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Acceptance of ChatGPT by Students in Academic Assessment

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Abstract

The development of artificial intelligence technology, particularly ChatGPT, has changed the way students complete academic assignments. This study aims to analyze the factors that influence students' intention to use ChatGPT for academic assessment using the extended Unified Theory of Acceptance and Use of Technology (UTAUT) model approach. This study uses a quantitative approach with a cross-sectional design and Structural Equation Modeling (SEM-PLS) method. The model was developed by adding three external variables, namely Moral Obligation (MO), Trust (TR), and Perceived Risk (PR). The results of the analysis show that Trust, Performance Expectancy, and Effort Expectancy have a significant effect on students' Behavioral Intention in using ChatGPT. Meanwhile, the influence of Moral Obligation, Perceived Risk, and Social Influence tends to be weak and marginal. This model successfully explains 67.5% of the variance in students' behavioral intentions, with Trust as the most dominant factor. This research provides important insights for the development of policies on the ethical use of AI in higher education settings as well as for technology developers in increasing user trust and comfort with ChatGPT.

Keywords: *ChatGPT, college students, behavioral intention, academic assessment, UTAUT*

1. Introduction

In recent years, the development of artificial intelligence (AI) technology has brought significant changes in various sectors, including higher education. One prominent AI innovation is ChatGPT, a language model capable of producing text similar to human writing. ChatGPT has been used in various educational applications, such as assisting students in computer programming and numerical methods. However, its use has also raised concerns regarding accuracy and potential misuse in academic tasks, especially in technical subjects such as math.

In Indonesia, the adoption of AI technology in education still faces various challenges. Although specific data regarding the use of ChatGPT by Indonesian students is not yet available, global trends show an increasing adoption of AI in education. For example, a survey in the United States between March and April 2023 showed that 58% of college students admitted to using ChatGPT, with 38% of them using without permission from the instructor. This data indicates the need for a deeper understanding of the factors that influence students' adoption of Chat GPT.

To analyze the acceptance of new technologies such as Chat GPT, one model that is often used is the Unified Theory of Acceptance and Use of Technology (UTAUT). This model evaluates user intention and behavior in adopting new technology based on factors such as performance expectancy, effort expectancy, social influence, and facility conditions. Several studies have developed the UTAUT model by adding variables such as online social support, self-efficacy, and perceived playfulness to understand technology adoption in an educational context.

UTAUT was first used by Venkatesh et al. in 2003 with a study that focused on technology adoption in an organizational context, specifically to understand the factors that influence employee intention and behavior in using new technology in the workplace. In its development, UTAUT has experienced several types of trends since its first use. Here are some of the main trends of UTAUT over time: In 2003 to 2010, UTAUT was widely used in organizational contexts to understand how technology adoption in the workplace. The main focus was on information and communication technology (ICT) used by employees. From 2010 to 2020 the use of UTAUT began to expand to various sectors, including education, healthcare, and e-commerce. Then in 2020 until now and with the development of more sophisticated technology, UTAUT is often used in terms of evaluating technology acceptance, especially in the context of digital education and AI-based technology. The main focus of UTAUT from evaluating technology acceptance is now to understand how technology can improve user experience and outcomes.

In the context of using ChatGPT to support academic assessment, it is important to explore the factors that influence students' intention to adopt this technology. Factors such as trust in the technology, moral obligation, and perceived risk may play an important role in students' decision to use ChatGPT. By understanding these factors, educational institutions can design effective strategies to integrate AI technologies in the learning and assessment process, and overcome potential challenges that may arise.

2. Literature review

2.1 UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of the latest technology acceptance models developed by Venkatesh, et al. in 2003. This method combines the successful features of eight technology acceptance theories into one theory (I Gusti Nyoman Sedana & St. Wisnu Wijaya, n.d.). The eight theories combined include Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM-TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) (Venkatesh et al., 2003). After evaluation, Venkatesh et al. found that seven components appear to be significant direct determinants of behavioral intention or use behavior in one or more of the models. The intended components are performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology, and self-efficacy. After further testing, four main components were found to have an important role as a direct determinant of behavioral intention and use behavior, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions. In addition, there are four moderators, namely gender, age, voluntariness, and experience which are positioned to moderate the impact of the four main components.

