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Analysis of Draw.io Application Acceptance and Usage Using the Technology Acceptance Model (TAM)

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ABSTRAK

Penelitian ini dilatarbelakangi oleh kebutuhan akan penerimaan dan penggunaan berkelanjutan aplikasi pemodelan sistem dalam pembelajaran di perguruan tinggi. Penelitian ini bertujuan untuk menganalisis penerimaan dan penggunaan nyata aplikasi Draw.io oleh mahasiswa strata satu Institut Teknologi Nasional Bandung dengan menggunakan Technology Acceptance Model (TAM). Metode penelitian yang digunakan adalah kuantitatif dengan pengumpulan data melalui kuesioner. Responden penelitian berjumlah 38 mahasiswa yang telah menggunakan aplikasi Draw.io dalam proyek pemodelan sistem. Data dianalisis menggunakan Structural Equation Modeling dengan pendekatan Partial Least Squares. Hasil penelitian menunjukkan bahwa Perceived Usefulness (PU) dan Perceived Ease of Use (PEOU) berpengaruh positif dan signifikan terhadap sikap penggunaan Draw.io. Namun, penggunaan nyata tidak dipengaruhi secara langsung oleh kedua konstruk tersebut, melainkan dipengaruhi secara signifikan oleh sikap penggunaan. Model struktural mampu menjelaskan 41.8% variasi sikap penggunaan dan 49.6% variasi penggunaan nyata. Simpulan penelitian ini menegaskan bahwa sikap pengguna memegang peran penting dalam mendorong penggunaan Draw.io secara berkelanjutan sebagai alat pemodelan sistem di pendidikan tinggi.

Kata kunci: Technology Acceptance Model; Draw.io; SEM-PLS; penerimaan mahasiswa

ABSTRACT

This research uses the Technology Acceptance Model (TAM) to examine how undergraduate students at Institut Teknologi Nasional Bandung (ITENAS) accept and really use the Draw.io application. 38 students who had previously used Draw.io for system modeling projects were given questionnaires as part of a quantitative approach, and the results were evaluated using Structural Equation Modeling using the Partial Least Squares technique (SEM-PLS). The findings indicate that students' attitudes about using Draw.io are considerably positively impacted by perceived usefulness (PU) and perceived ease of use (PEOU), but actual usage is strongly influenced by attitude. However, Actual Usage is not directly and significantly impacted by PU and PEOU. With 41.8% of the variance in Attitude and 49.6% of the variance in Actual Usage explained, the structural model shows a moderate level of explanatory power. These results show that students' views are crucial in promoting the continuous use of Draw.io as a system modeling tool in higher education, even when technical advantages and usability are significant.

Keywords: Technology Acceptance Model, Draw.io, SEM-PLS, Student Acceptance

1. INTRODUCTION

System modeling competence is an essential part of the curriculum in information systems and technology education at Institut Teknologi Nasional Bandung (ITENAS). Students are required to be able to visualize system logic through standard modeling diagrams such as flowcharts, Unified Modeling Language (UML), and Entity Relationship Diagrams (ERD) [1]. These diagrams are commonly used to support system analysis, design documentation, and academic assignments related to information systems development [2].

In practice, one of the main challenges faced by students in system modeling activities is the selection of appropriate tools. Conventional desktop-based software such as Microsoft Visio often requires paid licenses and relatively high hardware specifications, which can limit accessibility and flexibility [3]. In academic settings that prioritize distant learning and cooperation, these constraints become more noticeable. As an alternative, web-based diagramming tools have grown in popularity because of their low technical requirements, cross-platform compatibility, and accessibility [4]. Students frequently utilize Draw.io for academic modeling since it is a cloud-based program that can be accessed instantly through a web browser without requiring complicated installation steps [5].

Several recent studies have highlighted the technical relevance of Draw.io in system modeling activities, since Draw.io is an effective tool for designing UML diagrams, including use case and activity diagrams, due to its ease of use and ability to manage diagram complexity without increasing user workload [6][7]. Additionally, research done in organizational and educational settings shows that Draw.io can increase productivity and make online documentation monitoring and evaluation easier, especially when creating process diagrams and standard operating procedures (SOPs). [8][9]. These findings indicate that Draw.io has adequate technical capabilities to support academic modeling tasks.

