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A Preliminary Investigation of EFL Students' Intention to Use ChatGPT: A Structural Equation Modelling

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ABSTRACT

This study is encouraged by pervasive advocacy for generative AI, despite emerging debates on their ethical concerns and use in academic environments. The research explores a model assesssing students' beliefs and intentions to use ChatGPT. Utilizing the framework of Behavioral Reasoning Theory (BRT) and the Extended Theory of Planned Behavior (TPB), a post-positivist research design was employed. Overall model validity and reliability was gained along with dynamic correlation between variables in the model, including behavioral beliefs, perceived usefulness, social influence, perceived behavioral control and ethical considerations. In addition, this study suggests empirical data for the predictive power of beliefs and intention. As a pilot study, this research offers significant roles of motivational drives to use ChatGPT affecting students' beliefs of the technology. Moreover, initial insights on the significant effects of demotivating factors to use the technology towards the participants' subjective norms could be further explored in subsequent studies.

1. INTRODUCTION

The integration of artificial intelligence (AI) technology is becoming more prevalent nowadays, including the ones for educational purposes. Its popularity has grown exponentially due to its perceived potential benefits as well as acknowledgement of its drawbacks on teaching and learning (Alberth, 2023; Baskara & Mukarto, 2023; Huong & Tran, 2025). In addition, scholars have urged the necessity for assessing users' belief and readiness to use it (Khizar et al., 2025; Parveen et al., 2024; Slamet, 2024; Strzelecki, 2024).

The discourse surrounding AI technologies in higher education encompasses both advocacy for their use and critical assessments of their ethical implications (Farrokhnia et al., 2024; Khizar et al., 2025; Wang et al., 2025). In Indonesian context, a guideline of generative AI use for higher education has been issued by the Ministry of Education (MoE). However, to the researcher observation, elements of its ethical use are not comprehensively elaborated along with its practical parameters. In addition, numerous scholarly articles and academic presentations seem to inadequately address the balance between the potential benefits and inherent risks of ChatGPT use in educational contexts

Researching how pre-service teachers make sense of AI use along with their ethical beliefs is, therefore, pivotal. These students might be at the forefront of this new technology use in their future classrooms. Combining the frameworks of Behavioural Reasoning Theory (BRT) (Westaby, 2005) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991), motivational factors and ethical dimensions along with beliefs underpinning students' intentions to use ChatGPT for academic purposes were explored. BRT lists the reasons that students might opt for or against to use AI tools called "Reason For" (in this study called motivational drivers) and "Reason Against" (in this study transformed into ethical concerns). TPB further elucidates how these beliefs influence behavioural intentions through constructs of behavioural beliefs, outcome beliefs, subjective norms, and perceived behavioural control (Ajzen, 1991). The combination offers a comprehensive lens to assess how pre-service teachers navigate the integration of AI in their academic practices.

This research, therefore, aims to gain a preliminary assessment how variables of BRT and TPB predict intention to utilize ChatGPT for academic purposes. By addressing this question, this study seeks instrument validation, correlation, and model fit of the participants make sense of AI in their study, pondering motivational drives and ethical perspectives in their approach to technology adoption.

