

# Analyzing ChatGPT's Impact on Graduates' Communication, Collaboration, and Logical Thinking Skills Using an Extended Technology Acceptance Model

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## Abstract

The rapid rise of ChatGPT in Indonesia—now the third-highest user base worldwide—raises questions about its impact on essential soft skills for new graduates. Recent evidence warns that while ChatGPT supports academic and professional tasks, it may also reduce critical thinking, collaboration, and communication if not properly guided. This study aims to evaluate how ChatGPT usage affects communication, collaboration, and logical thinking skills among recent graduates in Jabodetabek. A cross-sectional survey of 384 respondents was conducted, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The modified Technology Acceptance Model (TAM) demonstrated strong explanatory power, with  $R^2$  values of 0.830 for Behavioral Intention, 0.699 for Actual Use, and 0.651 for Attitude Toward Use. Hypothesis testing confirmed significant effects, including Perceived Ease of Use on Perceived Usefulness ( $\beta = 0.946$ ;  $t = 172.023$ ;  $p < 0.001$ ) and Behavioral Intention on Actual Use ( $\beta = 0.836$ ;  $t = 50.416$ ;  $p < 0.001$ ). Positive attitudes toward ChatGPT were strongly associated with enhanced teamwork, communication, and logical reasoning. This study contributes to the discourse on digital literacy and educational technology in Southeast Asia, demonstrating that ChatGPT can strengthen graduate employability when integrated with proper guidance and ethical use. The findings provide practical implications for computer science and education fields, offering a framework for balancing AI adoption with the preservation of critical human skills.

**Keywords:** Artificial Intelligence, ChatGPT, Communication Skills, Critical Thinking, Soft Skills Development.

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## 1. INTRODUCTION

The emergence of ChatGPT as part of artificial intelligence (AI) technology marks a significant shift in education and employment globally. Indonesia has become the third-largest user of ChatGPT, accounting for 5.86% of 1.8 billion visits in April 2024. This phenomenon reflects that recent graduates, particularly in the Greater Jakarta (Jabodetabek) area, actively rely on ChatGPT to support academic and professional tasks, including research, report writing, and job interview preparation. Globally, ChatGPT has been recognized for enriching learning processes, facilitating engagement in discussions, and enhancing access to information [1], [2].

Despite these advantages, over-reliance on ChatGPT raises serious concerns. Prior studies highlight the risk of diminishing self-directed learning, critical thinking, and interpersonal communication [3], [4]. For example, Sallam et al. found that while AI can provide efficient access to information, it may hinder deeper engagement with learning materials crucial for professions that rely heavily on communication [3]. Other scholars emphasize that although AI adoption supports specific

learning outcomes, it also reduces opportunities for authentic interaction and soft skill development [5], [6].

Integrating artificial intelligence tools such as ChatGPT in education opens up innovative learning opportunities but poses challenges, particularly regarding the development of soft skills. The increasing reliance on AI tools among graduates raises concerns over the decline of critical thinking and collaborative skills [3]. Hussein emphasized that soft skills are critical in enhancing graduates' employability, especially interpersonal skills needed in the academic and professional world [7]. Choi et al. and Johnson & Johnson also highlighted the duality of AI as a learning support tool and a potential inhibitor of critical evaluation [8], [9]. In his Technology Acceptance Model (TAM) framework, Davis explains how perceptions of the usefulness and ease of technology influence user acceptance in this context [10].

Recent literature calls for the strategic integration of soft skills in the curriculum, especially in STEM fields prone to gaps between technical and interpersonal abilities [11]. The conceptualization of soft skills as cross-cutting competencies Dzhurylo et al. supports the urgency of collaboration between educational institutions and industry to craft curricula relevant to employment needs [12]. Thus, collaborative learning strategies that foster meaningful interactions are key in balancing the utilization of AI and strengthening critical human skills [10].

Addressing these implications, the study highlights the urgent need to improve soft skills essential to today's workforce, especially among graduates who may use ChatGPT extensively [4]. The study suggests that while AI tools such as ChatGPT can facilitate learning and offer practical support, the potential negative impact on critical thinking and collaborative skills requires careful consideration in educational strategies [4]. Integrating a modified Technology Acceptance Model (TAM) as an analytical framework can help clarify how perceived usefulness and ease of use contribute to developing critical competencies among graduates [13].

