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Analyzing Determinants of E-Government Use Among Students: An Integrated UTAUT and E-Government Adoption Model

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A B S T R A C T S

Digitalization in the education sector, particularly through e-government, is key to enhancing service effectiveness and efficiency in academic information systems. However, the application of this technology often faces challenges in terms of student acceptance, as it is the primary user. Using the Unified Theory of adoption and Use of Technology (UTAUT) and the E-Government Adoption approach, to identify the factors that influence the acceptance of the Academic Information System at Tidar University is the aim of this research. The variables studied include performance expectations, effort expectations, social influence, facilitating conditions, security and privacy risks, and trust in government. This study used quantitative methods and involved 247 active students of the State Administration Study Program as respondents. Data collection was carried out through responses obtained from questionnaires, and then analyzed using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) method. The analysis showed that the utilization of the system was substantially influenced by variables including performance expectancy, social influence, trust in governmental institutions, facilitating conditions, and behavioral intention. Meanwhile, effort expectancy, privacy risk, and security risk have no significant effect. These results verify that the optimal utilization of academic information systems on campus is significantly influenced by performance expectation, social influence, and trust in government.

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1. INTRODUCTION

In the digital era, information systems have become a vital component in the management of organizations across various sectors, including education, government, and business. Information systems are defined as a system comprising technology, human resources, and procedures that work together to gather, process, store, and disseminate information to aid decision-making and facilitate organizational activities [1]. In line with technological developments, information systems in public services have become a key strategy for enhancing the effectiveness and efficiency of bureaucratic operations [2].

Digital transformation has become a top priority in the delivery of public services, including those in the education sector, particularly at universities [3]. Several universities in Indonesia have developed academic information systems as part of the digitization process of lecture services. The implementation of an educational information system is a form of digitization that aims to accelerate, simplify, and increase transparency in lecture administration services, such as the KRS process, access to grades, and management of student academic data. This system aims to provide services effectively and efficiently [4].

Tidar University also develops an academic information system that the serve the entire scholarly community. Students, as the primary users, hold significant importance in the successful implementation of this system. Available technology will not be optimal if it is not accepted and actively utilized by users [5]. Acceptance of this technology is crucial so that digitalization functions as intended. Understanding the elements that drive students' acceptance of the academic information system at the university is therefore vital to ensuring its effective implementation.

Among the various models used to examine the acceptance or adoption of technology, the Unified Theory of Acceptance and Use of Technology (UTAUT) stands out as a widely recognized framework, comprising four primary constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions. Although this model has proven relevant in various contexts, UTAUT still lacks attention to aspects unique to e-government [6]. In the context of e-government services, factors such as data security risk, privacy risk, and trust in the government, specifically the system provider institution, are essential aspects that influence usage intention and behavior [7]. Several studies have demonstrated that users of public digital services consider aspects of security and trust before deciding to actively use the system. However, approaches that specifically combine UTAUT with the e-government adoption framework in the context of academic systems in public universities are still rare.

By integrating two theoretical approaches to technology adoption, namely the UTAUT and e-government adoption, this research offers a novel perspective and enriches the existing body of knowledge, to comprehensively identify the determinants of students' use of academic information systems in public universities. This comprehensive approach, which considers a wide range of factors influencing technology acceptance, provides a more robust and nuanced understanding of the dynamics of technology use in digital public services within the education sector. The findings of this research are therefore reliable and can be used to inform future studies and policy decisions.

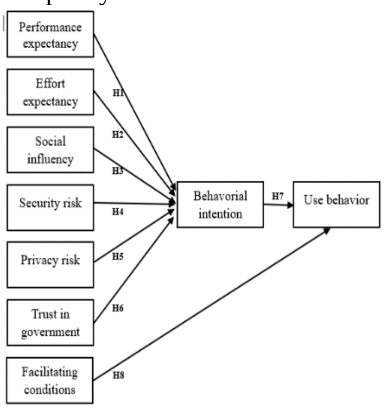

FIG 1. Proposed Structural Model

Based on this, this research seeks to identify the primary factors driving students' behavioral patterns at Tidar University accept and utilize the academic information system by integrating elements from both the UTAUT model and the e-government adoption framework. The outcomes of this study will not only contribute theoretically to the ongoing discourse on technology acceptance but also offer actionable insights for those managing academic information systems in higher education institutions. These insights can guide administrators and policymakers in making informed decisions about the implementation and management of e-government systems, thereby enhancing the efficiency and effectiveness of academic services.