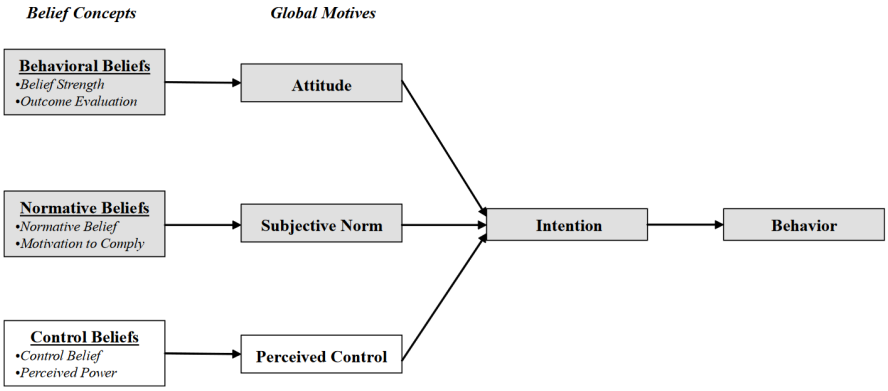
2. LITERATURE REVIEW

The rapid integration of artificial intelligence (AI) into educational settings has emerged as a growing area of research. ChatGPT as a product of generative AI is designed to produce new data by recognizing patterns and structures from pre-existing datasets capable of generating content, including text, images, music, and other media (Haleem et al., 2022; Kasneci et al., 2023; Ray, 2023). Previous studies on the effectiveness of digital technology use have suggested the essential roles of users' beliefs and attitudes (Afshari et al., 2013; Ali et al., 2023; Beacham & McIntosh, 2014; Chiu & Churchill, 2016). As ChatGPT has garnered attention for its potentials to support instruction (Alberth, 2023; Fitria, 2024), the need for systematic examination of user perceptions and intentions to use it is becoming more evident.

Behavioural Reasoning Theory (BRT) and the Theory of Planned Behaviour (TPB) originated from traditional behavioural intention model (Westaby, 2005) (figure 1). BRT posits that behaviour is influenced by a range of reasons, both for and against, aligning well with the motivational and ethical considerations surrounding AI usage in education (Kumar et al., 2021; Westaby, 2005). Dimensions of reason for reflect the motivational drives encouraging the use of ChatGPT, whereas variables reason against encapsulate ethical concerns that may deter such use. Previous research has highlighted that the strength of behavioural intentions is paramount in predicting actual user behaviours (Alhamami, 2018; Baydas & Goktas, 2016; Golombek, 2015; Smarkola, 2008).

Figure 1

Traditional Behavioral Intention Model (Westaby, 2005)



The TPB expands its previous models by including additional constructs that refine the predictive power of intentions. It integrates factors such as behavioural beliefs, outcome beliefs, subjective norms, and perceived behavioural control (Ajzen, 1991, 2002). Research has shown that these constructs interact to create a nuanced understanding of how personal, social, and environmental factors interplay to influence academic behaviours (Bai et al., 2021; Stahl, 2008; Strzelecki, 2024). For instance, positive behavioural beliefs about the utility of AI tools, coupled with supportive subjective norms (Van Acker et al., 2013), are likely to foster increased intentions to utilize ChatGPT among EFL students.

Considering these theoretical underpinnings, this study aims to elucidate the relationships between the identified constructs and the intention to use ChatGPT among EFL pre-service teachers in Indonesia. Specifically, it explores how motivational factors (reason for) and ethical concerns (reason against) impact the belief constructs that ultimately dictate students' intentions to engage with AI technology for educational purposes. By bridging BRT and TPB, this research attempts to provide valuable insights into the adoption of AI tools in higher education, contributing to ongoing discussions on its ethical and pedagogical implications (Dutta et al., 2022; Rua et al., 2024; Wang et al., 2025).