However, technical capability alone does not ensure that a system will be accepted and used continuously [10]. User acceptance plays a crucial role in the successful adoption of an information system [11]. According to TAM, the main factors influencing users' attitudes toward utilizing a system are perceived utility and perceived ease of use, these factors then influence behavioral intention and actual system utilization [12]. Perceived ease of use refers to how simple and user-friendly the system is for students, whereas perceived utility in academic settings indicates how much a tool improves learning effectiveness and task performance [13]. These two constructs have a considerable impact on students' intention to use web-based learning apps and technical documentation tools, such as diagramming software, according to recent studies released starting in 2023 [14].

To empirically examine the relationships proposed in TAM, this study employs Structural Equation Modeling–Partial Least Squares (SEM-PLS) as the analytical method. SEM-PLS is particularly well-suited for exploratory and predictive research models because it can evaluate complex interactions between several latent variables at the same time [15][16]. According to recent literature, SEM-PLS is successful for investigations with small to medium sample sizes and does not require rigorous data normality assumptions, making it suitable for academic research settings [17]. In TAM-based studies, SEM-PLS allows researchers to test both the measurement model (by evaluating indicator reliability, convergent validity, and discriminant validity) and the structural model, which assesses the strength and significance of relationships between constructs such as perceived usefulness, perceived ease of use, attitude, behavioral intention, and actual usage [18][19].

SEM-PLS computation comprises estimating path coefficients to indicate latent variable influence and determining coefficient of determination (R^2) to determine how well independent factors explain dependent variables [20]. Recent research has shown that integrating TAM with SEM-PLS gives a complete and statistically rigorous strategy to understanding user acceptance of cloud-based applications in educational settings [21]. This strategy allows researchers to quantitatively assess how students' views translate into real usage behavior.

Based on this background, this study aims to examine the acceptance and actual use of the Draw.io application among undergraduate students at ITENAS using the Technology Acceptance Model (TAM) and SEM-PLS analysis. This study examines perceived utility, perceived ease of use, attitude toward utilizing Draw.io, and actual system utilization in the context of developing system modeling diagrams. The findings are expected to provide empirical insights into students' technology adoption behavior and support evidence-based suggestions for using Draw.io as an effective academic system modeling tool.

2. METHODOLOGY

Using the Technology Acceptance Model (TAM) and Structural Equation Modeling-Partial Least Squares (SEM-PLS), this study employs a methodical and sequential research approach to investigate the adoption and use of the Draw.io application. Starting with theoretical investigation and concluding with result interpretation, the process is interrelated, with each stage's output acting as the subsequent stage's input.