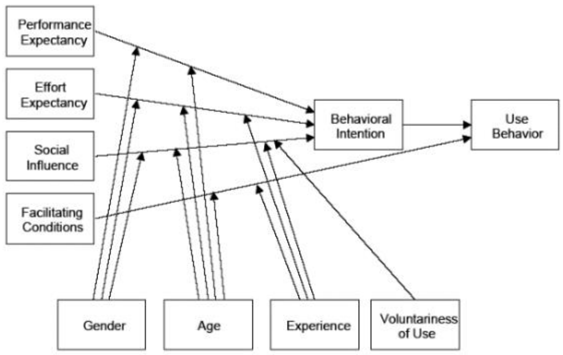

Fig 1: UTAUT Model Framework

Figure 1 shows that the performance expectancy factor is one of the important elements used to assess the extent to which a person believes that the use of information technology can improve their performance. This factor is strongly influenced by moderators such as gender and age of users. Meanwhile, effort expectancy relates to how easily a person can use information technology, which directly affects their comfort in completing tasks. This factor is also influenced by moderators such as gender, age, and user experience. In the context of social influence, a person's level of trust in using implemented information technology is strongly influenced by the surrounding environment. This factor has a close relationship with moderators such as gender, age, experience, and the level of user volunteerism. Meanwhile, facility conditions are used to measure how a person's level of trust can be influenced by existing organization and infrastructure. The availability of these facilities plays an important role in facilitating the use of applied information technology. This factor is also related to moderators such as age and user experience (Aprianto, 2022).

2.2 ChatGPT

Chat GPT (Generative Pre-trained Transformer) is a product developed by Open AI in 2018 and released to the public in 2022. GPT itself is a language model with a transformer architecture that can generate text similar to natural human language (Meilinaeka, 2024). The system used in GPT is trained using a large-scale database to later create a system with human-like language. GPT utilizes AI (artificial intelligence) in its utilization. This allows GPT to provide well-structured answers, and use words precisely and carefully. The way GPT chat works includes three steps. According to Amala et al, some of the important stages in the use of GPT chat are pre-processing, encoding, and decoding. Pre-processing is an important first step, where the text is cleaned of unnecessary characters and expressed in a machine-processable format. After that, in the encoding stage, the cleaned text is converted into a mathematical representation so that it can be understood by the machine learning model. Next, the parsing stage occurs when Chat GPT generates responses that are relevant to the question or query posed. This parsing process utilizes neural network models to predict the most appropriate words to use as responses (Wibowo, 2023).

3. Hypothesis Development

3.1 Moral Obligation (MO)

MO is defined as a personal obligation to perform or refrain from performing a specific task. According to previous research, when people engage in non-ethical behaviors, they are influenced not only by external social pressure but also internal MO and responsibility. Existing research has shown that MO is a significant finding of BI and that one can influence MO when they engage in non-ethical activities such as digital work. Individuals with high moral and ethical standards are not allowed to participate in opportunity-based research. The use of ChatGPT in research procedures raises awareness about the accuracy and accessibility of articles, which in turn raises issues related to academic integrity. As LLM is taught through online texts with multiple sources, it is now debatable whether ChatGPT results are entirely original or consist only of paraphrasing sources without appropriate citations. Based on this viewpoint, some universities have specifically condemned the use of AI-powered chatbots to detect plagiarism (Lai & Cheung, 2023). Given the unresolved ethical issues regarding the use of ChatGPT, students may feel embarrassed if they use it. ChatGPT to help them with their research. In this study, MO focuses on college students' perceptions of their willingness to use ChatGPT to improve their communication skills. Therefore, the following relationships are hypothesized:

H1. Moral obligation has a negative impact on college students' willingness to use ChatGPT to enhance their learning.