3. METHODS

3.1. Participants

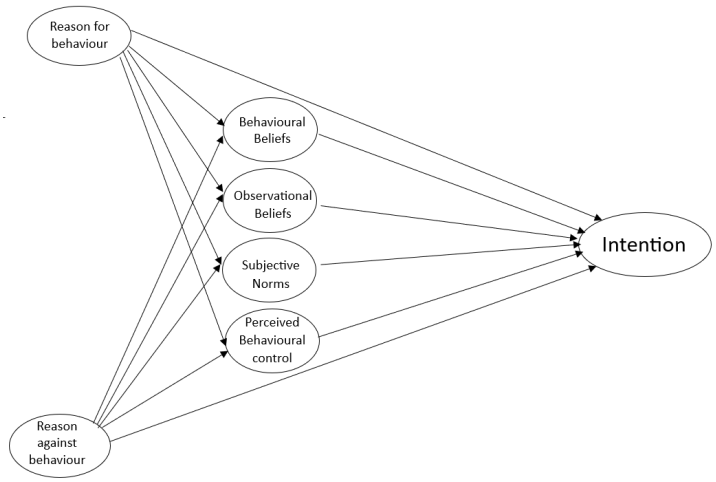
As a pilot study, this research was conducted with a sample of 59 pre-service English teachers enrolled at a private university in Yogyakarta (66.10% females and 33.90% males). They were selected from varied academic cohorts, with the highest representation from the 2021 cohort (27.12%), followed by the 2023 (25.42%) and 2024 (25.42%) with smaller proportions from the 2022 (16.95%) and 2020 (3.39%). It is acknowledged that the sample size falls short of the suggested adequacy benchmarks (Bentler & Bonett, 1980; Hu & Bentler, 1999), which recommend to have 5-10 cases/observations per variables. However, since this study is meant to serve as an initial investigation leading to a larger-scale investigation with a more robust sample size, the analysis was performed for exploratory reasons.

All participants confirmed their prior experience to use ChatGPT for academic purposes, including essay writing assistance, idea generator, and interactive discussion support. Regarding the frequency of usage, 42.37% of participants reported frequent use, while 47.46% indicated they utilized the tool occasionally. Infrequent users comprised 8.47% of the sample, with 1.69% reporting rare use. These findings suggested that majority of the samples are active users of ChatGPT for academic purposes.

3.2. Instrument

The questionnaire comprises several key dimensions (Figure 2) derived from Behavioural Reasoning Theory (BRT) and Theory of Planned Behaviour (TPB). The first dimension, reasons for, includes a series of statements that assess motivational factors that encourage ChatGPT use among students. This dimension explores various aspects such as its ability to provide instant answers, facilitate critical thinking, and offer 24/7 availability for academic inquiries. Meanwhile, reasons against identifies ethical concerns and potential drawbacks associated with ChatGPT's usage. This dimension probes issues such as risk of plagiarism, potentials for fostering dependency, and concerns about academic dishonesty.

Figure 2
The Theoretical Construct



The third dimension, attitude towards behaviour, is further divided into two subcategories: behavioural beliefs and outcome beliefs (Ajzen, 1991). It is further proposed that behavioural beliefs assess students' general attitudes regarding ChatGPT, including feelings of enjoyment and usefulness as well as apprehensions associated with its use for academic tasks. In contrast, outcome beliefs evaluate the perceived benefits resulting from using ChatGPT, such as its role in enhancing writing quality, aiding idea formulation, and serving as a conversational partner for academic discussions. Other models of technology integration called these as attitudes and perceived usefulness (Davis, 1989; Teo & Jarupunphol, 2015) or performance expectancy (Dwivedi et al., 2019; Venkatesh et al., 2002).

Subjective norms capture the influence of external opinions and societal pressures on students' decision-making (Ajzen, 1991; Venkatesh et al., 2003). This includes perceptions shaped by media narratives, faculty recommendations, and institutional policies concerning AI tool usage. Meanwhile, perceived behavioural control evaluates students' confidence in their ability to effectively use ChatGPT. It examines various factors such as access to technology, understanding of the application, and institutional permissions that may foster or hinder their use of the tool. Finally, intention directly assesses students' plans to use the tool for academic purposes (Ajzen, 1991; Davis, 1989; Fishbein & Ajzen, 1975; Venkatesh et al., 2003). This includes their willingness to rely on the tool for assignments, essay writing, and academic conversations.

3.3. Model Reliability and Validity

The assessment of reliability and validity among the constructs (Appendix) reveals notable results that require attention. Although most constructs demonstrate acceptable composite reliability, the generally low Average Variance Extracted (AVE) values raise concerns about convergent validity. These issues may originate from low-loading items identified in the confirmatory factor analysis (CFA) results and necessitate the revision or removal of problematic indicators.

