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Analyzing Students' Attitude Towards AutoCAD Software using Technology Acceptance Model

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Abstract
Integrating computer-aided design (CAD) tools, such as AutoCAD, in architecture and engineering education becomes increasingly vital in equipping students with essential design skills. Using the Technology Acceptance Model (TAM) as the theoretical framework, this study aims to understand what factors influence the students' perception and attitude toward using the software. With regard to this, an online survey was conducted with the use of a Google Forms questionnaire from 213 engineering and architecture students from different universities in Mindanao. Partial Least Squares Path Modeling (PLS-PM), or Structural Equation Modeling (PLS-SEM), was utilized to examine the data. The findings reveal there is a significant relationship between PU to Attitude towards AutoCAD with a coefficient of 0.325 ($T = 4.522$, $P < 0.001$). Similarly, the path between the PEU and Attitude towards AutoCAD has a coefficient of 0.316, which also exhibits a positive relationship. Furthermore, the findings do not support a positive relationship between PF and Attitude towards AutoCAD. With this, it is observed that TAM is a strong predictor for students' attitudes toward technology, specifically AutoCAD.

Keywords: AutoCAD Software, Technology Acceptance Model (TAM), Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Familiarity (PF), Partial Least Squares Path Modeling (PLS-PM), Attitude Toward AutoCAD.

1. Introduction

Computer-aided drafting has become popular as a replacement for traditional drafting tools due to technological advancements (Ozkan & Yildirim, 2016). With computer-aided design and drafting, manual drafting is replaced with an automated process for design and technical drawing (Lobitos et al., 2023). The integration of computer-aided design (CAD) tools, such as AutoCAD, in architecture and engineering education is becoming increasingly vital for equipping students with essential design skills (Maina, 2018). AutoCAD (Automatic Computer-Aided Designing) is one of the most widely used drawing programs for 2D and 3D drafting and design (Patpatiya et al., 2019). AutoCAD is a professional program used by professionals worldwide, including engineers, architects, designers, and other professionals (Arriagada & Zavala, 2022). Additionally, AutoCAD is a fundamental skill that is necessary to guarantee that students are competent in producing high-quality designs in both engineering and architecture (Lobitos et al., 2023; Yanti & Yeni, 2023) and is utilized by students in these professions as well (Codilla, 2024).

Attitude as a major factor affecting the learning processes may be implicit hence has not attracted enough attention from all stakeholders in education therefore, it is imperative to consider the fact that learners can mainly contribute to their learning outcomes because of their beliefs and perceptions about the subject matter (Quiminsao & Sumalinog, 2023). A learning attitude is a person's willingness and readiness to learn and develop in the learning process (Safitri, et al., 2023). A positive learning attitude is crucial to the learning process because it will make it easier for students to comprehend and master the material they are studying, increase their enthusiasm and motivation to learn, and improve their ability to apply what they have learned in real-world situations. Thus, a learner's learning efficacy and performance can be predicted in several ways by observing and evaluating their attitude toward the learning process.

Findings from the study conducted by Lobitos et al. (2023) reveal that 96% of participants reported having a positive impact from utilizing AutoCAD, highlighting its effectiveness in enhancing technical skills, improving design understanding, and streamlining drafting and modeling processes. Moreover, students expressed that the AutoCAD integration into the curriculum provided valuable hands-on training that will prepare them for the industry's demands. Although the majority of the students found AutoCAD beneficial, a smaller proportion of respondents encountered difficulties with the software, particularly those who were less computer literate or who lacked skilled faculty support. Nonetheless, this study only emphasizes the significant impact of AutoCAD's role for students in engineering and architecture programs in developing design creativity.

This study aims to fill the void and contribute to the understanding of the students' perception about AutoCAD software in the field of education using the framework of the Technology Acceptance Model (TAM). In regards to TAM, it will be helpful in showing how perceived ease of use, perceived usefulness, and perceived familiarity will affect students' attitudes toward using AutoCAD software. In relation to these variables, this study will answer what factors will influence students' willingness to use AutoCAD software. Considering the analysis through the lenses of TAM, this research will provide specific recommendations to educational institutions on effective strategies for software inclusion and improvement of the technology used among their students to suit the requirements of the employment sector.