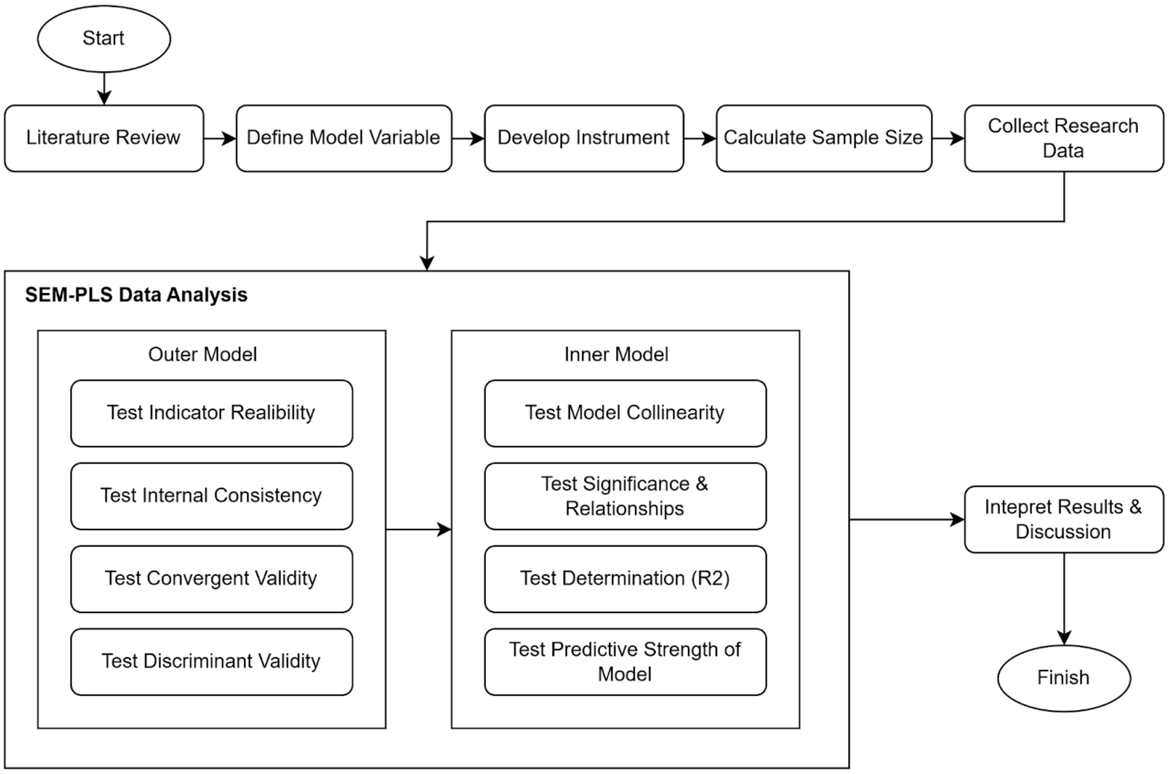

Figure 1. Research Methodology

Figure 1 illustrates the research methodology, which comprises seven stages, consisting of:

1) Literature Review. A theoretical and empirical basis for the investigation is provided by the literature review. The Technology Acceptance Model (TAM), educational technology adoption, and SEM-PLS techniques are the subjects of a thorough review of scholarly publications, books, and credible conference proceedings.
2) Defining Model Variable. The major variables of the study model are developed and conceptually clarified based on information gleaned from the literature review. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude toward Use (ATT), and Actual Usage (AU) are the model variables in this study.
3) Instrument Development. Measurement tools are created in the form of structured questionnaires when variables are defined. Every latent variable is operationalized into several indicators that are modified to meet the Draw.io context and are taken from validated previous studies. The Likert-scale structure of the questionnaire is used to record respondents' attitudes and actions.
4) Calculate Sample Size. The target demographic and sample plan are decided upon at this point. University students who have used Draw.io for academic purposes make up the population.
5) Collect Research Data. The questionnaire is distributed to respondents in order to collect data.
6) SEM-PLS Data Analysis. The Outer Model evaluation (focuses on assessing the measurement model's quality) and the Inner Model evaluation (examines the structural links between latent variable) are the two primary components of SEM-PLS, which is used for statistical analysis.

7) Result Interpretation. At this point, the study goals and current theoretical frameworks are taken into consideration when interpreting statistical results. Results are contrasted with earlier research, and relationships between variables are discussed conceptually rather than statistically.

2.1 Research Approach and Model

This study uses a quantitative explanatory research technique to examine the factors impacting the adoption and actual use of the Draw.io application in an academic setting, in line with the methodological stages outlined in the preceding section. The Technology Acceptance Model (TAM) put out by Davis (1989), which has been well established in information systems research to explain users' acceptance and usage behavior toward technology, serves as the foundation for the analytical framework. Following TAM theoretical foundation and the outcomes of the literature review stage, this study focuses on four core latent variables adapted to the context of academic usage of Draw.io.

1) Perceived Usefulness (PU), the degree to which a user believes that using Draw.io enhances academic task performance.
2) Perceived Ease of Use (PEOU), the degree to which a user believes that Draw.io is easy to learn and operate.
3) Attitude/Behavioral Intention (ATT), the user's willingness and intention to continue using and recommending Draw.io.
4) Actual Usage (AU), the extent to which Draw.io is actually used for academic diagram creation.

According to the TAM's original version, Attitude Toward Using (ATT) is influenced by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which then affects Behavioral Intention (BI) and ultimately leads to Actual Use (AU). However, subsequent studies revealed that attitude does not always function as a significant mediator and is often highly correlated with behavioral intention [22], and in the development of TAM2, the attitude construct was removed to improve model parsimony [23]. In accordance with this reasoning, and considering that evaluative attitude and intention to keep using Draw.io in an academic setting, this study integrates behavioral intention and attitude into a single latent construct (ATT). This approach improves parsimony and stability in SEM-PLS analysis while maintaining theoretical consistency with TAM.