Composite reliability (CR) values offer mixed results. According to Hair et al. (2019), CR values above 0.70 indicate satisfactory internal consistency. In this analysis, reason for (CR = 0.541) falls significantly short of this threshold. Conversely, reason against (CR = 0.774) meets the criteria, along with behavioural beliefs (CR =

0.749), outcome beliefs (CR = 0.780), subjective norms (CR = 0.723), perceived behavioural Control (CR = 0.768), and intention to Use (CR = 0.810), all of which satisfy or exceed the 0.70 benchmark.

The AVE values primarily highlight significant challenges in convergent validity. The threshold of 0.50, as recommended by Hair (2014). Fornell and Larcker (1981), delineates adequate convergent validity, yet only behavioural beliefs (AVE = 0.599) surpass this criterion. All other constructs, including reason for (AVE = 0.285), reason against (AVE = 0.368), outcome beliefs (AVE = 0.419), subjective norms (AVE = 0.473), perceived behavioural control (AVE = 0.455), and intention to use (AVE = 0.466), fall below the acceptable threshold, indicating that the measurement items inadequately capture the variance of their latent constructs.

Cronbach's alpha values generally corroborate the CR findings, with most constructs meeting or approaching the recommended threshold of 0.70 (Hair, 2014). Reason for exhibits the lowest reliability (α = 0.552), reinforcing concerns about its measurement adequacy. The remaining constructs show marginal to moderate internal consistency: reason against (α = 0.508), behavioural beliefs (α = 0.608), outcome beliefs (α = 0.573), subjective norms (α = 0.652), perceived behavioural control (α = 0.583), and intention to Use (α = 0.578), though some values are just below ideal levels.

4. RESULTS AND DISCUSSION

4.1. Measurement Model

As one of the stages of measuring optimum construct comparable to the data, confirmatory factor analysis was conducted resulting among others on analysis of reliability and validity. It is part of the stages structural equation modelling (Blunch, 2008; Collier, 2020) to gain model fit. The results of first analysis (figure 3) revealed several indicators with factor loadings below the acceptable threshold of 0.50, necessitating their removal from the model to enhance construct validity and reliability. Specifically, those showing inadequate contributions were from the variables of reason for: items RF3 (0.193), RF2 (0.298), RF6 (0.344), RF5 (0.437), RA5 (0.276) from reason against, and BB4 (–0.021) and BB5 (0.374) from behavioral beliefs dimensions. Similar results were suggested by the contstruct of outcome beliefs: OB3 (0.427), SN3 (0.413), SN4 (0.429) from subjective norms, and PBC5 (0.272) from perceived behavioral control. In contrast, the remaining items across these constructs as shown by figure 4 demonstrated sufficient loadings, indicating acceptable measurement models, particularly within the Intention construct, where all items fell within acceptable ranges. These results offer sufficient foundation upon subsequent data analysis of structural model to investigate model fit and correlation among dimensions in the construct.

Figure 3
Original Measurement Model

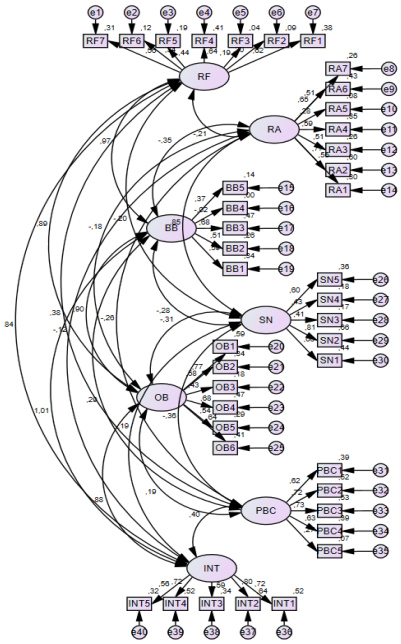
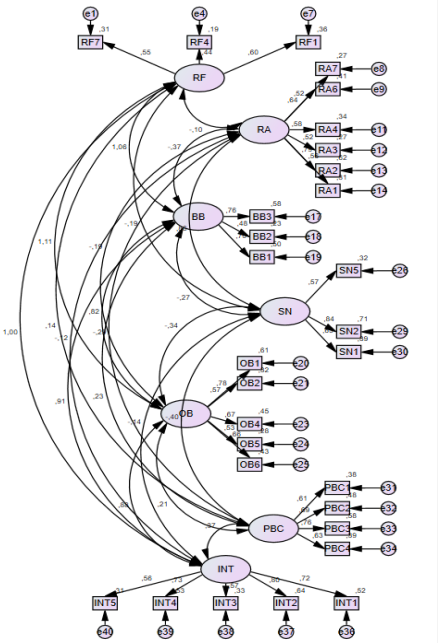


