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The Role of Lecturer's Moral Hazard Behaviour on Utilization of Students's Information and Communication Technology in Education of Indonesia

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A B S T R A C T

This study aims to examine the influence of lecturers' moral hazard behavior on students' utilization of Information and Communication Technology (ICT), employing the Technology Acceptance Model (TAM) and the Power Relationship Theor as theoretical frameworks. Several factors impact students' engagement with ICT, including (1) perceived trust, (2) perceived risk, (3) social influence, (4) perceived ease of use, (5) perceived usefulness, and (6) lecturers' moral hazard behavior. The research sample consisted of 305 students from various regions across Indonesia. Data analysis was conducted using SSIS 25 for statistical descriptions, while AMOS 25 was utilized to test all proposed hypotheses. The findings indicated that all identified factors significantly affected students' use of ICT. It is noteworthy that this study presents original research, as there exists a lack of prior investigations concerning ICT usage among students in Indonesia, as well as an exploration of lecturers' moral hazard behavior. Furthermore, the application of Power Relationship Theory contributes a novel theoretical perspective to this research domain.

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INTRODUCTION

The evolution and advancement of the economy, along with the proliferation of online public services—such as student registration, single tuition fees (UKT), Internet-based lecture systems, and mobile platforms have undoubtedly transformed the attitudes and behaviors of both lecturers and students in contrast to manual methods prevalent in the 1980s. In 2019, the Asia Pacific region recorded approximately two billion mobile Internet users. This platform serves as an effective resource for both students and lecturers, significantly enhancing their performance (Mallat, 2007). The utilization of the Internet by students and lecturers, through information and communication technology (ICT), has proven to be highly beneficial in educational activities across the globe (Ondrus and Pigneur, 2006), including in Indonesia. The integration of portable electronic devices such as smartphones, tablets, smartwatches, and laptoSI has markedly altered the pedagogical landscape for educators and learners alike. For instance, smartphones facilitate the use of Single Sign-On (SSO), Employee Performance Targets (SKP), and Integrated Resource Information Systems (SISTER) for academic puPRoses. This system is operational in educational institutions, such as Diponegoro University, aiming to enhance the performance of both lecturers and students by eliminating superfluous tasks, such as manual form completion (Pham and Ho, 2015), and increasing convenience and efficiency (Teo et al., 2015).

Given the aforementioned developments, it is essential to examine whether various factors and behaviors exhibited by lecturers influence the adoption of ICT by students. The rationale behind this inquiry is supported by a review of pertinent studies pertaining to ICT utilization, particularly those grounded in the Technology Acceptance Model (TAM) and Power Relation Theory (PRT).

Research has identified several factors impacting ICT adoption and utilization. In the context of cashless payment systems, influential elements include social influence, perceived ease of use (PEU), perceived usefulness (PU) (Koenig-Lewis et al., 2015; Kim et al., 2010), perceived trust (Lu et al., 2011), perceived security and risk (Arvidsson, 2014), cost considerations (Peng et al., 2011), privacy (Slade et al., 2013), user context (Mallat et al., 2009), culture (Alalwan et al., 2015), and social influence (SI) (Kesharwani and Bisht, 2012; Venkatesh and Davis, 2000). TAM and its extensions have been extensively employed in exploratory investigations concerning ICT utilization. This model provides a comprehensive framework for understanding the variables influencing ICT usage, particularly among students.

Although mobile devices are widely embraced by students, research focusing on the use of ICT within this demographic remains relatively limited (Deloitte, 2015). Therefore, it is imperative to investigate whether the aforementioned factors significantly impact ICT usage levels. This study is intended to inform ICT service providers with more targeted insights and guidance. It adopts an exploratory approach that integrates both social and technical adoption factors, drawing upon the Technology Acceptance Model (TAM) and Power Relationship Theory (PRT) as theoretical frameworks.

While previous studies on mobile-based platforms have provided valuable insights, they often remain confined to general technological and sociological aspects. For instance, although the adoption of Mobile-Based Online Payment Platforms (MOPP) and the utilization of Information and Communication Technology (ICT) have demonstrated significant growth trends across the Asian region (Jawad & Parvin, 2022), empirical research in this area still reveals important gaps. Jawad and Parvin (2022) identified several key determinants—namely perceived trust (PT), perceived risk (PR), social influence (SI), perceived ease of use (PEU), and perceived usefulness (PU)—across China, India, and Bangladesh, applying the TAM framework. However, their analysis does not account for institutional variables or power dynamics that can critically influence adoption behaviors, particularly in educational environments. This reveals a conceptual and contextual gap in the literature—specifically, the lack of studies that explicitly integrate institutional behavior perspectives, such as Power Relationship Theory, into MOPP and ICT adoption research. Such integration is particularly relevant in developing countries, where hierarchical structures and user behavior patterns may differ substantially from those in more developed settings. Accordingly, the present study aims to expand the TAM framework by incorporating PRT, offering a more comprehensive understanding of technology adoption determinants within the socially and institutionally embedded context of the education sector.

The primary objective of this study is to explore and identify the extent of ICT utilization by students. Within this framework, the critical factors anticipated to influence ICT adoption include (1) perceived trust, (2) perceived risk, (3) social influence, (4) perceived ease of use, and (5) perceived usefulness. Based on the principles of PRT, the researcher posits that the behavioral factors of lecturers play a crucial role in determining the level of ICT usage by students.