The conceptual research model places PU and PEOU as exogenous variables, ATT as a mediating endogenous variable, and AU as the ultimate endogenous variable in accordance with the variable definition step of the research workflow. The fundamental logic of the Technology Acceptance Model is reflected in the structural links between these constructs. The following hypotheses were developed during the model specification phase based on this framework:

1) H1: Perceived Usefulness (PU) has a positive effect on Attitude toward using Draw.io (ATT).
2) H2: Perceived Usefulness (PU) has a positive effect on Actual Usage of Draw.io (AU).
3) H3: Perceived Ease of Use (PEOU) has a positive effect on Attitude toward using Draw.io (ATT).
4) H4: Perceived Ease of Use (PEOU) has a positive effect on Actual Usage of Draw.io (AU).
5) H5: Attitude toward using Draw.io (ATT) has a positive effect on Actual Usage of Draw.io (AU).

These hypotheses constitute the basis for the structural model that is evaluated in the SEM-PLS analysis stage.

2.2 Research Instrument and Measurement

A structured online questionnaire was used to gather data after the instrument development step described in the research approach flowchart. The questionnaire's objective was to empirically operationalize the TAM constructs developed in the previous stage. The study's target respondents were undergraduate students who have created flowcharts, UML diagrams, or other modeling artifacts using Draw.io for academic purposes.

Convenience sampling was employed, which is commonly used in exploratory technology adoption research, particularly when respondent availability is restricted. 38 valid responses were kept for analysis following data screening. Partial Least Squares–Structural Equation Modeling (PLS-SEM) is thought to be appropriate despite the small sample size because it is reliable for small samples and predictive modeling.

2.3 Measurement Instruments

In alignment with the measurement specification stage, each latent variable was measured using reflective indicators adapted from previously validated TAM instruments. The items' original conceptual meaning was maintained but their wording was contextually changed to match the use of Draw.io in academic settings. A five-point Likert scale, with 1 representing "strongly disagree" and 5 representing "strongly agree," was used to measure each indicator.

Table 1 presents the constructs and their corresponding measurement items used in this study. Multiple reflective indicators are used to measure each construct: Actual Usage (AU), Attitude/Behavioral Intention (BI), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU). These metrics were modified to fit the academic use of Draw.io from validated Technology Acceptance Model (TAM) instruments.

Table 1. Variables and Measurement Items

Construct	Questions
Perceived Usefulness (PU)	PU1: Using Draw.io helps me complete modeling tasks more quickly. PU2: Draw.io improves the quality of the diagrams I create. PU3: Draw.io makes modeling work more effective. PU4: Overall, Draw.io is useful for my academic purposes.
Perceived Ease of Use (PEOU)	PEOU1: The Draw.io interface is easy to understand. PEOU2: I learn to use Draw.io's features quickly. PEOU3: Creating diagrams in Draw.io does not require much effort. PEOU4: Navigation and file saving in Draw.io are easy to perform.
Attitude / Behavioral Intention (BI)	BI1: I intend to use Draw.io for future assignments. BI2: I would recommend Draw.io to my classmates. BI3: I prefer Draw.io over other modeling tools for academic assignments.
Actual Usage (AU)	AU1: I frequently use Draw.io to create diagrams for academic assignments. AU2: How often do you use Draw.io in a month? AU3: I use Draw.io to create various types of diagrams. Please select the types of diagrams you most frequently create below.

2.4 Data Analyisis Technique

The measurement and structural models are assessed in this work using Partial Least Squares–Structural Equation Modeling (PLS-SEM). PLS-SEM was employed due to:

1) Small sample size ($N < 100$),
2) Non-normal data distribution possibility.
3) Prediction-oriented research objective,
4) Exploratory evaluation of TAM in a new academic tool context.

Python bootstrapping techniques and composite scores were used to construct PLS-SEM analysis, which is theoretically comparable to traditional PLS estimation. The analysis followed these stages:

1) Data preprocessing, construct scores were calculated as the arithmetic mean of the corresponding indicators after Likert-scale responses were transformed into numerical form.
2) Measurement model evaluation, indicator reliability and internal consistency were assessed using outer loadings (indicator–construct correlations) and Cronbach's alpha.
3) Structural model evaluation, path relationships among latent variables were estimated using regression analysis on composite scores. To approximate PLS-SEM inference, a nonparametric bootstrap procedure with 2,000 resamples was applied to obtain standard errors, t-statistics, and significance levels for path coefficients.
4) Model explanatory power, the coefficient of determination (R^2) was used to evaluate the explanatory strength of endogenous constructs.