Figure 4
Modified Measurement Model



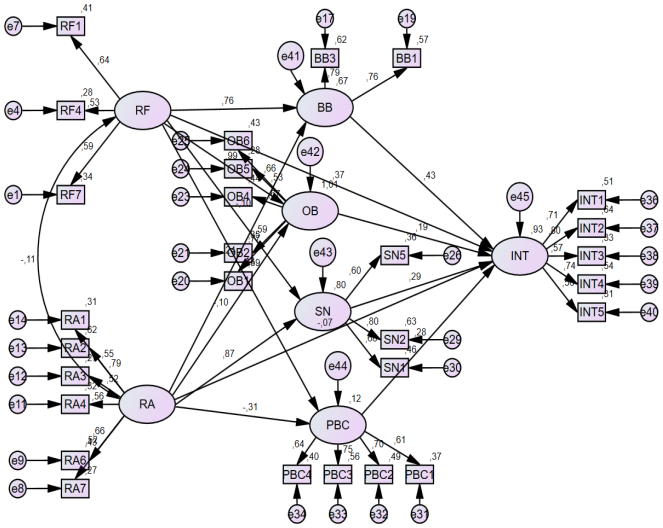
RF: Reason For, RA: Reason Against, BB: Behavioural Beliefs, OB: Outcome Beliefs,
SN: Subjective Norms, PBC: Perceived Behavioural Control, INT: Intention

4.2. Model Fit Analysis

As optimum measures of loading factors were gained, a structural model analysis was conducted exhibiting some indices of poor and acceptable fit to observed data (Figure 5). The model estimation resulted in a chi-square (χ^2) value of 481.370 with 339 degrees of freedom, indicating a statistically significant outcome ($p < .001$). A significant chi-square typically suggests a discrepancy between the model and the data; this result is probably caused by sensitivity to sample sizes (Hair, 2014; Hu & Bentler, 1999). However, this result should not be relied upon as the sole indicator of model fit, requiring alternative fit indices are considered (Collier, 2020; Maruyama, 1997).

Figure 5

The Structural Model



Model complexity and overall moderate fit was identified. The degrees of freedom (df = 339) indicate a balance of estimated parameters against the distinct sample moments. The Chi-square/df ratio of 1.420 is notably below the acceptable threshold of 2.0, suggesting an overall moderate fit of the model to the data (Hu & Bentler, 1999). However, other fit indices present a mixed picture. The Root Mean Square Residual (RMR) of 0.069 is acceptable but does not meet the ideal threshold of 0.05, indicating room for improvement in the model's suitability. Additionally, the Goodness-of-Fit Index (GFI) of 0.662 and the Adjusted Goodness-of-Fit Index (AGFI) of 0.595 fall significantly below the 0.90 cutoff, hinting at a less than adequate fit (Collier, 2020). These results serve as a baseline of model identification, informing that the proposed model could process the data resulting in measures of model notes. As a starting point, it indicates feasibility to proceed to next stages of the statistical analysis and for future development research of this model.