3.2 Trust (TR)

TR is defined as students' understanding of integrity, aptitude, and responsibility as well as technological advancement. It relates to a person's willingness to gain vulnerability based on a positive perspective about themselves or others in an environment that has a high risk of dependency. The level of confidence of decisions taken by actors about behavior is enhanced by competence (Cheung & Lai, 2022).
TR is identified as one of the factors influencing technology adoption by university students. shows that when users are dissatisfied with the system, their level of trust in the system is crucial in their decision to adopt e-learning. In the context of ChatGPT, Jo (2023) conducted a questionnaire survey among university students and identified trust as an important component of the benefits of ChatGPT for its users in general. When students believe that the knowledge and benefits of using ChatGPT outweigh their actual abilities, they have a greater desire to use it in an academic setting. The level of trust in the use of ChatGPT among Bangladeshi university students. They concluded that trust serves as a moderating factor affecting the relationship between enjoyment in use and attitude with respect to the use of ChatGPT for learning, which then suggests them to use BI by utilizing it. However, the lack of confidence in the use of ChatGPT for support analysis remains a literature phenomenon. In this study, TR focuses on students' understanding of ChatGPT's reliability and trustworthiness to strengthen their assessment. In line with previous research, we hypothesize that since users' perception of TR is an important component of ChatGPT usability for assessment, we state the following hypothesis:

H2. Positive trust has a positive impact on college students' willingness to use ChatGPT to enhance their research.

3.3 Perceived Risk (PR)

PR is defined as an individual's perception of the consequences and impacts associated with a particular action. Provides a more detailed definition of PR as a way for people to understand the potential for success when using certain technologies to produce desired outcomes. PR arises when a person is in a situation where there are unfavorable consequences or possible negative outcomes due to a significant or unexpected decision. Previous research shows that data privacy and security reduce users' motivation, which negatively impacts their ability to continue using the service (Cheng & Jiang, 2020). For example, that the greater the risk of using a new technology, the less people are willing to use it. Albayati (2024) has shown that privacy and security concerns have a positive impact on trust, which serves as a significant predictor of student behavior when using ChatGPT as a regulatory tool. The results showed that the PR associated with purchasing pirated software had no impact on consumers' willingness to pay for legal alternatives. The results suggest that consumers may have a tendency to believe that they are not at risk of significant harm and loss. ChatGPT has successfully implemented easy-to-read and interactive content (Lai & Cheung, 2023). Recent research has consistently highlighted the limitations of ChatGPT in producing literature analysis with theoretical frameworks, fictitious and non-existent references. In academic papers and theses, AI-chatbots have been shown to frequently replace author names with corresponding research titles and relevant journals. The inappropriate use of fake references by students makes them vulnerable to grade penalties in their own assessments.
In this study, we define PR as an individual's perception of the uncertainty, seriousness, and potential losses (including personal ones) associated with using ChatGPT for assessment. We explained that the PR of ChatGPT encourages students to use it for educational purposes. Therefore, the following relationship is hypothesized:

H3. The risk being discussed has a negative impact on students' willingness to use ChatGPT for assessment.

PR is an important component of the trust model as trust can aid individual risk assessment (Cheung & Lai, 2022). A number of studies have examined the relationship between risk and trust in the context of technology. (Albayati, 2024). In the context of internet technology, it describes TR as a non-linear precursor to BI through PR. Based on these studies, we hypothesize that college students' trust in ChatGPT may affect their PR and make them less trustworthy when using ChatGPT for communication purposes. For this reason, the following hypothesis is proposed:

H4. The discussed risks impact the relationship between students' trust and willingness to use ChatGPT for communication during the investigation.

3.4 Performance Expectancy (PE)

Previous research has consistently shown PE as a strong incentive from BI to use educational technology. PE has a positive correlation with the use of ChatGPT among university students. However, there are criticisms regarding generalizability and genuine insights that are not supported by ChatGPT. If students see its responses as general concepts without regard to domain of expertise, they may be inclined to use it in their research. In this study, PE addressed individual beliefs regarding the use of ChatGPT for support assessment. We provided PE students to the functions of ChatGPT, such as increasing productivity, improving learning efficiency, and using it to improve academic performance, which positively impacted BI's ability to use it in research. Therefore, we hypothesize as follows:

H5. The work environment has a positive impact on masters' willingness to use ChatGPT as an assessment support.