2. Research Objectives:

a) Assess the validity and reliability of the measurement model to ensure the accuracy and consistency of constructs measuring students' acceptance of AutoCAD software;

b) Determine the direct effects of Technology Acceptance Model (TAM) constructs on students' attitudes towards AutoCAD software, with a focus on how perceived usefulness and perceived ease of use influence their learning engagement and software adoption;
c) Evaluate the overall fit of the hypothesized structural model of students' attitudes towards AutoCAD software to provide insights into key determinants of technology adoption in educational settings, thereby informing instructional design improvements and educational policy development.

3. Literature Review

This study employs the Technology Acceptance Model (TAM) to assess students' attitudes towards AutoCAD by examining their intentions to use the software. According to TAM, technology acceptance is primarily shaped by perceived usefulness (PU) and perceived ease of use (PEOU), both of which significantly impact learning motivation and outcomes (Davis, 1989). In an educational context, PU reflects students' perceptions that learning AutoCAD will enhance their technical skills and improve their employability. PEOU, on the other hand, pertains to students' comfort in using the software and their ability to effectively utilize it (Kumar & Chhabra, 2021). Several factors influence PU and PEOU, including the quality of instruction, software usability, and the complexity of projects students undertake. Baj-Rogowska (2020) also highlighted the role of perceived physical accessibility (PPA), such as the availability of compatible hardware and software, which is particularly relevant in education where institutional resources vary. By considering these factors, TAM provides a useful framework for understanding students' confidence and positive attitudes toward AutoCAD.

To further enhance this analysis, this study also integrates the Unified Theory of Acceptance and Use of Technology (UTAUT), which expands upon TAM by incorporating additional constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Kim, 2014; Ammenwerth, 2019). Performance expectancy aligns closely with PU, as it relates to the degree to which students believe that using AutoCAD will improve their academic and professional outcomes. Effort expectancy is similar to PEOU but considers the ease of learning and mastering AutoCAD beyond initial usability (Ma & Luo, 2022). Social influence plays a significant role in students' adoption of technology, particularly in collaborative learning environments where peers and instructors shape attitudes toward software use. Facilitating conditions, which include access to technical support, institutional resources, and training, directly impact students' ability to effectively engage with AutoCAD (Ammenwerth, 2019).

Integrating UTAUT with TAM provides a more comprehensive perspective on technology adoption by addressing both individual perceptions and external factors. Although TAM remains a foundational model in technology acceptance research, its simplicity has led to criticism for not fully capturing the complexities of adoption in specific contexts (Shachak et al., 2019). By incorporating UTAUT, this study acknowledges the multi-dimensional nature of technology acceptance and adoption, particularly in educational settings where institutional support, social influences, and accessibility play crucial roles. Moreover, while some alternative models, such as the Value-based Adoption Model (VAM), have been found to outperform TAM and UTAUT in specific contexts, particularly in AI-based intelligent products (Sohn & Kwon, 2020), the combination of TAM and UTAUT remains well-suited for assessing students' adoption of AutoCAD in an academic setting.

4. Methodology

A quantitative, non-experimental approach, research design was utilized in the entire study. In the definition by Creswell and Creswell (2023), it was stated that quantitative research design applies experiment and survey procedures to gathering data. Furthermore, predefined tools that generate statistical measurements are used to acquire pieces of data. Moreover, in selecting participants, the researchers employed stratified random sampling to give equal opportunities to individuals and to present the results effectively without bias. Spreading out Google Forms questionnaires was the selected approach to surveying. In estimating complex cause-effect relationships for latent variable route models, partial least squares path modeling (PLS-PM) or structural equation modeling (PLS-SEM) can be utilized (Hair et al.,2017a). Incomparably, PLS-SEM highlights projection in statistical model estimation and deliberates on elucidating causality. Furthermore, this gave the researchers the permit to estimate large models that consist of multiple constructs, indicator variables, and structural paths without the assumption of distributional relationships (Sarstedt et al., 2017a). This data analysis approach is suitable for smaller sizes. Larger sample sizes should be applied whenever viable to infer sample results from the relevant population (Hair et al., 2022b; Kock & Hadaya, 2018).

The researchers used a modified questionnaire in the form of 5-point Likert Scales to collect data. The student's attitude toward the AutoCAD scale (Andrew et al., 2018), the cognitive component scales, the affective component scales, and the behavioral component scales. Additionally, the study included the following scales: perceived utility, perceived ease of use, and perceived familiarity scales. To ensure the validity and reliability of the research instrument, a rigorous validation process was conducted. Content validity was established through expert evaluation, where three subject matter experts in educational technology and engineering design reviewed the instrument for relevance, clarity, and completeness. Their feedback was integrated to refine item wording and alignment with the study's objectives. A pilot test was conducted with 30 students who were not part of the final sample to assess preliminary reliability and validity. Based on their responses, minor modifications were made to improve question clarity.