2. RESEARCH METHODOLOGY

An explanatory framework underpins the quantitative method used in this study design to investigate the interrelationships among variables influencing students' acceptance and use of Tidar University's academic information system. The study uses a blended application of the UTAUT and e-government adoption models, which are particularly relevant to implemented through e-government services in the field of education education sector.

The research location is at the Faculty of Social and Political Sciences, Universitas Tidar, Magelang. The study population comprised all active students enrolled in the State Administration Study Program, amounting to 850 individuals. The sample determination was carried out using a proportionate stratified random sampling technique, because the population has diverse characteristics based on class [8]. A 5% margin of error was taken into account using the Slovin formula to determine the appropriate sample size, as follows: $n = N / (1 + N * e^2)$. This calculation yields a total sample size of 247. The second step involves determining the proportional stratified sample using the sample fraction formula $f = n / N$, with *n* denoting the number of samples and *N* indicating the overall population. The outcomes are summarized in the subsequent table.

TABLE 1. Distribution of Samples by Student Batch Year at Tidar University

Batch Year	Sample fraction	Number of sample
2020	45/850*247	13
2021	181/850*247	53
2022	197/850*247	57
2023	183/850*247	53
2024	244/850*247	71
Total		247

Data was gathered via a survey employing a closed questionnaire utilizing a five-point Likert scale. A total of five response choices are offered in the scale, varying from "Strongly Agree" to "Strongly Disagree," assigned values from 5 to 1. The questionnaire was developed utilizing indicators from the UTAUT framework (performance expectancy, effort expectancy, social influence, facilitating conditions), alongside variables related to e-government adoption (security risk, privacy risk, trust in government), as well as behavioral intention and usage behavior variables.

SmartPLS (v4.1.1.2) was employed to analyze the data through the Partial Least Squares Structural Equation Modeling approach. This analytical approach was selected due to its capacity to simultaneously assess relationships among latent variables, even when working with a moderately sized sample. This study has objectives and characteristics that align with the criteria for employing the PLS-SEM method. It is exploratory in nature and to enrich the existing structural theory, focusing on estimating the primary constructs of interest and identifying the key constructs that influence the use of the academic information system [9]. The reflektif constructs in the structural model used in this study are, from a methodological perspective, more appropriately analyzed using PLS-SEM. The complexity of the structural model is also one of the criteria for choosing PLS-SEM. A relatively small sample size is not an issue in PLS-SEM [10]. Considering these factors, PLS-SEM is the most appropriate approach to achieve the objectives of this study.

SmartPLS has the capability to interpreting the intricate relationships among variables and to develop predictive models. The simple interface facilitates the visual design of path models while allowing simultaneous analysis of relationships and interpretation of results, which is one of the software's advantages. These features allowing analyses to be conducted more effectively and efficiently. With the use of SmartPLS, the requirements for data processing in this study can be fully met [11].

The analytical procedure was conducted in two main phases. The initial phase entailed assessing the measurement model (outer model) to ascertain construct validity and reliability through metrics including outer loadings, Average Variance Extracted (AVE), Heterotrait-Monotrait (HTMT) composite reliability, and Cronbach's alpha. Can be stated in the following form [12]:

$$\eta = B\eta + \Gamma\xi + \zeta \quad (1)$$

Description:
η : vector of endogenous latent variables
ξ : vector of exogenous latent variables
B : coefficient matrix for relationships among endogenous latent variables
Γ : coefficient matrix from exogenous latent variables to endogenous latent variables
ζ : measurement error in latent variables
The AVE can be obtained using the following formula [13]:

$$AVE = \left(\frac{\sum_{i=1}^{m} l_i^2}{M}\right) \quad (2)$$

The Composite reliability can be obtained using the following formula [14]:

$$\rho_c = \frac{(\Sigma\lambda)^2}{(\Sigma\lambda)^2 + \Sigma\, var(\varepsilon)} \quad (3)$$