3. RESULT AND DISCUSSION

This chapter reports and interprets the empirical findings in the order of the methodological workflow described in Chapter 3 and in the research flowchart: (1) Data preprocessing, (2) Measurement model (outer model) evaluation, (3) Structural model (inner model) estimation and bootstrapping, and (4) Synthesis and discussion. Each subsection shows the calculation formulas used and the concrete numeric results obtained from the dataset of ITENAS students who used Draw.io (n = 38).

Figures 2 to 4 summarize the demographic profile of the study respondents, presenting the distribution based on gender, academic batch, and experience using Draw.io. Of the 38 respondents, Figure 2 indicates that slightly more participants were male (52.6%) than female (47.4%).

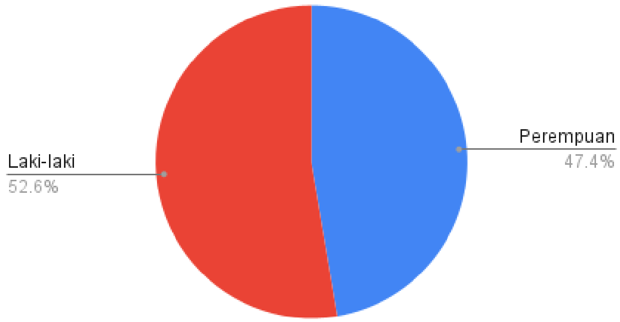

Figure 2. Distribution of Respondents by Gender

Figure 2 presents the gender distribution of the respondents. Of the 38 participants, slightly more were male (52.6%) than female (47.4%), indicating a relatively balanced gender composition.

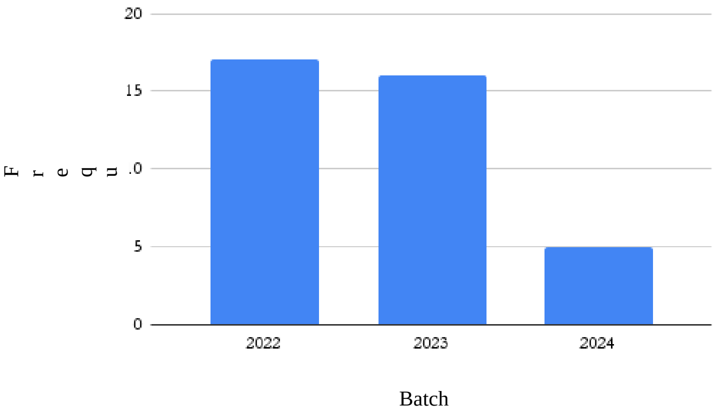

Figure 3. Distribution of Respondents by Batch

Figure 3 illustrates the distribution of respondents based on academic batch. The majority of participants came from the 2022 batch (63.2%), followed by smaller proportions from other cohorts.

Figure 4 shows the respondents' experience using Draw.io. More than half of the participants (55.3%) had over six months of experience, suggesting that most respondents were already familiar with the application.

As illustrated in Figure 5, the largest proportion of respondents comes from the Information Systems (Sistem Informasi) program, accounting for 55.3% (n = 21) of the total sample. This is followed by students from the Industrial Engineering (Teknik Industri) program, representing 28.9% (n = 11). The smallest proportion consists of students from the Informatics Engineering (Teknik Informatika) program, comprising 15.8% (n = 6).