The study used the 10-times rule to identify the number of participants. This technique is frequently used to find the minimum sample size in PLS-SEM. This method suggests that the sample size should be equivalent to 10 times the number of independent variables in the complex regression in the PLS path model while considering other factors such as measurement and structural model (Hair et al., 2017a). After the appropriate sample size selection process, the researchers selected 200 students, especially engineering and architecture students from different universities in Mindanao, to ensure the accuracy of the results.
Furthermore, the researchers used Cronbach's alpha to compare the amount of shared variance, or covariance, between the scales creating an instrument for the overall variance (Collins, 2007). The study made use of Average Variance Extracted (AVE) to assess the convergent validity of the structural model. To evaluate the discriminant validity of the structural model, the researchers used the Hetero-Monotrait Ratio (HTMT) (Henseler et al., 2015). Additionally, the researchers used the Variance Inflation Factor (VIF) to measure the collinearity between different variables. For structural model design, the researchers utilized the SmartPLS 4.0 and Jamovi software, using the features of the software to acquire the necessary data for the study.

5. Results and Discussion

The most common measurements used to determine internal consistency are Cronbach's Alpha and Composite Reliability. The interrelationship of the variables is measured using these two measurements (Taber, 2017). Table 1 shows the reliability of the instruments used in the research. In evaluating the reliability of the methods used, it is determined that Cronbach's

Alpha and the Composite reliability have both exceeded the threshold of 0.70. Cronbach's alpha values for the questionnaire are as follows: 0.875 for Affective Components (AC), 0.934 for Behavioral Components (BC), 0.786 for Cognitive Components (CC), 0.771 for Perceived Ease of Use (PEU), 0.872 for Perceived Familiarity (PF), and 0.912 for Perceived Usefulness (PU). While for Composite Reliability (ρ_a) values for the questionnaire are: 0.922 for AC, 0.939 for BC, 0.816 for CC, 0.835 for PEU, 0.961 for PF, and 0.917 for PU. These values have exceeded the threshold of 0.60 to 0.70 demonstrating an excellent internal consistency reliability (Hair, Hult, et al., 2014). For more advanced stages, it is recommended that the values should be more than 0.70 (Hair et al, 2014). Moreover, Sarstedt et al. (2016) stated that higher composite reliability values ensure measurement precision while avoiding redundancy. Average Variance Extracted (AVE) was used in examining the instruments' convergent validity. Convergent validity is the measurement of the level of agreement about the relationship of several measures of the same concept (Taber, 2017). The AVE values shown in Table 1 are as follows: AC (0.571), BC (0.934), CC(0.786), PEU(0.771), PF(0.871), and PU(0.912). These values show that the AVE of the indicators has exceeded 0.50 as a threshold value. The 0.50 value is considered to be an acceptable value when assessing the instruments' convergent validity. Fornell and Larcker (1981) state that if the AVE value exceeds 0.50 for all measures, the construct indicators explained more than half of the variance.

Table 1: Construct Reliability and Variability

	Cronbach's Alpha	**Composite Reliability (rho_a)**	**Composite Reliability (rho_c)**	**Average Variance Extracted (AVE)**
Affective Component	0.875	0.922	0.902	0.571
Behavioral Component	0.934	0.939	0.944	0.628
Cognitive Component	0.786	0.816	0.872	0.694
Perceived Ease of Use	0.771	0.835	0.864	0.679
Perceived Familiarity	0.872	0.961	0.905	0.705
Perceived Usefulness	0.912	0.917	0.938	0.790

The evaluation of HTMT results is based on how the different variables discriminate against each other empirically (Henseler et al., 2015). From the table below, the result shows the values of HTMT ratios between AC and Attitude (0.884), Attitude and BC (0.480), BC and CC (0.716), CC and PEU (0.490), PEU and PF (0.813), PF and PU (0.575), AC and BC (0.762), Attitude and CC (0.514), BC and PEU (0.723), CC and PF (0.459), PEU and PU (0.745), AC and CC (0.773), Attitude and PEU (0.583), BC and PF (0.636), CC and PU (0.695), AC and PEU (0.793), Attitude and PF (0.379), BC and PU (0.817), AC and PF (0.548), Attitude and PU (0.562), AC and PU (0.802). From the results presented, it is evident that there is a significant discriminant validity with all the HTMT values below the threshold of 0.90 (Kline, 2011). Furthermore, Gold et al., 2001 recommended a value of 0.90 as the threshold of discriminant validity. The result displayed that the highest HTMT ratio was between AC (Affective Component) and Attitude with 0.884. Meanwhile, the lowest link was between Attitude and PF (Perceived Familiarity) with 0.379. HTMT ratios closer to the threshold value of 0.90 indicate that the variables lack discriminant validity toward each other (Roemer et al., 2021).