The Cronbach's alpha can be obtained using the following formula:

$$r_{ac} = \left(\frac{k}{k-1}\right)\left[1 - \frac{\sum {\sigma_b}^2}{{\sigma_t}^2}\right] \quad (4)$$

The second phase concentrates on the structural model (inner model) for determining both the intensity and orientation of the interrelationships between constructs. This is accomplished through the use of path coefficients, R^2 values, and hypothesis ing through t bootstrapping method. This dual-stage approach facilitated a comprehensive overall calculation factors that influence the adoption of academic information systems by students in public universities, thereby providing a comprehensive understanding of the direct and indirect influences among variables. Since the indicators in this study are reflective, the equation is [12]:

$$x = \lambda x\xi + \delta x$$
$$y = \lambda y\eta + \varepsilon y$$
$$Xjk = \lambda jk\xi j + \delta jk \qquad (5)$$

Description:

x : indicator of an exogenous latent variable
y : indicator of an endogenous latent variable
λx,λy : loading matrices representing simple regression coefficients between indicators and latent variables
δξ,εη : residuals from the regression in the indicator block

3. Results And Discussion

Data were obtained throughout this research involved 247 active students of the State Administration Study Program at Tidar University, who were selected through a proportionate stratified random sampling technique. PLS-SEM method is used to evaluate the model in two stages: the outer model and the inner model.

The Outer Model

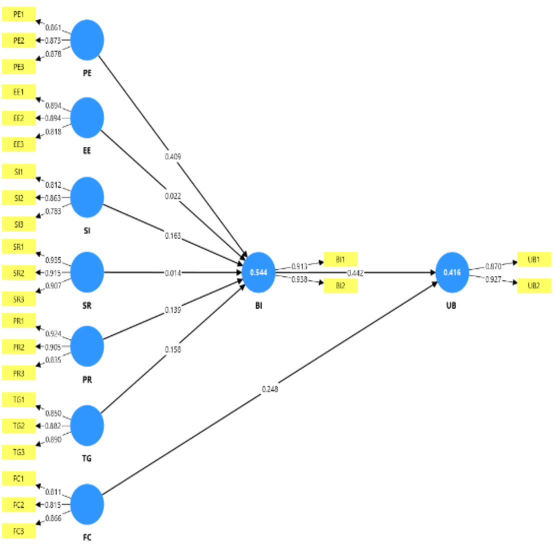

Fig 2. The outer model from PLS-SEM Analysis

Assessing the outer model serves to examine how valid and reliable the indicators in representing constructs. Research validity indicates the extent to which the instrument used is capable of accurately measuring the intended concept and accurately reflecting the actual reality of the object under study [15]. Using the SmartPLS 4.1.1.2 tool, validity testing is conducted through two tests: convergent validity and discriminant validity [16].

Table 2. Outer Model Evaluation Results

Variable	Indicator	*Outer Loadings*	AVE	Note
Performance Expectancy	PE1	0.861		Valid
	PE2	0.873	0.758	Valid
	PE3	0.878		Valid
Effort Expectancy	EE1	0.894		Valid
	EE2	0.894	0.756	Valid
	EE3	0.818		Valid
Social Influence	SI1	0.812		Valid
	SI2	0.863	0.673	Valid
	SI3	0.783		Valid
Security Risk	SR1	0.935		Valid
	SR2	0.915	0.845	Valid
	SR3	0.907		Valid
Perceived Risk	PR1	0.924		Valid
	PR2	0.905	0.790	Valid
	PR3	0.835		Valid
Trust in Government	TG1	0.850		Valid
	TG2	0.882	0.764	Valid
	TG3	0.890		Valid
Facilitating Conditions	FC1	0.811		Valid
	FC2	0.815	0.690	Valid
	FC3	0.866		Valid
Behavioral Intention	BI1	0.913	0.857	Valid
	BI2	0.938		Valid
Use Behavior	UB1	0.870	0.808	Valid
	UB2	0.927		Valid

Convergent validity indicates that indicators measuring a construct should have a high correlation with one another. In other words, to ensure that the instrument used for a construct represents the construct [17]. In this study, convergent validity was evaluated using SmartPLS 4.1.1.2 through the outer loadings and AVE values [16]. Outer loadings are declared valid if> 0.70, while AVE is considered qualified if> 0.50, which means meaning the construct is responsible for explaining at least 50% of the indicators' variance [13].