The Parsimonious Goodness-of-Fit Index (PGFI) of 0.553 suggests a moderate fit relative to the model's complexity. The comparative fit indices, however, paint a more favourable yet still inadequate picture, with the Incremental Fit Index (IFI) at 0.790 and the Comparative Fit Index (CFI) at 0.777, both below the 0.90 benchmark (Hu & Bentler, 1999). Lastly, the RMSEA at 0.085, along with a confidence interval exceeding the acceptable threshold, indicates that some misfit persists within the model (Collier, 2020). Consequently, the implication drawn from these findings is that the model cannot conclusively depict an ideal-good fit for the data. Although the model exhibits some level of fit based on certain indices, it falls short on some accepted benchmarks, signaling that modifications, re-specifications, and refinement may be necessary in incoming studies for more reliable and accurate insights (Perry et al., 2015; Peugh & Feldon, 2020).

4.3. Correlation Analysis

The structural model analysis proceeded to observe correlations among variables (table 1). The path analysis portrays dynamics between motivational drivers (as shown by items of reason for dimension) and ethical considerations (as indicated by items of reason against). Dimension of reason for had a substantial impact on both behavioral beliefs ($\beta = .757$, $p < .001$) and outcome beliefs ($\beta = .991$, $p < .001$). This finding highlights that students' motivation drives (variable of reasons for) to use ChatGPT significantly enhance their behavioural beliefs and outcome beliefs. However, it is notable that variable of reason for did not exhibit a significant relationship with subjective norms ($\beta = –.104$, $p = .394$) or perceived behavioral control ($\beta = .130$, $p = .412$), suggesting that

while motivation play a pivotal role in shaping students' beliefs in the usefulness and evaluations of ChatGPT, it does not directly affect perceived social expectations. This result confirms the recommendation of behaviour reasoning theory (Westaby, 2005) proposing ones' motivational drives to affect their perception of usefulness and positive evaluation towards technology use.

These results confirm some findings of previous studies of behavior prediction as suggested by technology acceptance model (Davis, 1989) by positing that users' beliefs of technology usefulness and ease of use are affected by external variables. For instance, Teo & Jarupunphol (2015) introduced an attachment variable, while Abdullah & Ward (2016) included self-efficacy, enjoyment, and experience. Furthermore, Fathema et al. (2015) enhanced the model by adding perceived self-efficacy and facilitating conditions. Huang & Teo (2020) further extended the model to incorporate users' perceptions of policy, teachers' constructivist beliefs, and subjective norms. Moreover, in the light of unified theory of acceptance and use of technology (Venkatesh et al., 2003) as later development of TAM, these results add empirical evidence of necessary modification of user belief assessment by adding external variables, as also suggested by behavior reasoning theory (Kwon & Silva, 2020; Westaby, 2005).

Table 1

Correlation Analysis

Hypotheses			Est	S.E.	P	Label
Reason For	→	Behavioural Beliefs	.757	.181	***	Significant
Reason For	→	Outcome Beliefs	.991	.248	***	Significant
Reason For	→	Social Norms	-.104	.145	.394	Not Significant
Reason For	→	Perceived Behavioural Control	.130	.132	.412	Not Significant
Reason Against	→	Behavioural Beliefs	-.243	.183	.111	Not Significant
Reason Against	→	Outcome Beliefs	-.097	.198	.471	Not Significant
Reason Against	→	Subjective Norms	.875	.271	***	Significant
Reason Against	→	Perceived Behavioural Control	-.309	.166	.076	Not Significant
Behavioural Beliefs	→	Intention	.426	.304	.132	Not Significant
Perceived Behavioural Control	→	Intention	.277	.163	.022	Significant
Subjective Norms	→	Intention	.292	.355	.437	Not Significant
Outcome Beliefs	→	Intention	.193	5.831	.977	Not Significant
Reason For	→	Intention	.366	7.231	.954	Not Significant
Reason Against	→	Intention	-.066	,898	.924	Not Significant