3.5 Effort Expectancy (EE)

EE refers to “the degree of ease associated with using the system.” In the early days of technology use, the degree of ease significantly affects acceptance performance (Cimperman). In this study, we define EE as the energy required to learn how to use ChatGPT and interact with it to enhance learning. Previous research in education has shown that students' increased energy levels encourage them to use ChatGPT in an academic setting. Nonetheless, Habibi et al.'s (2023) study failed to show a significant relationship between EE and the use of ChatGPT for learning in higher education. Following most of the previous studies, we assume that EE is a strong motivator for BIs to use ChatGPT as an assessment support. Thus, we formulate the following hypothesis:

H6. The business perspective has a positive impact on masters' willingness to use ChatGPT as an assessment support.

3.6 Social Influence (SI)

SI describes "the extent to which a person believes that other people are important enough to believe that I need to use a new system". SI has been repeatedly identified as an important factor in the adoption of e-learning technologies among university students. In the context of ChatGPT, SI has demonstrated a high level of prediction accuracy for the general use of ChatGPT in the context of higher education. In this study, SI examined how individuals send important messages to others, such as school-related themes, themes, and instructions, and concluded that they should use ChatGPT to facilitate communication. We believe that if there are other important reasons why students should use ChatGPT, they will be more likely to do so. For this reason, we propose the following hypothesis:

H7. Social influence has a positive impact on students' ability to use ChatGPT as an assessment tool.

3.7 Behavioral Intention (BI)

BI is a measure of one's readiness to carry out a particular task. Numerous studies support the idea that BI maintains an important role in daily operations. According to this study, BI encourages students to use ChatGPT for support research. It is one of the endogenous variables in the model that is determined by other endogenous variables.

4. Research methods

4.1 Research Design

This study used a quantitative approach with a cross sectional design to investigate the acceptance of ChatGPT in student assessment based on the adapted Unified Theory of Acceptance and Use of Technology (UTAUT) model. The UTAUT 1 model was adapted by adding Moral Obligation (MO), Trust (TR), and Perceived Risk (PR) variables to analyze behavioral intention (BI) in the use of ChatGPT for student assessment. A cross-sectional design was chosen as it allows data collection at one specific point in time from the target population, which in this context is defined as the blind population i.e., university students in Indonesia who use ChatGPT for academic assessment with no known total population size.

4.2 Population and Sample

The population of this study is active university students in Surabaya who are involved in academic activities and have experience using ChatGPT. Given that this population is widespread in various educational institutions in Indonesia and no official data is available on the total number of students who meet these criteria, this study adopts a blind population approach. This approach is applied when the population size cannot be determined explicitly due to the absence of accurate demographic information or limited access to data. To ensure the relevance of the respondents, this study used non-probability sampling techniques, specifically purposive sampling, which allows for the selection of respondents based on specific criteria. The inclusion criteria included: (1) active university students in Surabaya, (2) having at least one experience using ChatGPT for academic assessment, and (3) willing to participate in the online survey.

The sample size was determined using Lemeshow's method, which is suitable for calculating the minimum sample in an infinite population as in the case of a blind population. Lemeshow's formula is as follows:

$$n = \frac{Z^2 \cdot p \cdot (1-p)}{d^2}$$

n: Minimum sample size.
Z: Z score according to confidence level, with Z = 1.645 for 90% confidence level.
p: The proportion of the population that has a particular characteristic, assumed to be p = 0.5 to maximize variability when there is no prior estimate.
d: Margin of error, set at 8.31% (d = 0.0831) to generate an appropriate sample size.
The calculation was done as follows:
Z2 = (1.645)2 = 2.706025.
p. (1 - p) = 0.5 . 0.5 = 0.25.
Numerator: 2.706025 . 0.25 = 0.67650625.
Denominator: (0.0831)2 = 0.00690561.
Sample size: n = = 97.96 = 98

Based on these calculations, the minimum sample size required is 98 respondents. This sample is considered adequate for preliminary research with Structural Equation Modeling (SEM) analysis on simple models, although the guidelines of Hair et al. and Bentler & Chou recommend 100-200 respondents for models with seven constructs and 28 items. To overcome the limitation of the relatively small sample size, respondents were selected from various universities in Surabaya to increase representation. This limitation will be discussed further in the research limitations section, with a recommendation to increase the sample size in future studies to strengthen the generalizability of the results.