This holistic approach aims to evaluate how the use of ChatGPT affects critical skills - critical thinking, collaboration, and communication - thus providing a comprehensive understanding of its consequences in a technology-intensive environment. In summary, while ChatGPT offers valuable support for improving educational outcomes, it also poses significant challenges that threaten the development of important non-technical skills necessary for professional success. This requires a thoughtful approach to integrating such technologies into educational frameworks to ensure balanced competency development in new graduates.

Although prior studies have examined ChatGPT's role in learning, very few have evaluated its simultaneous influence on three critical soft skills—communication, collaboration, and logical thinking—within a tested theoretical framework such as TAM. Furthermore, most existing research focuses on isolated skills or general technology adoption, leaving a gap in empirical evidence that integrates ChatGPT usage with holistic soft skill development in a Southeast Asian context. The novelty of this study lies in adopting a modified TAM that incorporates soft skills as external constructs, providing both theoretical advancement and practical insights for AI integration in education.

Therefore, this study aims to evaluate the impact of ChatGPT usage on critical soft skills—communication, collaboration, and logical thinking—among recent graduates in Jabodetabek using a modified Technology Acceptance Model (TAM). By addressing this research gap, the study contributes empirical evidence from Indonesia to the broader discourse on digital literacy and educational technology in Southeast Asia, offering valuable guidance for educators, institutions, and policymakers in preparing graduates for a digitally competitive workforce.

## 2. METHOD

### 2.1. Research Design and Approach

This study employs a quantitative approach using a descriptive methodology to examine the relationship between ChatGPT usage and developing critical thinking, teamwork, and communication skills among fresh graduates in Jabodetabek. A cross-sectional research design is used, where data is collected at a single time to assess participants' current behaviors [14], attitudes, and perceptions regarding ChatGPT usage. The cross-sectional approach was chosen due to its efficiency in collecting large-scale data within a limited timeframe, minimizing cost and respondent attrition risks [15].

### 2.2. Population and Sampling Technique

The study population consists of fresh graduates in Jabodetabek who have used ChatGPT, specifically those who graduated between 2023 and 2024. The study employs simple random sampling to avoid selection bias to ensure a representative sample. Given that the total population size is uncertain, the Lemeshow formula determines the appropriate sample size, resulting in 384 respondents. The formula used is:

$$n = \frac{z_{1-\alpha/2}^2 \times P(1-P)}{d^2} \quad (1)$$

where:

- $n$  = required sample size;
- $Z$  = 1.96 (for a 95% confidence level);
- $P$  = estimated proportion in the population (assumed at 50% or 0.5);
- $d$  = margin of error (set at 5% or 0.05)

### 2.3. Data Collection Method

The primary data in this study were obtained through a structured survey questionnaire distributed to respondents who met the predetermined inclusion criteria. The sample size of 384 participants was calculated using the Lemeshow formula, which ensured adequacy and representativeness despite the unknown size of the overall graduate population in the Jabodetabek area.

To maintain the principle of randomness in respondent selection, the survey was disseminated through several digital platforms, including email invitations, professional networking groups, and official university alumni channels. Within these channels, the selection of participants was randomized using automated randomization features available in distribution tools such as Google Forms and alumni mailing list systems. This approach minimized potential selection bias by providing equal opportunities for participation across different graduate cohorts.

The questionnaire was carefully designed to capture several core constructs of the modified Technology Acceptance Model (TAM). These constructs included Perceived Usefulness (PU), which measured respondents' perceptions of ChatGPT's practical benefits; Perceived Ease of Use (PEOU), which assessed the convenience and effort required to operate ChatGPT; Behavioral Intention to Use (BIU), which indicated the likelihood of continued use; Actual Use (AU), which recorded the frequency and intensity of usage; and Attitude Toward Use (ATU), which reflected participants' overall perceptions of ChatGPT's role in enhancing soft skills such as communication, collaboration, and logical thinking.

This combination of rigorous sample selection and carefully structured measurement ensured that the data collected were both valid and reliable for answering the research questions.