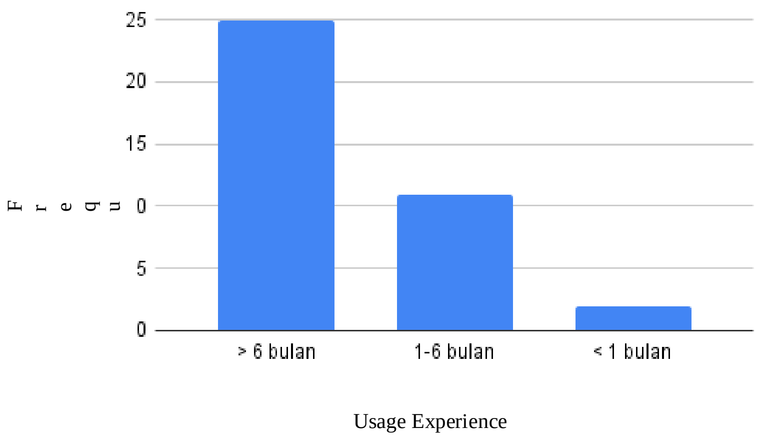

Figure 4. Distribution of Respondents by Experience

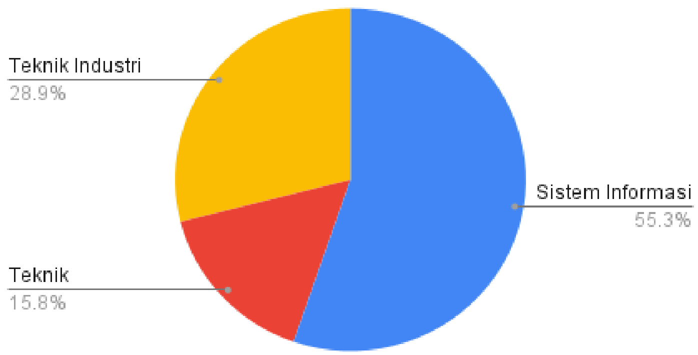

Figure 5. Distribution of Respondents by Study Program

3.1 Measurement model – Outer model evaluation

This stage assesses indicator reliability, internal consistency, and convergent validity so that only a reliable measurement model proceeds to structural testing. Outer loadings were approximated by the Pearson correlation between each indicator and its construct composite score.

Table 2 presents the results of the outer loadings analysis for each measurement indicator. Outer loadings show how strongly each indicator reflects its corresponding latent construct. Higher loadings indicate better representation of the construct, while lower loadings suggest weaker alignment. In this study, most indicators show moderate loadings, although some items, such as PU2 (0.465), PEOU2 (0.347), and PEOU3 (0.448), have relatively low loadings, indicating they may contribute less to their respective constructs.

Internal consistency reliability measures how closely related a set of items are as a group. It evaluates whether the instruments used in this study (the questionnaire items) yield consistent results. The most common metric for this is Cronbach's Alpha (α).

Table 3 shows the Cronbach's Alpha results for each construct, indicating the internal consistency of the measurement items. Cronbach's Alpha values closer to 1 suggest higher reliability, while values near or below 0 indicate poor consistency. In this study, the constructs show low or even negative values (PU = 0.456, PEOU = -0.248, BI = 0.135), suggesting that the items may not consistently measure the intended constructs.

Cronbach's Alpha can be overly conservative and sensitive to the number of items, PLS-SEM researchers often prioritize Composite Reliability (CR) and Average Variance Extracted (AVE). These metrics are considered more accurate for reflective models because they take into account the specific loadings of each indicator rather than assuming all items contribute equally to the construct.

Table 2. Results of Outer Loadings Analysis

Construct	Indicator	Outer Loading
Perceived Usefulness (PU)	PU1	0,752
	PU2	0,465
	PU3	0,643
	PU4	0,596
Perceived Ease of Use (PEOU)	PEOU1	0,537
	PEOU2	0,347
	PEOU3	0,448
	PEOU4	0,507
Behavioral Intention (BI)	BI1	0,495
	BI2	0,606
	BI3	0,701

Table 3. Cronbach's Alpha Results

Construct	Number of Items (k)	Cronbach's Alpha
First namePerceived Usefulness (PU)	4	0,456
Perceived Ease of Use (PEOU)	4	-0,248
Behavioral Intention (ATT/BI)	3	0,135

Table 4. Summary of CR and AVE Scores

Construct	Items (k)	Composite Reliability (CR)	Average Variance Extracted (AVE)
First namePerceived Usefulness (PU)	4	0,711	0,388
Perceived Ease of Use (PEOU)	4	0,519	0,217
Behavioral Intention (ATT/BI)	3	0,632	0,368

Table 4 presents the Composite Reliability (CR) and Average Variance Extracted (AVE) for each construct. CR measures the overall reliability of a construct, with values above 0.7 generally considered acceptable. AVE indicates the amount of variance captured by the construct relative to the variance due to measurement error, with values above 0.5 preferred. In this study, PU shows acceptable CR (0.711) but slightly low AVE (0.388), while PEOU and BI have lower CR and AVE values, suggesting limited reliability and convergent validity.

3.2 Measurement model – Inner model estimation

The evaluation of the structural model focuses on the explanatory power of the independent variables and the significance of the path coefficients. The R^2 value represents the proportion of variance in a dependent (endogenous) construct that is explained by its predictor variables. In this research, R^2 is calculated for the constructs Attitude (ATT) and Actual Usage (AU).