4.3 Research Instruments

The research instrument was an online questionnaire developed based on previous literature. The questionnaire used a 1-4 Likert scale (1 = strongly disagree, 4 = strongly agree) to measure each construct. The items were organized based on UTAUT 1 constructs (PE, EE, SI) as well as additional constructs (MO, TR, PR) adapted from related studies. The following table details the constructs, measurement items, and their sources:

Table 1: Constructs, Measurement Items, and Sources

Konstruk	Item Pengukuran	Sumber
Performance Expectancy (PE)	1. ChatGPT meningkatkan produktivitas saya dalam menyelesaikan penilaian akademik. 2. ChatGPT membantu saya menyelesaikan tugas penilaian lebih cepat. 3. ChatGPT meningkatkan kualitas hasil penilaian saya.	Lai et al. (2024)
Effort Expectancy (EE)	1. ChatGPT mudah digunakan untuk keperluan penilaian akademik. 2. Saya dapat mempelajari cara menggunakan ChatGPT dengan cepat. 3. Interaksi dengan ChatGPT jelas dan mudah dipahami untuk penilaian.	Lai et al. (2024)
Social Influence (SI)	1. Teman saya merekomendasikan penggunaan ChatGPT untuk penilaian. 2. Dosen saya mendukung penggunaan ChatGPT dalam penilaian akademik. 3. Orang-orang di sekitar saya memengaruhi saya untuk menggunakan ChatGPT.	Lai et al. (2024)
Moral Obligation (MO)	1. Saya merasa tidak etis menggunakan ChatGPT untuk penilaian akademik. 2. Menggunakan ChatGPT bertentangan dengan nilai akademik saya. 3. Saya merasa bersalah jika menggunakan ChatGPT secara berlebihan.	Lai et al. (2024)
Trust (TR)	1. Saya percaya ChatGPT memberikan informasi yang akurat untuk penilaian. 2. Saya merasa ChatGPT dapat diandalkan untuk mendukung penilaian akademik. 3. Saya yakin dengan keamanan data saya saat menggunakan ChatGPT.	Lai et al. (2024)
Perceived Risk (PR)	1. Saya khawatir penggunaan ChatGPT dianggap sebagai plagiarisme. 2. Saya takut mendapat penalti akademik karena menggunakan ChatGPT. 3. Saya merasa penggunaan ChatGPT berisiko terhadap privasi saya.	Cheng & Jiang (2020); Lai et al. (2024)
Behavioral Intention (BI)	1. Saya berniat menggunakan ChatGPT untuk penilaian di masa depan. 2. Saya akan merekomendasikan ChatGPT kepada teman untuk penilaian akademik. 3. Saya berencana terus menggunakan ChatGPT dalam tugas penilaian.	Lai et al. (2024)

4.4 Data Analysis

Data were analyzed using Structural Equation Modeling (SEM) with AMOS software to test the relationship between variables. Analysis steps included:

1. Convergent validity was measured using (Average Variance Extracted - AVE with a minimum threshold of > 0.5) to ensure that each construct is adequately explained by its measurement items. Internal reliability is tested with (Composite Reliability - CR with CR > 0.7 criteria) to ensure consistency between items within each construct.
2. Multicollinearity Test, To ensure that there is no excessive correlation between independent variables that can distort SEM results, the Variance Inflation Factor (VIF) test is performed. A VIF value of <5 is considered an indicator that multicollinearity is not a significant problem in the model. This step is important in the context of a blind population, where the data distribution may not be completely homogeneous due to non-probability sampling techniques.

3. Goodness of fit (GOF) test with criteria:
   1. Chi-Square/Degrees of Freedom (CMIN/DF) < 3, which indicates the fit of the model to the data without overfit.
   2. Goodness of Fit Index (GFI) > 0.9, which indicates the proportion of variance explained by the model.
   3. Comparative Fit Index (CFI) > 0.9, which evaluates the fit relative to the base model.
   4. Root Mean Square Error of Approximation (RMSEA) < 0.08, which reflects the level of approximation error in the population (Hu & Bentler, 1999).
4. Hypothesis Testing, relationships between constructs are tested using path estimation in SEM, with the level of statistical significance set at $p < 0.05$. Path coefficients were analyzed to determine the strength and direction of influence of each independent variable.