Table 2: HTMT (Heterotrait-Monotrait Ratio)

	Affective Component	**Attitude**	**Behavioral Component**	**Cognitive Component**	**Perceived Ease of Use**	**Perceived Familiarity**	**Perceived Usefulness**
Affective Component							
Attitude	0.884						
Behavioral Component	0.762	0.480					
Cognitive Component	0.773	0.514	0.716				
Perceived Ease of Use	0.793	0.583	0.723	0.490			
Perceived Familiarity	0.548	0.379	0.636	0.459	0.813		
Perceived Usefulness	0.802	0.562	0.817	0.695	0.745	0.575	

Before evaluating the structural relationships, it is necessary to guarantee that it does not introduce any bias into the regression results; thus, there is a need to investigate the collinearity. Hair et al. (2019), state that variance inflation factor (VIF) values that are greater than five may indicate probable collinearity issues among the predictor constructs. However, collinearity issues can also occur at lower VIF values ranging from three to five (Mason & Perreault, 1991; Becker et al., 2014). Thus the VIF values should ideally be less than or close to three.
The effect size f-square in the table clarifies the strength of relationships in the structural model, based on Hair et al. (2021). An f^2 value above 0.35 indicates a large effect, between 0.15 and 0.35 a medium effect, and between 0.02 and 0.15 a small effect (Cohen, 1988).

The results show mixed data on the factors affecting attitude. Perceived Usefulness (PU) has a small effect size ($f^2 = 0.095$) and Perceived Ease of Use (PEU) has an even smaller effect ($f^2 = 0.068$). In contrast, Perceived Functionality (PF) shows no effect ($f^2 = 0.000$). These findings align with Chin (1998), who noted that not all predictors have equal influence. While PU and PEU play a role in shaping attitudes, their impact is secondary to other factors. The lack of effect from PF suggests the need for further investigation into its relevance.
Gefen et al. (2000) recommend exploring alternative model configurations in structural equation modeling (SEM) to identify missing determinants that could explain the outcomes.

These findings enhance our understanding of SEM and illustrate the subtle differences between causes and results.

Table 3: Variance Inflation Factor and Effective Size

	VIF	f-square
Attitude -> Affective Components	1.000	3.325
Attitude -> Behavioral Components	1.000	0.291
Attitude -> Cognitive COmponents	1.000	0.290
Perceived Ease of Use -> Attitude	2.286	0.068
Perceived Familiarity -> Attitude	1.840	0.000
Perceived Usefulness -> Attitude	1.732	0.095

Assessment of the Structural Model

Examining the path of PU (Perceived Usefulness) to Attitude towards AutoCAD, the coefficient of 0.325 indicates a positive relationship, which suggests that as the student's perceived utility increases, the attitude also becomes more favorable. The statistical analysis reveals there is a significant connection ($T = 4.522$, $P < 0.001$). Similarly, the path between the PEU (Perceived Ease of Use)and Attitude towards AutoCAD has a coefficient of 0.316, which exhibits a positive relationship. This implies that higher levels of Perceived Ease of Use are associated with the Attitude towards AutoCAD. This relationship is highly significant ($T = 3.853$, $P < 0.001$), indicating its substantial impact.

The findings are in line with the assertions made by Wicaksono & Maharani (2020), who stated that PU and PEU are factors that can affect Behavioural Intention (BI) in the Technology Acceptance Model (TAM). With further examination, it is pointed out that PU is a primary factor and PEU is a major secondary determining factor, which is found to be good determining factors towards student's adoption of e-learning technologies (Pituch & Lee, 2006; Davis, et al., 1989) and had a significant impact on student's intentions and attitude towards the use of online learning technologies (Lee, et al., 2005; Liao, et al., 2022).