## 2.4. Data Analysis Technique

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS software to analyze the relationships among the research variables. This method is chosen for its strength in handling small to moderate sample sizes and its capability to model complex associations between latent constructs [16]. The analytical process includes descriptive statistical analysis to capture key response trends, along with validity and reliability assessments using Average Variance Extracted (AVE) and Cronbach's Alpha to ensure the robustness of the measurement model. Hypothesis testing is conducted through bootstrapping techniques to determine the strength and significance of the relationships among variables. In addition, traditional statistical assumption tests – such as normality, multicollinearity, and heteroscedasticity – are performed to confirm the adequacy of the data and linear regression analysis is applied to examine the effects of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) on Behavioral Intention to Use (BIU), as well as the influence of BIU on Actual Use (AU) and Attitude Toward Use (ATU).

## 2.5. Research Model

The study adopts a modified Technology Acceptance Model (TAM) to assess how ChatGPT affects critical thinking, teamwork, and communication (Figure 1). The research model integrates these three skills as external variables influencing TAM constructs, allowing for a more comprehensive analysis of ChatGPT adoption in the context of graduate employability skills.

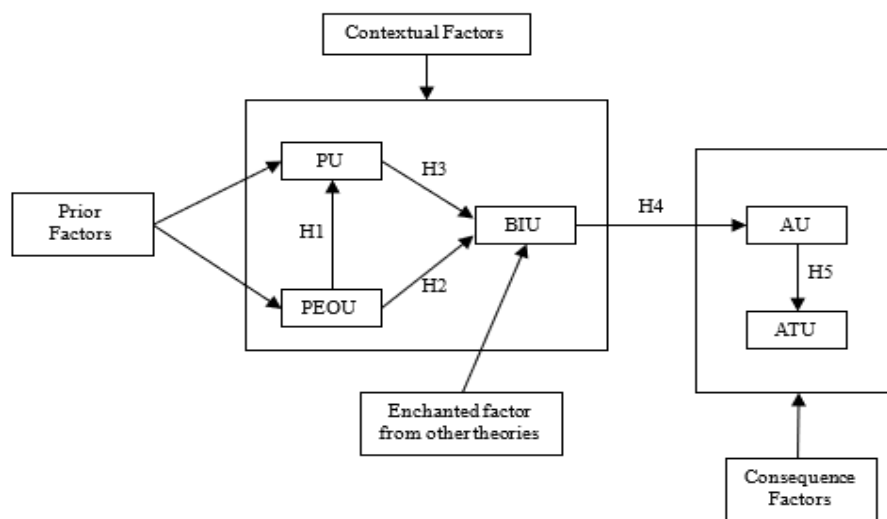


Figure 1. Modified TAM model

## 3. RESULT

### 3.1. Validity Test

Table 1. AVE Results

Variable	Average Variance Extracted (AVE)
ATU	0.657
AU	0.574
BIU	0.531
PEOU	0.773
PU	0.761

Table 2. Fornell-Larcker Criterion Processing Results

	ATU	AU	BIU	PEOU	PU
ATU	0.810				
AU	0.807	0.758			
BIU	0.815	0.836	0.728		
PEOU	0.864	0.872	0.895	0.879	
PU	0.866	0.866	0.901	0.946	0.872

Table 3. Cross Loading Results

Variable	PEOU	PEOU	PEOU	PEOU	PEOU
ATU1	0.822	0.827	0.786	0.775	0.887
ATU2	0.628	0.641	0.593	0.592	0.768
ATU3	0.626	0.611	0.577	0.569	0.770
AU1	0.628	0.616	0.600	0.722	0.568
AU2	0.654	0.649	0.635	0.722	0.590
AU3	0.686	0.698	0.648	0.780	0.651
AU4	0.611	0.644	0.601	0.734	0.557
AU5	0.717	0.741	0.678	0.826	0.679
BIU1	0.642	0.663	0.728	0.605	0.584
BIU2	0.666	0.671	0.726	0.632	0.595
BIU3	0.656	0.668	0.741	0.598	0.616
BIU4	0.644	0.665	0.746	0.619	0.564
BIU5	0.659	0.661	0.719	0.620	0.601
BIU6	0.642	0.651	0.706	0.622	0.633
BIU7	0.662	0.645	0.748	0.583	0.602
BIU8	0.644	0.626	0.712	0.588	0.553
PEOU1	0.890	0.835	0.781	0.782	0.760
PEOU2	0.873	0.826	0.769	0.754	0.738
PEOU3	0.854	0.802	0.764	0.728	0.756
PEOU4	0.890	0.852	0.797	0.794	0.800
PEOU5	0.887	0.842	0.798	0.768	0.766
PEOU6	0.880	0.834	0.813	0.771	0.737
PU1	0.803	0.871	0.778	0.772	0.747
PU2	0.818	0.865	0.789	0.760	0.743
PU3	0.830	0.870	0.796	0.774	0.762
PU4	0.818	0.875	0.775	0.769	0.767
PU5	0.839	0.886	0.790	0.781	0.761
PU6	0.815	0.863	0.773	0.757	0.749
PU7	0.861	0.886	0.808	0.794	0.781
PU8	0.818	0.864	0.782	0.776	0.734