The testing results demonstrate that the correlation between each indicator and its construct appears strong, as indicated by all indicators having outer loading values >0.7. Moreover, AVE for nine construct >0.5. Simultaneously, both Composite Reliability and Cronbach's Alpha values exceed the 0.7 threshold, indicating that the constructs employed in this research are valid.

The concept of discriminant validity concerns the separateness of one construct from the others in the framework, thereby preventing any redundancy or conceptual overlap [16]. Cross loadings, the Fornell-Larcker criterion, and HTMT ratio are the three leading indicators used to evaluate this aspect of validity. Cross loadings are considered acceptable when each indicator has a stronger correlation with its assigned construct than with any other [14]. A construct passes the Fornell-Larcker test when the square root of its AVE surpasses its correlations with other constructs. Simultaneously, the discriminant validity must be satisfactory when the HTMT ratio is less than 0.90. [18].

TABLE 3. Cross Loadings of Items

	BI	EE	FC	PE	PR	SI	SR	TG	UB
BI1	0.913	0.181	0.591	0.526	0.459	0.459	0.293	0.438	0.571
BI2	0.938	0.189	0.746	0.744	0.659	0.640	0.194	0.373	0.582
EE1	0.184	0.894	0.238	0.153	0.141	0.102	0.280	0.380	0.078
EE2	0.180	0.894	0.227	0.150	0.120	0.108	0.202	0.318	0.030
EE3	0.157	0.818	0.187	0.142	0.157	0.127	0.212	0.325	0.051
FC1	0.585	0.275	0.811	0.619	0.490	0.560	0.144	0.390	0.468
FC2	0.518	0.149	0.815	0.575	0.557	0.562	0.173	0.289	0.446
FC3	0.702	0.201	0.866	0.614	0.586	0.566	0.205	0.357	0.503
PE1	0.634	0.110	0.613	0.861	0.544	0.637	0.177	0.332	0.587
PE2	0.514	0.095	0.629	0.873	0.721	0.671	0.072	0.283	0.429
PE3	0.649	0.230	0.652	0.878	0.635	0.584	0.223	0.412	0.514
PR1	0.574	0.143	0.619	0.654	0.924	0.666	0.280	0.339	0.441
PR2	0.558	0.149	0.524	0.628	0.905	0.573	0.386	0.410	0.480
PR3	0.497	0.132	0.612	0.644	0.835	0.585	0.164	0.251	0.379
SI1	0.476	0.033	0.515	0.584	0.525	0.812	0.107	0.216	0.443
SI2	0.512	0.127	0.572	0.674	0.557	0.863	0.171	0.233	0.533
SI3	0.491	0.152	0.577	0.513	0.601	0.783	0.132	0.233	0.376
SR1	0.221	0.299	0.188	0.218	0.269	0.130	0.935	0.534	0.238
SR2	0.235	0.316	0.222	0.144	0.299	0.162	0.915	0.496	0.220
SR3	0.254	0.133	0.170	0.160	0.299	0.167	0.907	0.558	0.297
TG1	0.387	0.314	0.352	0.339	0.315	0.242	0.476	0.850	0.323
TG2	0.343	0.389	0.416	0.394	0.378	0.259	0.507	0.882	0.343
TG3	0.405	0.333	0.331	0.318	0.303	0.229	0.528	0.890	0.368
UB1	0.511	0.025	0.372	0.415	0.261	0.381	0.260	0.333	0.870
UB2	0.600	0.078	0.622	0.625	0.578	0.585	0.240	0.374	0.927