However, the path from the Perceived Familiarity to Attitude towards AutoCAD demonstrates weaker relationships, as shown in their p-value ($P = 0.752$). This suggests that the Perceived Familiarity conditions do not strongly influence the Attitude towards AutoCAD.

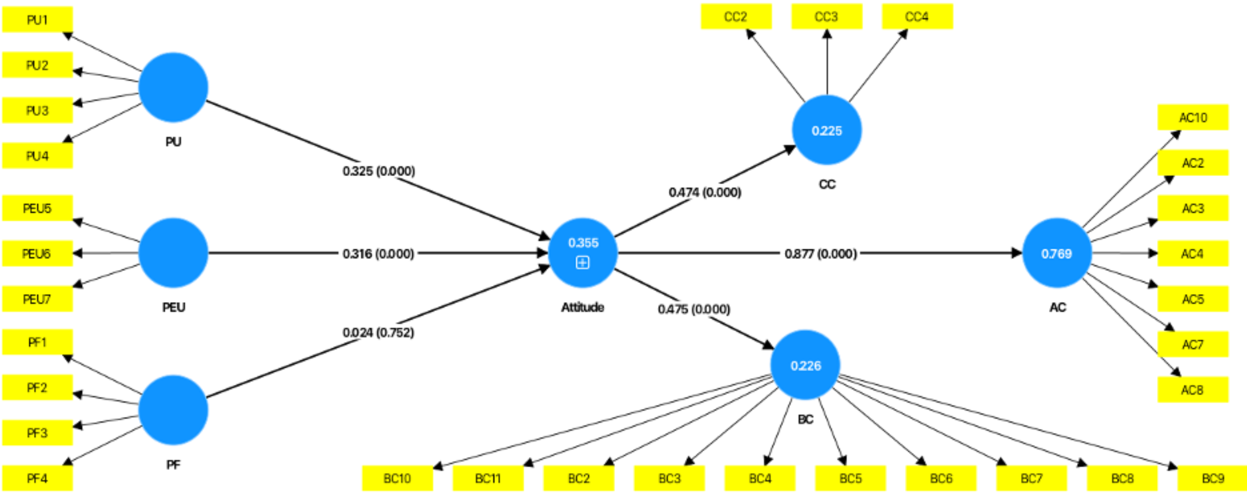

Figure 1: Structural Model

The table below presents different statistical measures utilized in the study to assess the structural equation model (SEM) that concentrates on analyzing the university students' attitudes toward AutoCad software using the Technology Acceptance Model. The table presents the R-square values, R-square adjusted values, Q² predict, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) for the component Attitude. The statistical measures R-squared and adjusted R-squared are frequently utilized to assess model fit. However, it might overestimate predictive performance because of overfitting (Chen & Qi, 2023). Moreover, RMSE and MAE are used in performance metrics (Shanmugavalli & Ignatia, 2023; Zamani et al., 2023; Hardini et al., 2023). Meanwhile, the Q² value compares the error of prediction of the PLS path model against simple mean predictions (Hair et al., 2022). In addition, a Q² value larger than zero implies that the model has predictive relevance.

On the R-squared and adjusted R-squared table, the former holds the value of 0.355, indicating that approximately 35.5% of the variation in the dependent variable can be determined by the independent variable Attitude. In addition, the R-squared value indicates that Attitude moderately influences the outcome variable. However, this further implies that a significant portion of 64.5% of the variation in the results remained undetermined by this variable alone. On the other hand, the adjusted R-squared records a value of 0.346 which is quite lesser than the R-squared, implying that the model is moderately parsimonious and does not overfit the data. This supports Ursava's (2013) description of TAM, which states that the model mentioned is robust and parsimonious. This also reinforces King and He's (2006) statement that TAM consistently exhibits a good model fit for analyzing attitudes toward educational technologies in various studies, with PEU and PU as the key factors. Furthermore, TAM's relevance expands to different types of users, such as students and professionals, making it a versatile tool for technology acceptance studies. Furthermore, the component Attitude under Q² Predict is 0.337, displaying a moderate predictive performance. Moreover, the RMSE holds a value of 0.822, indicating a moderate error degree in predicting the Attitude variable. The MAE value of 0.652 implies that the model's predictions have moderate prediction accuracy.