The validity test results using Average Variance Extracted (AVE) show that all variables in the model have values above 0.5 [17]. This indicates that the instrument has met the requirements of convergent validity.

The validity of the measurement model was evaluated using Average Variance Extracted (AVE) and Fornell-Larcker criterion. As shown in Table 1, all constructs have AVE values above the 0.5 threshold (e.g., ATU = 0.657; AU = 0.574; BIU = 0.531; PEOU = 0.773; PU = 0.761), indicating

satisfactory convergent validity. The Fornell-Larcker criterion results in Table 2 further confirm discriminant validity, with the square root of each construct's AVE (e.g., ATU = 0.810; PU = 0.872) being higher than its correlation with other constructs.

Supporting evidence from Table 3 (cross-loading analysis) shows that all indicators load highest on their intended constructs, strengthening the conclusion that the measurement model is both convergent and discriminant valid.

As the table demonstrates, each indicator's outer loading value against the measured variable has been higher than its association with other variable constructs. This consistent pattern confirms that each indicator effectively measures its designated latent variable and does not significantly overlap with other constructs. According to the aforementioned cross-loading and Fornell-Larcker criterion calculations, the study's validity has been satisfied, as determined by discriminant validity. Therefore, the findings of the earlier computations verify that the convergent validity and discriminant validity tests have successfully demonstrated the validity of this study.

### 3.2. Reliability Test

The reliability analysis, summarized in Table 4, shows that all constructs exceed the recommended thresholds for Cronbach's Alpha and Composite Reliability ( $\geq 0.7$ ). For instance, PU recorded  $\alpha = 0.955$  and CR = 0.926, while PEOU had  $\alpha = 0.941$  and CR = 0.953. These results demonstrate that the instrument consistently measures the intended constructs, ensuring internal reliability.

Table 4. Results of measuring Composite Reliability and Cronbach's Alpha values

Variable	Cronbach's Alpha	Composite Reliability
ATU	0.738	0.851
AU	0.813	0.870
BIU	0.874	0.900
PEOU	0.941	0.953
PU	0.955	0.926

### 3.3. Structural Model

The explanatory power of the model was assessed using the coefficient of determination ( $R^2$ ). As presented in Table 5, all endogenous constructs achieved strong values: ATU = 0.651, AU = 0.699, BIU = 0.830, and PU = 0.895. These values indicate that the independent variables account for a substantial proportion of variance in the dependent variables, confirming the robustness of the structural model.

Table 5. R-Square measurement results

Variable	R Square
ATU	0.651
AU	0.699
BIU	0.830
PU	0.895

### 3.4. Hypothesis Test

Bootstrapping results, shown in Table 6, indicate that all hypothesized relationships are statistically significant ( $p < 0.001$ ). Key findings include the strong positive influence of AU on ATU ( $\beta = 0.807$ ;  $t = 44.690$ ), BIU on AU ( $\beta = 0.836$ ;  $t = 50.416$ ), and PEOU on PU ( $\beta = 0.946$ ;  $t = 172.023$ ). Moreover, PU significantly affects BIU ( $\beta = 0.520$ ;  $t = 8.287$ ). These results validate the TAM



framework in this context, demonstrating that perceived usefulness and ease of use drive behavioral intention, which in turn enhances actual usage and positive attitudes toward ChatGPT.

By integrating communication, collaboration, and logical thinking into the TAM framework, the results suggest that ChatGPT positively contributes to the development of these soft skills. This is reflected in the high ATU scores, reinforcing the role of ChatGPT in improving graduates' job readiness through enhanced teamwork, communication, and logical reasoning abilities.