5. Result and Discussion

5.1. Demographic Analysis

Table 2: Demographic Profile of Participants (N = 98)

Variabel	N	%
	Gender	
Laki-laki	31	31.63%
Perempuan	67	68.37%
	Usia	
18 - 20 tahun	56	57.14%
21 - 23 tahun	38	38.78%
24 -26 tahun	5	4.08%
	Tingkat Pendidikan	
D4	5	5.1%
S1	93	94.90%

The demographic profile of the participants is shown in Table 2 The findings indicate that the majority of the participants were female 68.37%, while males amounted to 31.63%, reflecting the higher participation of female students in this study. In terms of age, most participants were aged 18-20 years (57.14%), followed by the 21-23 years age group (38.78%), and the rest were in the 24-26 years age range (4.08%). This shows that the majority of respondents are in the early to mid-graduate education age. Regarding education level, almost all respondents were undergraduate students (S1) at 94.90%, while Diploma 4 (D4) students only accounted for 5.1%. This finding shows that this study is dominated by undergraduate students.

Table 3: Confirmatory Factor Analysis Results (N = 98)

Variabel	Indikator	Factor Loading	AVE	CR	Cronbach Alpha
Performance Expectancy	PE1	0.831	0.648	0.880	0.819
	PE2	0.773			
	PE3	0.819			
	PE4	0.795			
Effort Expectancy	EE1	0.726	0.572	0.842	0.752
	EE2	0.788			
	EE3	0.768			
	EE4	0.742			
Social Influence	SI1	0.854	0.637	0.875	0.808
	SI2	0.849			
	SI3	0.772			
	SI4	0.710			
Moral Obligation	MO1	0.759	0.595	0.854	0.779
	MO2	0.864			
	MO3	0.726			
	MO4	0.729			
Trust	TR1	0.875	0.772	0.931	0.899
	TR2	0.871			
	TR3	0.973			
	TR4	0.787			
Perceived Risk	PR1	0.992	0.904	0.974	0.964

	PR2	0.992			
	PR3	0.927			
	PR4	0.888			
Behavioral Intention	BI1	0.884	0.748	0.922	0.887
	BI2	0.845			
	BI3	0.897			
	BI4	0.832			

Based on the results of confirmatory factor analysis (CFA) in table 3 with 98 respondents, all variables in the model show good validity and reliability. The factor loading value for each indicator is above 0.7 (except for some close to 0.7 such as MO3 and MO4), which means that each indicator is strong enough to represent its construct. All AVE (Average Variance Extracted) values are above 0.5, indicating convergent validity is met, and the CR (Composite Reliability) and Cronbach's Alpha values for all variables are also above 0.7, indicating high internal consistency and reliability. Overall, these results indicate that the instruments used in this study are feasible and reliable for measuring each of the constructs in the ChatGPT acceptance model by university students.

Table 4: Discriminant Validity of Measurement Models

	BI	EE	MO	PE	PR	SI	TR
BI							
EE	0.775						
MO	0.270	0.282					
PE	0.797	0.939	0.344				
PR	0.249	0.326	0.722	0.413			
SI	0.606	0.478	0.146	0.662	0.083		
TR	0.832	0.660	0.265	0.674	0.225	0.483	

Based on Table 4 regarding discriminant validity, it can be concluded that most of the constructs in the model have met the criteria for discriminant validity. This is indicated by the correlation value between constructs that is lower than the square root AVE value (shown on the diagonal, such as BI = 0.884, EE = 0.775, etc.). For example, the correlation values between BI and other constructs such as EE (0.775) and TR (0.832) are still below the threshold indicating a clear separation between constructs. However, some correlation values such as between PE and EE (0.939) are quite high and close to 1, which could indicate a potential overlap problem between constructs, so it needs to be further examined whether the two constructs are really conceptually independent. In general, the model shows fairly good discriminant validity, although there are some pairs of variables whose correlations need to be watched out for.