The Standardized Root Mean Square Residual (SRMR) is a fit indication utilized in structural equation modeling (SEM) to evaluate model fit. It is strong for estimation methods, which need different cutoff values for distinct estimators (Shi & Maydeu-Olivares, 2020). Furthermore, SRMR values that are less than 0.08 are considered good. The SRMR in this study is 0.086 for the saturated model, indicating a good fit. However, the estimated model's

SRMR is 0.192, implying a less good fit. The Unweighted Least Squares Discrepancy (d_ULS) is a discrepancy function wherein the smaller the value, the better the model fit. In this case, the d_ULS is 3.879 for the saturated model, implying a lesser discrepancy. The estimated model's d_ULS is 19.532, displaying a larger discrepancy and implying that the estimated model does not fit well. This shows that the saturated model is significantly a better fit than the estimated model due to its lower SRMR and higher d_ULS values. This further implies that the estimated model might be overfitting the data or may have issues with the model's specifications.

Table 4: Model Fit

Endogenous Variables	**Q^2 Predict**	**RMSE**	**MAE**	**R-Square**	**R-Square Adjusted**
Attitude	0.337	0.822	0.652	0.355	0.346
	Saturated Model	**Estimated Model**			
SRMR	0.086	0.192			
d_ULS	3.879	19.532			

5.1 Theoretical Implications

The Technology Acceptance Model (TAM) has been frequently used to predict students' attitudes and intentions toward technology. By incorporating perceived usefulness (PU), perceived ease of use (PEU), and perceived familiarity (PF) as factors of students' attitudes, this study increases the explanatory power of TAM in the educational setting. Many studies have revealed that perceived usefulness (PU) and perceived ease of use (PEOU) are significant predictors of students' attitudes toward technology (Seyal et al., 2015; Siang & Santoso 2015). These results support Davis' (1989) primary framework, which asserts that PU and PEOU significantly affect user acceptance of technology. However, the results still emphasize the limitation of PF, underlining the need for theoretical re-evaluation or the incorporation of other factors like perceived institutional support or self-efficacy (Geffen et al., 2000). The small effect size of PEU and the non-significant influence of PF interestingly challenge TAM's presumption of uniform construct relevance. This supports Chin's (1998) argument that predictors in structural models are not all influentially equal. The TAM remains a prominent framework for evaluating technology adoption in various contexts, including education (Granić & Marangunić, 2019).

TAM is consistently influenced by its core constructs, perceived usefulness (PU), and perceived ease of use (PEOU)(Rahman, 2018; Dhingra & Mudgal, 2019). PU is a strong predictor of adoption intentions across multiple domains, while PEOU has less impact or context-dependent (Gefen & Straub, 2000). Researchers have explored various ways to enhance TAM's explanatory power. They have suggested incorporating more technology-based variables that align with PU and PEOU definitions (Rahman, 2018). TAM's adaptability allows it to be used for applications in various fields, which include e-commerce, education, and healthcare (Dhingra & Mudgal, 2019). However, despite its widespread use, there is a need for further investigation into the additional factors that could improve TAM's predictive capabilities in specific contexts (Granić & Marangunić, 2019).

While TAM remains a dominant model in technology adoption research, the findings of this study align with critiques that not all TAM constructs exert equal influence (Chin, 1998). Specifically, the small effect size of PEU and the non-significant influence of PF challenge TAM's assumption of uniform construct relevance. This finding echoes prior research suggesting that PU is a more robust predictor of technology adoption than PEU, whose influence can be context-dependent (Gefen & Straub, 2000). Given these limitations, an expansion of the theoretical framework is warranted. The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a broader perspective by incorporating additional determinants of technology adoption, namely performance expectancy, effort expectancy, social influence, and facilitating conditions (Kim, 2014; Ammenwerth, 2019). Unlike TAM, which primarily focuses on individual perceptions of technology, UTAUT accounts for the socio-organizational context, making it particularly relevant in settings where external factors shape adoption behaviors (Ammenwerth, 2019).

The integration of UTAUT into this study's framework would address some of TAM's limitations, particularly by considering social influence and facilitating conditions as moderating factors in students' technology acceptance.

Recent research has demonstrated the effectiveness of combining TAM and UTAUT in understanding technology adoption in specific contexts, such as older adults using medical applications during the COVID-19 pandemic (Ma & Luo, 2022). This integration highlights the importance of attitudes toward technology use, with PU and facilitating conditions emerging as significant predictors of adoption. Applying a similar approach in educational settings could provide a more comprehensive understanding of the factors driving student adoption of technology-based learning tools. Despite the utility of TAM and UTAUT, both models have been criticized for their focus on individual beliefs and behavioral intentions while overlooking more complex, multidimensional influences on technology adoption (Shachak et al., 2019). Comparative studies suggest that alternative models, such as the Value-based Adoption Model (VAM), may offer superior predictive power in certain contexts by incorporating factors like enjoyment and subjective norms (Sohn & Kwon, 2020).

