications display outer loading values ranging from 0.50 to 0.69.

Table 4 – Construct Reliability and Validity

Variables	Cronbach's Alpha (CA)	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Varianced Extracted (AVE)	Results
AU	0.705	0.792	0.832	0.630	Valid, Reliable
IQ	0.902	0.914	0.927	0.717	Valid, Reliable
ITU	0.832	0.833	0.899	0.748	Valid, Reliable
PEOU	0.888	0.888	0.923	0.749	Valid, Reliable
PU	0.848	0.850	0.898	0.688	Valid, Reliable
SEQ	0.883	0.884	0.919	0.740	Valid, Reliable
SQ	0.707	0.810	0.798	0.512	Valid, Reliable

Table 4 presents the findings on construct reliability and validity, demonstrating that all variables possess an Average Variance Extracted (AVE) value beyond 0.50, hence confirming the validity of each variable. The Composite Reliability (CR) values for all variables reach 0.70, meaning that all variables indicate good reliability (Cheung et al., 2024).

Table 5 – Mean

Variables	Mean
AU	3.747
IQ	3.880
ITU	3.906
PEOU	3.855
PU	3.911
SEQ	3.938
SQ	3.922

Table 5 shows the average values for each variable taken from respondents' opinions.

Table 6 – Hypothesis Test Results

Hypothesis	Path	Path Coefficient	t-statistics	p-values	Results
H1	IQ → PU	-0.031	0.990	0.322	Not Accepted
H2	IQ → PEOU	-0.062	1.386	0.166	Not Accepted
H3	SQ → PU	0.208	3.758	0.000	Accepted
H4	SQ → PEOU	0.301	3.719	0.000	Accepted
H5	SEQ → PU	0.241	4.577	0.000	Accepted
H6	SEQ → PEOU	0.480	7.156	0.000	Accepted
H7	PEOU → PU	0.552	11.622	0.000	Accepted
H8	PU → ITU	0.563	7.607	0.000	Accepted
H9	PEOU → ITU	0.246	3.189	0.001	Accepted
H10	ITU → AU	0.803	36.332	0.000	Accepted

Table 6 shows the results of hypothesis testing for calculating the validity of hypotheses by coefficient values, t-statistics, and p-values. Path coefficients range from -1 to +1, with stronger associations signified by values exceeding 0, regardless of the value being negative or positive (Harris & Gleason, 2022). To verify a hypothesis, the t-statistic must exceed 1.96, and the p-value must be below 0.05 (Utami et al., 2025). Each hypotheses that proposed have valid findings except for H1 (IQ→PU) and H2 (IQ→PEOU). Both hypotheses are declared not accepted since their T-Statistics values are 0.990 and 1.386, which are lower than the permissible minimum of 1.96. These results imply that H1 and H2 do not have good outcomes in this research.

Discussion

From the results above, it indicates that the adoption of chatbot is influenced by system quality and services offered. The connection between System Quality (SQ) and Service Quality (SEQ) with Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) indicates that chatbot usage is dependent based on the system and service stability. Users will consistently interact with chatbots when the system offers stable interactions and suitable assistance, causing them to view chatbots as simple and helpful tools. This fits to the TAM framework which claims that Perceived Usefulness (PU) significantly predicts Perceived Ease of Use (PEOU), which are key indicators of the intention to use. The research accomplished with earlier research like Aswar et al. (2023) and Xia et al. (2026), indicating when chatbot provide quick responses and detailed problem-solving, users are possible to consider the technology as effortless to apply.

The high correlation between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) demonstrates that simplicity of usage is necessary for technology to be thought effective. In addition, these conclusions of usefulness and ease of use considerably affect the Intention to Use (ITU) which ends up in Actual Use (AU). This boosts the theory by Kim & Park. (2023); Kukul (2023) and Porat-Packer et al. (2025), that explained about the connections perceived ease of use and perceived usefulness for intention to use. The successful combination of TAM and ISSM in this research shows that the usage of chatbots in industry significantly influenced by interaction and the solidity of system performance.

The results of the research indicate that Information Quality (IQ) does not accepted in relation to Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). These findings vary with the study by (Hussein et al., 2022; Lisana & Susanto, 2026) that claims Information Quality (IQ) has significant advantages on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). This indicates that users prioritize interaction speed and system performance than the complexness of information itself. The usage of chatbots mostly on user experience and searching velocity rather than the precision of information.

This study investigates the implementation of chatbots as information search engines in industry by combining the Technology Acceptance Model (TAM) and the DeLone and McLean Information Systems Success Model (ISSM). The findings show that system quality and service quality significantly impact users' perceived ease of use and perceived usefulness, which is it affect intention to use and actual use of chatbots. It means that the adoption of the chatbots as search engine influenced by the reliability, response time, availability, and usability.

However, information quality has minimal impact on users' insight, indicating that chatbot use in companies driven by communication efficiency and system performance rather than information quality. In the context of chatbot usage, users prior responsiveness and system reliability over the completeness of information.

This research contributes to the theoretical development of the integration of the TAM-ISSM framework by providing empirical evidence from IT industries, which are currently underrepresented in the literature. The insignificant impact of Information Quality on Perceived Usefulness and Perceived Ease of Use provides insights on chatbot adoption and TAM constructs like Perceived Ease of Use and Perceived Usefulness as a connection with System Quality and Service Quality. While from the practical, the findings imply that developers should improving the chatbot performance by minimizing downtime, optimizing processing speed, and consistent output accuracy.

5. Conclusion

This study shows the expectation that related to importance of information quality may not be entirely suitable for chatbots. Chatbots are rated based on the interaction quality, response, and advantage than the information quality that offered. These results expand the TAM–ISSM framework by focusing on differences in system adoption.

The method of a cross-sectional design could restrict analysis of enhancement in user perspective, and reliance on self-reported data may result in response bias. This study focuses on IT industrial context, which reduces the scope of its findings. A forthcoming analysis could correct these conditions by using a longitudinal approach, incorporating objective usage metrics, and exploring chatbot adoption across various industries or cultural contexts.

These findings have major conclusion for system developers and users. Developers should focused on improving system respons, conversation accuracy, and service reliability than focusing on advancing information. Users that using chatbots as finding informations should prioritize minimal interaction effort and unchanging service performance to improve the acceptance and continuing usage. Furthermore, future research may explore additional relevant factors, including user trust and satisfaction, to improve the understanding of chatbot adoption behavior within organizations.

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