Meanwhile, variables of reason against, which reflect students' ethical and normative concerns, emerged as a significant predictor of subjective norms ($\beta = .875$, $p < .001$). This indicates that ethics-related apprehensions are closely tied to perceived social judgments and peer influence. This result is in line with Rua et al. (2024) suggesting correlation between ethical decisions and social influences. Moreover, this adds to empirical evidence on the role of ethical consideration of generative AI. This is in relation with the fact that previous model of technology acceptance and readiness such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003) nor theories of behaviour prediction such as TRA (Fishbein & Ajzen, 1975) or TPB (Ajzen, 1991) did not include this variable. Meanwhile, ethical concerns did not have a significant impact on behavioural beliefs ($\beta = –.243$, $p = .111$), nor outcome beliefs ($\beta = –.097$, $p = .471$), nor perceived behavioural control ($\beta = –.309$, $p = .076$). The results suggest that while students recognize specific ethical issues associated with the utilization of ChatGPT, their belief systems—especially in relation to their perceived usefulness, their positive evaluation, and their perceived supporting control over ChatGPT use—continue to be significant. In other words, ethical concerns over this gerenative AI does not likely affect their beliefs on these dimensions. This implies different findings compared to the argument that ethical concerns are strongly correlated with variables of perceived literacy (Wang et al., 2025), leading to an urgent need for scrutinizing its ethical use (Alberth, 2023; Baskara & Mukarto, 2023).

Examination of predictors directly influencing the intention to use ChatGPT, only perceived behavioural control demonstrated a statistically significant relationship ($\beta = .277$, $p = .022$). Ajzen (2002) states that this dimension is a fundamental construct in the Theory of Planned Behaviour (TPB), acting as a mediator that influences intention and actual behaviour. This finding is supported by research demonstrating the importance of self-efficacy in technology adoption (Afari et al., 2023; Bandura, 1991). Therefore, educators and developers should focus on creating user-friendly interfaces and providing adequate training to enhance students' perceived control over technology usage.

Other constructs, including behavioural beliefs ($\beta = .426$, $p = .132$), subjective norms ($\beta = .292$, $p = .437$), and outcome beliefs ($\beta = .193$, $p = .977$), did not gain direct significant paths toward intention to use ChatGPT. Furthermore, neither reason for ($\beta = .366$, $p = .954$) nor reason against ($\beta = –.066$, $p = .924$) had a significant direct effect on intention, suggesting that possible influence could be mediated through other belief constructs. This mirrors findings in the literature on ChatGPT behavioral studies where other variables such as perceived usefulness

(Ebadi & Raygan, 2023; Ma et al., 2025), perceived usefulness and perceived ease of use (Hussain et al., 2025; Yan et al., 2024) pose mediating effects of behavioral intention. More empirical data are required to explore how these variables correlate directly and indirectly.

4.4. Squared Multiple Regression

The results of squared multiple regression offer crucial insights into the predictive capabilities of the model representation in respect to empirical data in the context (table 2). The R^2 value for the intention to use ChatGPT is notably high at .932, indicating that approximately 93.2% of the variance in students' intentions is explained by the model. This suggests a robust collective influence of these constructs, underscoring the effectiveness of the extended TPB in capturing the determinants of beliefs on AI technology adoption. Despite admittance that this study was constrained by limited number of participants, previous studies of technology intention substantiate the critical roles of belief system dimensions (Alhamami, 2018; Smarkola, 2008; Teo, 2009).