Nevertheless, TAM and UTAUT remain foundational in technology acceptance research, and their integration can enhance explanatory power and applicability across diverse scenarios. The findings of this study have significant implications for curriculum development and instructional methods in engineering and architecture programs. Given the strong internal consistency and validity of the constructs related to students' attitudes toward AutoCAD, educators can leverage these insights to enhance student engagement and learning outcomes. Specifically, curriculum designers may integrate targeted interventions that improve perceived usefulness (PU) and perceived ease of use (PEU), as these were found to be strong predictors of students' attitudes. By embedding hands-on AutoCAD training with industry-relevant applications, instructors can reinforce PU, demonstrating the software's direct applicability to professional practice. Additionally, structured scaffolding techniques and interactive learning modules can be introduced to address PEU, ensuring that students experience a smooth learning curve with the software. Furthermore, since perceived familiarity (PF) showed a weaker influence, educational institutions should explore strategies to provide early exposure to AutoCAD through preparatory workshops or pre-course training modules. These modifications could ultimately lead to increased technology adoption, greater student confidence, and improved learning efficiency in design-related disciplines.

5. Conclusion

The study utilized the Technology Acceptance Model (TAM) to predict students' attitudes toward AutoCAD. Given the result of the study, it is observed that TAM is a strong predictor for students' attitudes toward technology, specifically AutoCAD. Through the analysis of different variables such as perceived usefulness (PU), perceived ease of use (PEU), and perceived familiarity (PF), it is safe to conclude that PU and PEU have a significant impact on student's attitudes toward AutoCAD. However, PF is seen as having no significance in influencing students' attitudes.

Additionally, the results of the study show a good model fit, shown by the statistical measures used. All measures exceeded the 0.70 threshold on Cronbach's Alpha and Composite Reliability which means that there is internal consistency. Moreover, with a value of 0.355 on the R-squared, TAM as a model moderately explained the students' attitude toward AutoCAD, which validates its application in understanding technology acceptance among students.

6. Recommendation

The results emphasize the importance of educational programs for promoting AutoCAD acceptance. Key strategies include establishing trust, raising awareness, and fostering positive social influence. Future research should explore why performance and effort expectancy are not significant factors and how social influence affects technology adoption in education. The link between awareness of AutoCAD and willingness to use it highlights the need for initiatives that improve AutoCAD literacy. This education should cover not only technical skills but also ethical, social, and practical implications. Integrating AutoCAD topics into the curriculum can help foster better understanding and attitudes toward the technology. While trust in AutoCAD influences attitudes, it may not directly lead to usage, indicating that building confidence should address both reliability and students' fears or misconceptions. As AutoCAD becomes central in various fields, teaching students about AutoCAD is essential for their future careers. Proficiency in AutoCAD will be crucial, and early exposure can provide a competitive edge.

7. Limitations and Future Research

This study has several limitations that should be considered. The Technology Acceptance Model (TAM), while useful for explaining technology adoption behaviors, does not account for broader contextual factors such as institutional support, prior digital literacy, or socio-cultural influences, which may also shape students' attitudes toward AutoCAD. Additionally, the insignificant relationship between Perceived Familiarity (PF) and Attitude toward AutoCAD suggests that TAM alone may not fully capture the complexity of students' technology adoption experiences. Future research should consider integrating alternative models like the Unified Theory of Acceptance and Use of Technology (UTAUT) to gain deeper insights. Another limitation is the reliance on self-reported data, which may introduce biases such as social desirability and recall bias, potentially affecting the accuracy of responses. Observational methods or performance-based assessments could provide a more objective measure of students' engagement with AutoCAD. Furthermore, the cross-sectional design of this study does not account for changes in students' attitudes over time. Longitudinal research could offer a clearer understanding of how perceptions and intentions evolve as students gain experience. Expanding the sample size and including students from diverse academic backgrounds and geographic regions would improve the generalizability of findings. Future studies should also integrate advancements in AutoCAD software, explore innovative instructional strategies, and incorporate additional constructs to refine the understanding of technology acceptance in educational settings.

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