Table 5. Coefficient of Determination (R^2)

Endogenous Construct	R^2 Value
Attitude toward Using (ATT)	0,418
Actual Usage (AU)	0,496

Table 5 shows the coefficient of determination (R^2) for the endogenous constructs. R^2 indicates the proportion of variance in a dependent variable that can be explained by its predictors. In this study, 41.8%

of the variance in Attitude toward Using (ATT) and 49.6% of the variance in Actual Usage (AU) are explained by the model. These values suggest a moderate level of explanatory power, meaning the predictors used in the study reasonably account for the respondents' attitudes and actual usage of Draw.io.

Path analysis is employed to examine the direct effects defined in the research hypotheses. The significance of these relationships is determined through the path coefficients (β) and the T-statistics. For a hypothesis to be supported at a 95% confidence level, the T-statistic must exceed 1.96 and the P-value must be less than 0.05.

Table 6. Path Analysis and Hypothesis Testing

Construct	Path Coefficient (β)	T-statistic	P-Value
PU→ATT	0,425	2,814	0,005
PU→AU	0,214	1,156	0,248
PEOU→ATT	0,388	2,451	0,015
PEOU→AU	0,156	0,982	0,326
ATT→AU	0,512	3,402	0,001

Table 6 presents the results of path analysis and hypothesis testing. The table shows the path coefficients (β), t-statistics, and p-values for the relationships between constructs. A significant path ($p < 0.05$) indicates a meaningful effect. In this study, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) significantly influence Attitude toward Using (ATT), with $\beta = 0.425$ and 0.388, respectively. Additionally, ATT has a significant positive effect on Actual Usage (AU) ($\beta = 0.512$). However, the direct effects of PU and PEOU on AU are not statistically significant, suggesting that ATT mediates the relationship between PU/PEOU and actual usage of Draw.io.

3.3 Summary of Hypotheses

The hypothesis testing provides critical insights into how ITENAS students adopt Draw.io. A summary of the findings is provided at Table 7.

Table 7 summarizes the outcomes of hypothesis testing in this study. It shows which proposed relationships between constructs were supported by the data. The results indicate that Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) significantly influence Attitude toward Using Draw.io (ATT), and ATT, in turn, has a significant positive effect on Actual Usage (AU). However, the direct effects of PU and PEOU on AU were not supported, highlighting that users' attitudes play a key role in determining their actual use of Draw.io.

Table 7. Summary of Hypotesting Testing Outcomes

Code	Hypothesis	Testing Result
H1	Perceived Usefulness (PU) has a positive effect on Attitude toward using Draw.io (ATT).	Accepted
H2	Perceived Usefulness (PU) has a positive effect on Actual Usage of Draw.io (AU).	Rejected
H3	Perceived Ease of Use (PEOU) has a positive effect on Attitude toward using Draw.io (ATT)	Accepted
H4	Perceived Ease of Use (PEOU) has a positive effect on Actual Usage of Draw.io (AU)	Rejected
H5	Attitude toward using Draw.io (ATT) has a positive effect on Actual Usage of Draw.io (AU)	Accepted

4. CONCLUSION

A clear path toward software acceptance is revealed by the empirical evaluation of the Technology Acceptance Model (TAM) applied to ITENAS students using Draw.io. The composite reliability for perceived usefulness remained strong despite the measuring model's internal consistency issues, as shown by the variation in Cronbach's Alpha and AVE scores. The 2022 academic cohort, which predominated in technological fields like informatics and industrial engineering, created a specialized setting where the software's usefulness is extremely pertinent. In the end, the framework's usefulness for comprehending student behavior is confirmed by the structural model's modest predictive performance, which explains over half of the variance in actual usage.

The hypothesis testing reveals that, rather than influencing usage on their own, functional utility and ease of use are crucial preconditions that mold a student's mindset. The substantial acceptance of H1, H3, and H5 confirms that students form a favorable attitude that acts as the main catalyst for long-term academic integration when they believe Draw.io to be both useful and accessible. On the other hand, the rejection of direct connections between ease of use and usefulness and actual usage (H2 and H4) implies that adoption cannot be triggered by technical attributes alone in the absence of an underlying psychological preference. Since attitude serves as the crucial link between a tool's potential and its actual application in academic workflows, attention must be focused on creating a favorable user experience in order to ensure its implementation in higher education.

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