Table 5: Hypothesis Results

	Original Sample (O)	Sample Mean(M)	Standart Deviation(STDEV)	T Statistics (|o/STDEV|)	P Values
PE-> BI	0.210	0.208	0.096	2.18	0.029
EE->BI	0.208	0.205	0.095	2.19	0.028
TR->PR	-0.211	-0.217	0.098	2.155	0.031
MO->BI	0.167	0.165	0.085	1.96	0.050
PR->BI	0.151	0.148	0.077	1.96	0.050
SI->BI	0.152	0.151	0.073	2.084	0.037
TR->BI	0.459	0.455	0.067	6.825	0.000

The hypothesis test results in Table 5 show that the research results have a significant impact on the expected results, as indicated by the T-Statistics value ≥ 1.96 and P-Value ≤ 0.05. The significance of the PE→BI, EE→BI, MO→BI, PR→BI, SI→BI, and TR→PR paths indicates that perceived ease of use, efficiency, motivation, risk, social impact, and trust are important factors that influence users' behavioral intention or risk perception. The TR→BI path may indicate the strongest influence with the highest T value (6.825), indicating that trust is a key factor in determining performance and determining behavioral intentions.

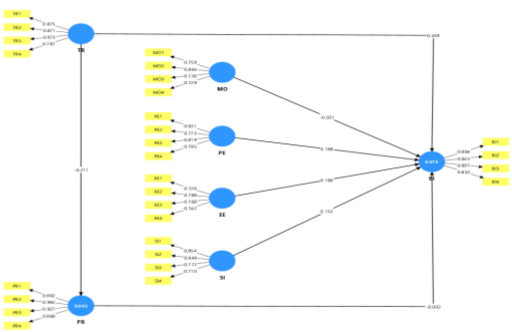

Fig 2: Analysis Results

The structural model of Partial Least Squares (PLS) analysis results in Figure 2 shows the relationship between latent constructs and their indicators. Each indicator has an outer loading value above 0.70, which indicates that each indicator has a significant contribution to the indicator construct and meets the convergence validation criteria. Effort Expectancy (EE), Motivation (MO), Performance Expectancy (PE), Perceived Risk (PR), Social Influence (SI), and Trust (TR) are exogenous constructs that explain 67.5% of the variance in Behavioral Intention (BI), according to the coefficient of determination (R2) value for BI, which is about 0.675. This suggests that the model has a high degree of predictability with respect to user actions.

In addition, the Perceived Risk (PR) construct has an R2 value of about 0.045 compared to the Trust (TR) construct, which means that only 4.5% of the PR variation can be explained by TR, indicating a stronger relationship between the two constructs. In terms of path coefficient, the TR → BI path has the highest coefficient (0.459) and is significant, indicating that the level of user trust is very important in using a system or technology. In contrast, the paths PR → BI (-0.002) and MO → BI (-0.031) show a negative correlation with a very small coefficient of determination, indicating a low and insignificant contribution to BI. This is also supported by the p-value, which shows no significant change (<0.05). Thus, the results of the analysis provide insight into the main factors influencing work intensity, where trust is the most important construct, while discussed risk and motivation do not contribute significantly to the analyzed model.

6. Conclusion

This study aims to analyze student acceptance of the use of ChatGPT in academic assessment using an extended UTAUT model, including the variables Moral Obligation (MO), Trust (TR), and Perceived Risk (PR). With 98 respondents and analysis using SEM-PLS, the results show that Trust is the most dominant factor influencing students' Behavioral Intention (BI) in using ChatGPT. In addition, Performance Expectancy (PE) and Effort Expectancy (EE) also have a significant effect on BI, indicating that benefits and ease of use are the main reasons for students to adopt ChatGPT. In contrast, Perceived Risk, Moral Obligation, and Social Influence have a weaker effect, indicating that the decision to use ChatGPT is personal and not heavily influenced by social pressure or ethical considerations. The model explained 67.5% of the variance in BI, and all constructs were valid and reliable. These findings strengthen the UTAUT model and provide insights for educational institutions to encourage ethical, safe, and beneficial use of ChatGPT in an academic context.

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