TABLE 3. Fornell-Larcker Criterion

	BI	EE	FC	PE	PR	SI	SR	TG	UB
BI	0.926								
EE	0.200	0.869							
FC	0.728	0.252	0.831						
PE	0.695	0.171	0.726	0.871					
PR	0.612	0.159	0.656	0.721	0.889				
SI	0.601	0.128	0.677	0.721	0.684	0.820			
SR	0.259	0.267	0.210	0.188	0.315	0.167	0.919		
TG	0.435	0.393	0.417	0.398	0.378	0.277	0.577	0.874	
UB	0.623	0.061	0.570	0.592	0.489	0.551	0.276	0.395	0.899

TABLE 4. HTMT (Heterotrait-Monotrait Ratio)

	BI	EE	FC	PE	PR	SI	SR	TG	UB
BI									
EE	0.239								
FC	0.893	0.310							
PE	0.810	0.198	0.898						
PR	0.709	0.188	0.803	0.854					
SI	0.748	0.161	0.885	0.890	0.846				

SR	0.301	0.310	0.250	0.208	0.350	0.200			
TG	0.519	0.469	0.517	0.469	0.441	0.348	0.656		
UB	0.773	0.071	0.715	0.709	0.570	0.704	0.331	0.486	

The analysis of discriminant validity confirms that all constructs comply with the established benchmarks. For each construct, the highest cross-loading consistently appears on its corresponding indicators. Similarly, the Fornell-Larcker assessment indicates that the AVE square root of a construct must be greater than the correlation it shares with any other construct. Moreover, HTMT values were all found to be below the 0.90 threshold, affirming the presence of clear distinctions among constructs and the absence of conceptual overlap within the model.

After the validity is fulfilled, the construct reliability is measured. Reliability is consistency, both in terms of time and place. In other words, reliability measures the consistency of scores between items, thus reflecting the accuracy of the measurement scale [15]. In PLS-SEM, reliability can be analyzed using SmartPLS 4.1.1.2 through two leading indicators: composite reliability to assess internal consistency, and Cronbach's alpha for examining the degree of reliability across the scale items [17]. Composite Reliability and Cronbach's Alpha are declared eligible if each is > 0.70 for all constructs.

TABLE 5. Cronbach's Alpha and Composite Reliability

	Cronbach's alpha	Composite reliability (rho_a)
BI	0.834	0.850
EE	0.838	0.845
FC	0.775	0.779
PE	0.841	0.849
PR	0.866	0.873
SI	0.755	0.757
SR	0.908	0.911
TG	0.846	0.850
UB	0.766	0.807

Reliability testing demonstrated that all constructs fulfilled the required thresholds for both Cronbach's Alpha and Composite Reliability. This suggests that the assessment tool used is highly reliable and capable of consistently assessing the constructs, making it suitable for research applications

The Inner Model

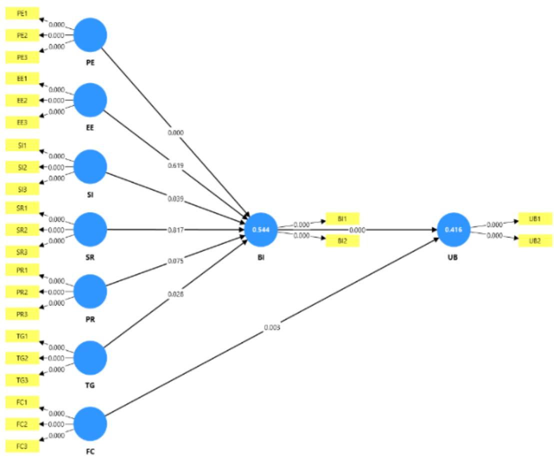

FIG 3. The inner model from PLS-SEM Analysis

The analysis then proceeded to evaluate the inner or structural model, which is designed for analyzing the interrelationships between the underlying constructs, after the measurement model satisfied the necessary conditions. Key metrics in this evaluation include the R-squared (R^2) value, path coefficients, and hypothesis testing procedures [16]. Path coefficients reflect both the direction and intensity how the latent constructs interact within the framework of the model. These values range from -1 to +1, with figures near +1 signifying strong positive associations, and those near -1 indicating strong negative ones. A positive coefficient indicates that the dependent variable increases in tandem with the independent variable, while a negative coefficient indicates an inverse relationship.