Table 6. Ootstrapping Measurement Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics ( O/STDEV )	P Value
AU → ATU	0.807	0.807	0.018	44.690	0.000
BIU → AU	0.836	0.835	0.017	50.416	0.000
PEOU → BIU	0.403	0.402	0.064	6.302	0.000
PEOU → PU	0.946	0.946	0.005	172.023	0.000
PU → BIU	0.520	0.521	0.063	8.287	0.000

## 4. DISCUSSIONS

### 4.1. The Influence of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU).

Based on the analysis results, Perceived Ease of Use (PEOU) significantly and positively influences Perceived Usefulness (PU) in the context of using ChatGPT under study. This is indicated by the path coefficient value of 0.946, which shows that fresh graduates in Jabodetabek perceive ChatGPT as much more helpful when perceived as easy to use. The robust correlation between the two variables is confirmed by the coefficient values that are getting closer to 1. In addition, the t-statistic value of 172.023, which significantly exceeds the important t-table value of 1.65 at the 5% significance level for a one-sided test, reinforces the significance of the effect. The effect is significant at the 99.9% confidence level, as indicated by the p-value of 0.000. The high path coefficient value and strong significance level indicate that the study participants' perception of ChatGPT's utility was continuously and significantly influenced by its perceived ease of use.

This finding is consistent with the Technology Acceptance Model (TAM) theory [13], which states that the perceived usefulness of a technology is primarily determined by its perceived ease of use. Users are more likely to assess a system or technology as something that helps improve their performance and productivity when they believe it is easy to use. This is because the ease of use of technology decreases the time and effort required to perform specific tasks, increasing the user's perceived utility value.

Holden and Karsh elaborate further on this aspect by defining PEOU as a measure of the effort required to use the technology [18]. Their analysis underlines that when users find a system easy to navigate, their evaluation of its usefulness increases, aligning with findings in research on modern technology. Similarly, Venkatesh and Davis developed TAM, documenting how PEOU is an important determinant of PU, reinforcing the applicability of these results in a technology context such as ChatGPT among recent graduates in Greater Jakarta [19]. Their longitudinal study showed a strong correlation between these constructs, confirming that better user perceptions of ease would result in more significant benefits from the technology [19].

Mardhiah et al. provided additional empirical evidence by investigating the influence of PEOU and PU in the context of home technology. Their research corroborates that PEOU positively impacts user intention to adopt technology [20]. This correlation aligns with various studies highlighting that

perceived ease of use enhances users' experience and impacts their assessment of technology usability [21], [22].

In addition, Ismail's work emphasizes the belief that systems designed with high user-friendliness will improve task performance. This conclusion adds depth to the findings related to ChatGPT, suggesting that perceived ease of use plays an important role in perceived effectiveness and utility [23]. The synthesized results of various studies support the governance principle that easy-to-use technologies promote better acceptance and perceived utility, which confirms the basic premise of TAM across various technology contexts [18], [19], [20], [21], [22].

In summary, the available evidence strongly supports the claim that PEOU substantially influences PU, as reflected in the study of ChatGPT usage by recent graduates in Greater Jakarta. The relationship demonstrated by the statistical analysis aligns with existing theories in technology acceptance research, confirming the interrelationship between these constructs.

#### **4.2. The Influence of Perceived Ease of Use (PEOU) on Behavioral Intention to Use (BIU)**

The analysis findings show that, when it comes to utilizing the technology under study, Perceived Ease of Use (PEOU) significantly and positively affects Behavioral Intention to Use (BIU). The relationship between PEOU and BIU yielded a path coefficient of 0.403, indicating that users' intention to adopt technology is positively influenced by their perception of its ease of use. The t-statistic value of 6.302, which is significantly higher than the important t-table value of 1.65 at the 5% significance level for the t-test, supports the relevance of this effect. At the 99.9% confidence level, the p-value of 0.000 indicates this relationship is significant. Therefore, the intention of users to use a technology increases with ease of use.

This result is consistent with the [13] Technology Acceptance Model (TAM), which views PEOU as one of the main factors influencing user behavior in adopting new technology. Because simplicity of use lowers adoption and adoption barriers, consumers are more likely to intend to use technology when they believe it is easy to use.