Table 2
Results of Squared Multiple Regression

Dimensions	Estimate
Perceived Behavioural Control	.12
Subjective Norms	.79
Outcome Beliefs	1.01
Behavioural Beliefs	.67
Intention	.93

The outcome beliefs demonstrated the highest variance at 1.013, which raises concerns about potential model overfitting or estimation errors. It might be caused by limited number of samples in this study or response bias caused by self-evaluation of beliefs. Subjective norms also presented a substantial R^2 of .796, highlighting a significant impact of social influences accounted for by the reason for and reason against constructs. Behavioural beliefs and perceived behavioural control yielded R^2 values of .672 and .121, respectively. These reveal that while the model and data could explain students' evaluative beliefs toward ChatGPT, more investigation is required to disclose perceptions of ease or control in utilizing the tool. This suggests the possibility of additional unmeasured external factors influencing this dimension, such as access, digital literacy, and institutional policies (Wang et al., 2025).

These results of R^2 values underscore the explanatory power of the integrated model in delineating key belief and intention constructs. However, they reveal areas for potential refinement, particularly concerning perceived behavioural control. These findings substantiate the theoretical assertion that both motivational factors and ethical considerations intricately shape students' attitudes and intentions regarding the use of generative AI in educational contexts. This study was bound into limitation of respondent numbers resulting in several areas that lack of explanatory power. Revisions of instrument items will be conducted along with comparative study of structural covariance analysis with larger number of respondents in the subsequent study.

5. CONCLUSIONS AND SUGGESTIONS

This research offers an initial investigation of a construct combining variables of pre-service teacher belief system to predict their intention to use ChatGPT for academic purposes. The results of validity and reliability measures in general resulted in moderate acceptability as further supported by measurement model assessment. Through stages of confirmatory factor analysis, the model had resulted in its generally acceptable measures, as confirmed by the results of model fit analysis, despite limitation of participant samples. These combined results along with path analysis gains implied intricate interaction between motivational, beliefs, and ethical variables of in shaping behavioural intentions toward ChatGPT use.

The results offer possible areas for model improvement, especially maximizing the validity and reliability of the instruments along with examination of correlation between belief and intention to use ChatGPT. These align with the theoretical perspective that both motivational factors and ethical issues play intricate yet important roles in influencing student attitudes and intentions toward the use of generative AI in educational environments. Moreover, these preliminary results offer valuable insights for educators and policymakers seeking to promote the effective and responsible integration of AI tools in higher education.

6. LIMITATIONS

Some unsatisfactory measures obtained in this study might be correlated with insufficient numbers of respondents for advanced Multivariate Analysis, however initial data on validity and reliability measures have been gained. Secondly, the self-reported data collection method could introduce biases in investigating real use of ChatGPT.

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8. APPENDIX

Validity and Reliability Analysis

Variable/Items			Loading	CR	AVE	Mean	S DEV	Cronbach Alpha
Reason For				.541	.285	3.04	.552	
RF	→	RF7	.551					.749
RF	→	RF4	.441					.830
RF	→	RF1	.598					.721
Reason Against				.774	.368	3.20	.508	
RA	→	RA7	.519					.817
RA	→	RA6	.638					.868
RA	→	RA4	.580					.696
RA	→	RA3	.518					.786
RA	→	RA2	.787					.655
RA	→	RA1	.557					.653
Behavioural Beliefs				.749	.599	2.80	.608	
BB	→	BB3	.803					.629
BB	→	BB1	.744					.733
Outcome Beliefs				.780	.419	2.99	.573	
OB	→	OB1	.778					.753
OB	→	OB2	.570					.865
OB	→	OB4	.668					.651
OB	→	OB5	.533					.707
OB	→	OB6	.660					.730
Subjective Norms				.723	.473	2.76	.652	
SN	→	SN5	.566					.710
SN	→	SN2	.844					.863
SN	→	SN1	.622					.915
Perceived Behavioural Control				.768	.455	3.30	.583	
PBC	→	PBC1	.603					.622
PBC	→	PBC2	.682					.774
PBC	→	PBC3	.764					.851
PBC	→	PBC4	.638					.784
Intention to Use				.810	466	2.83	.578	
INT	→	INT1	.714					.744
INT	→	INT2	.797					.689
INT	→	INT3	.573					.799
INT	→	INT4	.737					.831
INT	→	INT5	.558					.860