TABLE 6. Path Coefficients and Confidence Intervals (Bootstrapping Results)

Variable	Original sample (O)	Sample mean (M)	2.5%	97.5%
BI -> UB	0.442	0.441	0.267	0.613
EE -> BI	0.022	0.025	-0.074	0.100
FC -> UB	0.248	0.252	0.078	0.401
PE -> BI	0.409	0.410	0.250	0.579
PR -> BI	0.139	0.137	-0.006	0.304
SI -> BI	0.163	0.164	0.010	0.320
SR -> BI	0.014	0.021	-0.104	0.126
TG -> BI	0.158	0.152	0.015	0.297

TABLE 7. R^2 and Adjusted R^2

Variable	*R-Square*	*R-Square Adjusted*
BI	0.544	0.532
UB	0.416	0.412

TABLE 8. Hypothesis Testing Results (p-values and t-values)

	Hypothesis	p-value	t-value
PE→BI	H1	0.000	4.761
EE→BI	H2	0.619	0.498
SI→BI	H3	0.039	2.069
PR→BI	H4	0.075	1.778
SR→BI	H5	0.817	0.232
TG→BI	H6	0.028	2.193
BI→UB	H7	0.000	4.995
FC→UB	H8	0.003	3.005

Analytical findings reveal that all variables within the model are positively associated with the usage of Tidar University's Academic Information System. The most substantial impact is observed in the linkage between performance expectancy (PE) and behavioral intention (BI), followed closely by the connection between behavioral intention (BI) and actual usage behavior (UB).. Meanwhile, facilitating conditions (FC), trust in government (TG), social influence (SI), and privacy risk (PR) variables also contributed positively, although to a smaller extent. The variables of effort expectancy (EE) and security risk (SR) show a minimal influence on the use behavior (UB).

Furthermore, to evaluate how well the exogenous variables predict the endogenous ones, the R-squared value is employed. In models with more than one exogenous variable, the adjusted R-squared value is considered more accurate [19].

The adjusted R-squared value for the Behavioral Intention (BI) variable is 0.532, signifying that the exogenous variables are responsible for 53.2% of the explained variance in BI in the framework. Conversely, the remaining 46.8% is ascribed to factors external to the model. Referring to [10], this value is in the medium category. Meanwhile, the adjusted R-squared value for the use behavior (UB) variable is 0.412, implies that 41.2% of the variation in UB is explained by BI and FC, which falls into the low category. Thus, this model is quite effective in presenting the influence on BI, although its impact on UB remains limited.

The last test in the inner model is hypothesis testing. Hypothesis testing was executed through SmartPLS software version 4.1.1.2 with the bootstrapping method. A hypothesis is declared significant and accepted if it meets the conditions of t-value> 1.96 or p-value <0.05. Conversely, if the t-value < 1.96 or p-value > 0.05, the hypothesis is declared insignificant and rejected.

Of the eight hypotheses tested in this study, five received empirical support, whereas three failed to meet the criteria, the analysis confirmed H1, H3, H6, H7, and H8 as valid, whereas H2, H4, and H5 were not supported.

The first hypothesis found that performance expectancy has a positive and significant influence on behavioral intention, meaning that the perceived benefits of the system encourage an increase in students' intention to use the academic information system at Tidar University. Consistency can be found between this result and existing literature, which proposes that when users perceive technology systems as providing direct and relevant benefits, they tend to be more motivated to use them [20]. In this study, indicator PE3, namely "The Untidar application system makes work easier", became the indicator with the highest average value of 3.65. This indicates that most students believe the use helps them complete academic tasks more quickly and efficiently. Thus, a system that makes academic activities easier will encourage students to continue using the service. This finding confirms that expectations of system performance are an essential factor in shaping the intention to use technology in the campus environment.