Research conducted by Alfani et al. strengthens the positive relationship between PEOU and BIU by showing that ease of use is an important factor in users' intention to adopt mobile banking technology. Their findings align with previous research, which confirms that perceived ease significantly mediates behavioral intentions, especially in the context of users where technological complexity may hinder adoption [24]. Furthermore, a study by Putra et al. corroborates the influence of PEOU and Perceived Usefulness (PU) on BIU, highlighting the combined effect that shapes consumer attitudes to adopt technology in the context of mobile applications [25].

Zhang et al. contribute additional insights by exploring how PEOU interacts with other factors influencing BIU among electric vehicle users. Their findings suggest that PEOU plays a mediating role, echoing a basic premise of TAM that emphasizes the importance of users' perceptions of usefulness in determining behavioral intentions [26]. These findings align with evidence provided by Rahayu et al., who outlined the critical nature of PEOU and PU in shaping individuals' intention to use information systems [27].

Further support is provided by Krisdina et al., who found that PEOU directly influences BIU and improves consumer attitudes toward using e-health services. Their research underscores the importance of easy-to-use technology as a determinant of adoption behavior [28]. This reinforces the idea that when users find technology easy to navigate, their intention to adopt it is substantially strengthened.

Overall, the convergence of findings across these studies aligns consistently with the Technology Acceptance Model framework, which states that PEOU is a significant determinant of behavioral intention to use a new technology. This illustrates the important role of perceived usefulness in the technology adoption process.



#### 4.3. The Influence of Perceived Usefulness (PU) on Behavioral Intention to Use (BIU)

According to the analysis findings, behavioral intention to use (BIU) is positively and significantly influenced by perceived usefulness (PU). The path coefficient value of 0.520 illustrates this finding, indicating that users' intention to use the technology will increase when they believe it is functional. The t-statistic value of 8.287 and the p-value of 0.000, which is significantly below the 0.05 significance level, support the relevance of this effect. Therefore, people are more likely to use technology if they think it will help them achieve their goals or complete certain activities.

This result is in line with the idea conveyed in the Technology Acceptance Model (TAM), which states that perceived usefulness is one of the main elements that directly affect behavioral intention to use. [13] asserts that consumers are more likely to accept and use technology when they feel significant benefits because they believe it will increase their effectiveness, efficiency, or productivity.

The effect of Perceived Usefulness (PU) on Behavioral Intention to Use (BIU) is the foundation of the Technology Acceptance Model (TAM), as proposed by Davis [13]. This model suggests that individuals are significantly more likely to accept technology when they perceive it to help increase their productivity and effectiveness. Empirical evidence gathered in various studies underlines this statement, showing a strong relationship between PU and BIU.

Recent research by Putra et al. shows that PU and Perceived Ease of Use (PEOU) serve as important determinants of users' intention to use an application, reinforcing the central role of PU in technology acceptance [25]. Their findings are consistent with previous TAM research, highlighting PU as a significant factor driving BIU across various technology contexts. Venkatesh and Davis provided longitudinal evidence supporting TAM, confirming that PU consistently accounts for a significant amount of variance in BIU, thus reinforcing the importance of perceived benefits in driving technology adoption [19].

In addition, Yousafzai et al. emphasized that PU significantly affects user acceptance of new technologies. Their meta-analysis proved that higher perceived usefulness can reliably translate into increased BIU across a wide range of technology applications, aligning with the essential elements of TAM [29]. Al-Suqri corroborates this by illustrating that PU and PEOU jointly influence users' decisions to adopt electronic resources, reaffirming the centrality of perceived benefits in the acceptance framework [22].

In the context of new technologies, findings by Kim and Park illustrate how PU acts as a bridge between health behaviors and technology acceptance, indicating that when users perceive health information technology as beneficial, they are more likely to adopt it [30]. This reflects the widely accepted idea that the perceived utility of technology plays an important role in shaping users' behaviors and intentions, consistent with Davis' initial statement regarding TAM.

Evidence from various studies clearly shows that PU positively and significantly affects BIU. The coefficients reported in the studies and the underlying significance levels underscore the critical nature of PU in driving technology adoption, confirming the validity of TAM as a model for understanding technology acceptance.

#### 4.4. The Influence of Behavioral Intention to Use (BIU) on Actual Use (AU)

The analysis findings show that Actual Use (AU), which represents the actual use of the technology under study, is positively and significantly influenced by Behavioral Intention to Use (BIU). Behavioral intention to use technology directly increases the likelihood and frequency of technology use, as indicated by the path coefficient value of 0.836. The t-statistic value of 50.416 and the p-value of 0.000 support the significance of this effect, indicating that this effect is highly significant at the 99.9% confidence level. Therefore, the stronger a person intends to use a technology, the more likely they will use it daily. The Technology Acceptance Model (TAM) and other technology adoption models

emphasize that behavioral intention (BIU) is a significant predictor of actual use behavior (AU), and this conclusion is consistent with these concepts. In this case, people are more likely to use technology in daily activities, whether at work, school, or personal, when they firmly intend to do so.

Evidence links intention to behavior, reinforcing that stronger behavioral intentions correlate with increased actual use [5]. Their research aligns with numerous other studies showing that BIU is an important predictor of AU. For example, Oteyola et al. state that higher technology acceptance correlates with greater actual use, further validating that intentions significantly predict behavior in technology adoption [2].

Furthermore, the study by Chen et al. discusses how behavioral intentions serve as reliable predictors of desired actions, noting that intentions can precede behavior changes [21]. Likewise, Ginting illustrates how community engagement positively affects intentions and subsequent actual use, indicating that user engagement translates directly into utilization patterns [25].

In another relevant study, Palau-Saumell et al. emphasized that habits can influence BIU and AU, suggesting that established usage patterns likely manifest in actual usage behavior [31]. This highlights the link between intention as a driver of habitual use, consistent across multiple contexts, including educational settings [3].

Finally, exploratory research by Efendi et al. supports the idea that perceived ease of use and usefulness significantly influence BIU, which in turn influences actual technology use. Their study emphasizes that positive perceptions lead to stronger intentions and increased actual app usage among users [27]. This underscores the importance of intention as a mediating construct in technology adoption across multiple contexts. The evidence supports that Behavioral Intention to Use (BIU) is a fundamental antecedent of Actual Use (AU) of technology, consistent across multiple contexts and supported by rigorous empirical research.

#### **4.5. The Influence of Actual Use (AU) on Attitude Toward Using (ATU)**

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#### **4.6. The Influence of Actual Use (AU) on Attitude Toward Using (ATU)**

The findings from the analysis show that Actual Use (AU) has a significant favorable influence on Attitude Toward Using (ATU), underscored by a path coefficient of 0.807, indicating a strong correlation. This relationship is also supported by a t-statistic value of 44.690 and a p-value of 0.000, confirming this effect's statistical significance at the 99.9% confidence level. This empirical evidence aligns with the Technology Acceptance Model (TAM), which states that actual usage experience significantly influences users' attitudes toward technology [32], [33]. Davis' foundational research on TAM suggests that users' attitudes reflect their interactions with the technology, where positive experiences can foster favorable perceptions, increasing future intentions to use the technology [32], [34].

The relationship between actual use (AU) and attitude towards use (ATU) in the context of technology acceptance has been extensively researched across multiple domains, reinforcing the basic tenets of the Technology Acceptance Model (TAM). Significant findings highlight the important role of perceived ease of use (PEU) and perceived usefulness (PU) in shaping user attitudes, aligning with previous research by Yutdhana, Kohler, and Cao et al. Yutdhana and Kohler found that users' perceived ease of use and usefulness significantly influenced positive attitudes toward technology, specifically focusing on pre-service English teachers [35]. Further corroborating this claim, Cao et al. illustrated that college students' perceptions of AI technologies are directly related to their attitudes and intentions to use, which are explicitly linked to the basic constructs of TAM [36].

Recent studies further elucidate this relationship. For example, research by Huang et al. showed that using the TAM framework to evaluate user acceptance of a clinical decision support system yielded the insight that standardizing usability factors can significantly improve user engagement and acceptance [37]. This assertion is supported by rich literature confirming that meaningful interactions with technology are critical to shaping user attitudes.

Significantly, the implications of such findings go beyond the theoretical framework. They emphasize the need for educational strategies and interventions to improve user experience. Research integrating TAM with the Value-Based Adoption Model offers insights into how the perceived value of educational technology and usability factors can drive student acceptance [38].

This convergence of insights illustrates a consistent pattern where actual use drives positive attitudes, thus strengthening the premise of TAM across different technologies and settings. The findings validate that enhancing user interaction with technology through tailored training, user-friendly design, or increased perceived value can play an important role in fostering a culture of technology acceptance and utilization over the long term.