The second hypothesis shows that although a favorable relationship exists between EE and BI, this relationship doesn't hold statistically meaningful. This aligns with the findings of Kiswanto & Syamsuar (2021), who argue that EE does not always significantly influence intention, particularly when the system is mandatory. In this case, the EE1 indicator, *"The academic information system is easy to understand"*, received the highest mean score of 3.94. This indicates that students generally find the system accessible and easy to use. However, ease alone does not determine whether they intend to keep using it. Since the system is required for academic activities, students may use it out of obligation rather than motivation based on usability. Therefore, in this context, effort expectancy is not a decisive factor in forming BI.

Social influence is found to have a significant and positive impact on students, as indicated by the third hypothesis intention to use the academic information system. This supports the study by Ardiyani et al. (2023), it was evident that social encouragement and institutional pressure can influence behavioral intention toward digital services. In this study, the SI2 indicator, "The university strongly encourages the use of the academic information system," obtained the highest average score of 3.82. This reflects the influence of university policies, lecturers' instructions, and general academic culture, which collectively shape students' behavior. When the use of the system is consistently promoted within the educational environment, students are more likely to adopt and utilize it regularly. Such results demonstrate the significance of social and institutional norms in shaping intention.

The analysis reveals that privacy risk fails to show a statistically meaningful effect on students' intention to utilize the academic information system, despite a positive direction of the relationship. This suggests that although students may be aware of the risks related to data privacy, such concerns do not strongly influence their intention to use the system [22]. The highest average score was found in indicator PR3: *"The academic information system uses a username and password to log in"*, with a mean of 3.94. This suggests that students feel relatively secure with the system's login mechanism, which may explain why privacy risks are not perceived as a significant barrier to their use. The perception that basic protection is already in place may reduce privacy concerns, resulting in a minimal impact on behavioral intention.

The fifth hypothesis suggests that security risk, like privacy risk, has a positive but non-significant relationship with BI. This means that even if students are concerned about security issues, such as data misuse, it does not significantly shape their intention to use the system [22]. Indicator SR3: *"The academic information system is safe from misuse of address information"* had the highest mean score of 3.92. Students may perceive the system as generally secure, which reduces their concern about potential risks. As a result, security risk is not a determining factor in their decision to continue using the system.

The sixth hypothesis confirms TG has a significant influence on students' intention to use the academic information system. When students trust the institution managing the system, they are more willing to use it consistently [23]. The highest score came from TG1: *"I trust the services provided by the system administrator"*, with a mean of 4.03. This reflects strong confidence in the university's management of the system, including data handling and system reliability. Without trust, the likelihood of adoption is considerably reduced of digital public services, particularly in systems managed by government institutions, such as public universities.

The analysis supports the seventh hypothesis, indicating that there is a strong and direct relationship between behavioral intention and actual use of the academic information system. In other words, higher levels of intention to utilize the system, the more frequently students use it [24]. The indicator with the highest average was BI2: *"I plan to use the academic information system for all academic processes"*, with a mean of 3.62. This suggests that students not only intend to use the system occasionally but also aim to rely on it for all academic needs, reinforcing the direct link between intention and usage.

Finally, the eighth hypothesis indicates that facilitating conditions have a significant impact on students' actual use of the academic information system. This includes the availability of support, system compatibility, and user guidance [25]. The top indicator here is FC3: *"The academic information system is compatible with the device I use"*, with a mean score of 3.93 There is a higher likelihood that students will utilize the system on a regular basis when they perceive it as user-friendly works smoothly with their devices and when they can access help if needed. This confirms that technical support and system readiness are essential in supporting consistent system usage.

4. CONCLUSIONS

According to this study, *performance expectancy*, *social influence*, *trust in government*, *facilitating conditions*, dan *behavioral intention* all have an impact on Tidar University's use of academic information systems. The system benefit factor is the principal determinant, whereas effort expectancy, privacy risk, and security risk exert no substantial influence. privacy.

Operators are advised to enhance features that communicate the system's benefits, foster trust, and offer responsive technical support. Although some factors do not have a significant impact, aspects such as convenience and security still need improvement to enhance the overall user experience

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