The multifaceted interaction between AU and ATU, supported by contemporary studies, underscores the importance of PEU and PU in user acceptance in diverse educational and technological contexts. This literature synthesis heralds continued exploration in optimizing the user experience to enhance the adoption of emerging technologies.

#### 4.7. The Impact of ChatGPT on New Graduates' Communication, Teamwork, and Logical Thinking Skills in the Jabodetabek Area

The comprehensive hypothesis testing conducted in this study provides empirical evidence on how ChatGPT use affects three essential graduate competencies: communication, collaboration, and logical thinking. Within the modified Technology Acceptance Model (TAM), these competencies are integrated as external variables influencing and reflecting Attitude Toward Using (ATU).

The findings show that a positive ATU strongly correlates with graduates' perception that ChatGPT enhances their communication clarity, ability to coordinate tasks collaboratively, and logical reasoning in problem-solving. This relationship is not merely theoretical but supported by cross-loading results and high  $R^2$  values ( $ATU = 0.651$ ). In this study, ATU functions as a proxy for soft skill development because it reflects the culmination of perceived usefulness (PU), perceived ease of use (PEOU), and actual use (AU) into evaluative judgments about ChatGPT. When graduates report favorable attitudes, these are closely tied to their self-assessment of improved competencies in expressing ideas, engaging in teamwork, and approaching tasks analytically.

However, it must be acknowledged that measuring soft skills through ATU involves certain limitations. The model captures attitudes and perceptions as aggregated indicators of skill improvement, rather than directly measuring each skill domain through behavioral observation or performance-based assessment. This implies that while the results suggest a positive influence of ChatGPT on communication, teamwork, and logical thinking, they represent perceived rather than objectively tested competencies. Future studies could complement TAM-based perception analysis with performance metrics, such as peer evaluations, collaborative task outputs, or critical thinking assessments, to validate these findings more robustly.

These insights align with recent research indicating that generative AI tools, when guided, can enhance students' analytical reasoning, collaborative engagement, and language expression [2], [39]. Similarly, structured adoption fosters distributed dialogue and peer knowledge-building [40]. Nonetheless, as Smutny & Schreiberova caution, unguided reliance on AI risks weakening authentic engagement, underscoring the importance of educational frameworks that balance AI benefits with intentional soft skill development [6]. In this regard, the structured framework of TAM provides an evidence-based foundation to understand how intention and usage translate into attitudes and soft skill development [33].

In conclusion, ChatGPT demonstrates substantial potential to strengthen soft skills among Jabodetabek graduates, provided its integration is accompanied by critical pedagogy and digital literacy reinforcement. The reliance on ATU as a proxy for soft skills, while supported by statistical validity, highlights the need for complementary approaches in future research to ensure comprehensive measurement of communication, collaboration, and logical thinking competencies.

## 5. CONCLUSION

This study concludes that ChatGPT usage significantly and positively impacts the development of essential soft skills—communication, collaboration, and logical thinking—among recent graduates in the Jabodetabek area. The findings confirm that perceived ease of use and perceived usefulness strongly shape behavioral intentions, which in turn drive actual use and foster positive attitudes toward the technology. These attitudes are closely associated with graduates' perceptions of improved soft skills, suggesting that ChatGPT can serve as a valuable enabler in preparing young professionals for the demands of the modern, digitally driven workforce. Beyond the local context, this study contributes to the broader discourse on digital literacy in Southeast Asia, offering empirical evidence on how generative AI tools can support skill development while highlighting the importance of guided adoption. The results imply that educational institutions and training programs should consider integrating

ChatGPT or similar AI technologies to strengthen students' critical competencies, provided that usage is accompanied by ethical guidelines and digital literacy reinforcement. However, the study also acknowledges its limitations, as soft skills were measured in aggregate rather than individually. Future research is recommended to isolate the specific effects of ChatGPT on each competency—communication, collaboration, and logical thinking—and to examine moderating factors such as peer interaction, institutional support, and levels of digital literacy. Such efforts would allow the development of more targeted strategies for integrating AI into education and workforce readiness initiatives, ensuring that graduates are not only technologically adept but also holistically equipped for a competitive labor market.

## CONFLICT OF INTEREST

The authors declare that there is no conflict of interest among the authors or between the authors and the object of this research.

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