THEORETICAL REVIEW

Utilization of Information and Communication Technology

In reviewing various studies, it is evident that multiple factors influence the utilization of Information and Communication Technology (ICT). These influential factors encompass social influence, perceived ease of use (PEU), perceived usefulness (PU) (Koenig-Lewis et al., 2015; Kim et al., 2010), perceived trust (Lu et al., 2011), perceived security and risk (Arvidsson, 2014), cost (Peng et al., 2011), privacy (Slade et al., 2013), user context (Mallat et al., 2009), culture (Alalwan et al., 2015), and social influence (SI) (Kesharwani and Bisht, 2012; Venkatesh and Davis, 2000). These studies predominantly rely on the rationale established by the Technology Acceptance Model (TAM).

Within the framework of TAM, it is plausible to investigate the role of lecturer behavior in influencing students' levels of technology adoption. Lecturers are perceived by students as possessing the requisite academic competence and skills that warrant emulation. To enhance and facilitate this adoption and imitation process, students require a conceptual framework such as TAM.

This study specifically examines whether the primary factors within TAM significantly impact its acceptance among students. Furthermore, this research aims to provide a novel contribution by exploring the extent to which lecturer behaviors influence students' acceptance of TAM. It stands to reason that lecturer behavior has a considerable effect on student performance within the context of TAM. The successful execution of students' educational responsibilities is fundamentally dependent on the activities and conduct of their lecturers.

This study's relevance extends to the enhancement and development of ICT services provided by educational institutions. Such improvements are anticipated to yield continuous advancements in the performance of both lecturers and students. The subsequent implications of this research also include boosting the overall effectiveness of the industries and economies in which these individuals are employed. Moreover, the findings of this study are invaluable to ICT service providers, particularly in educational settings.

Technology Acceptance Model

According to Davis et al. (1989), the Technology Acceptance Model (TAM) is one of the most widely applied frameworks for elucidating technology acceptance and user engagement (Glavee-Geo et al., 2017). TAM seeks to understand how users accept and utilize various technologies, aiming to clarify the determinants that influence technology adoption. The model comprises two critical independent variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU reflects the level of confidence an individual has regarding the potential performance enhancement afforded by a specific system, while PEU denotes the degree to which prospective users anticipate a system to operate without complications.

TAM critically examines the mediating roles of PEU and PU on the likelihood of system use (Legris et al., 2003). In this framework, PU and PEU are significant predictors of user attitudes and behavioral intentions. Prior studies suggest that further exploration of TAM could be enriched by incoPRorating additional constructs, such as self-efficacy, institutional support, ambiguity, voluntariness, and perceptions of user mobility. Thus, Mehrad and Mohammadi (2016) foresee that future studies on ICT utilization will potentially enhance the original TAM model by integrating constructs such as relative advantages, perceived trust, perceived risk, perceived usage costs, lifestyle compatibility, and perceived security.

Perceived Trust and Information and Communication Technology

Mayer et al. (1995) define trust as the positive expectations that users hold towards service providers. According to Palvia (2009), trust generally comprises three key components: integrity, ability, and good deeds. Integrity reflects the capability of a service entity to fulfill its obligations. Ability denotes the requisite technical knowledge and expertise that the service provider possesses to meet its commitments. Meanwhile, good deeds pertain to the service provider's responsibility to safeguard users' interests.

Yan et al. (2009) and Mallat (2007) emphasize that within the realm of electronic services, trust is a critical determinant influencing user perceptions. In

alignment with this perspective, Gupta and Sareen (2001) underscore that consumer acceptance of information and communication technology hinges on the belief that user concerns will be adequately addressed. An empirical study conducted by Srivastava et al. (2010) in Singapore introduced a trust theory model, identifying trust as the paramount construct in comparison to other factors (Shankar & Datta, 2018).

Zhou (2011) further identifies that perceived uniqueness, knowledge, privacy protection and perceived security significantly influence user's initial trust, which subsequently determines their interest in utilizing information and communication technology. Hwang, Tsai, and Yang (2008) elaborate that the concept of uniqueness can be understood as the condition whereby users have the ability to access an application at any time and from any location.

In the context of online information and communication technology, Lu et al. (2011) proposed a trust-based decision-making model anchored in trust-transfer theory and the valence framework. The findings indicate that trust significantly impacts cross-environmental relationshiSI and users' behavioral intentions regarding technology adoption. Furthermore, the quality of information and services positively influences trust, ultimately guiding users to continue utilizing information and communication technology (Zhou, 2013). Given that users typically share personal and financial information when engaging with such technology, Duane et al. (2014) and Kim et al. (2010) emphasize that trust is pivotal in fostering interest in online information and communication technology services via mobile devices. Trust has been examined as a multidimensional construct within the social sciences (Carlos-Roca et al., 2009; Bhattacherjee, 2002).

The aforementioned literature indicates that Perceived Trust (PT) is a significant factor in the adoption and utilization of various technology types, especially utilization of Information and Communication Technology (UICT). Based on the arguments presented by existing researchers, the following hypothesis is formulated for empirical testing:

H1: PT has a positive effect on the utilization of information and communication technology among students.

Perceived Risk and Information and Communication Technology

Before adopting new technology, users typically analyze two potential risks: the level of uncertainty and the potential seriousness of the technology's impact. This evaluation helSI them determine whether they are willing to accept the associated risks (Featherman & Pavlou, 2003). Consumers will assess both the direct and internal impacts in order to weigh the benefits and risks of adopting new technology (Cho, 2004). It is assumed that potential or new users are open to experimenting with new technology before committing to its long-term use. According to Rogers (2003), potential users will test the benefits and consequences of the technology before fully committing. This trial period can reduce users' perceptions of uncertainty and encourage them to adopt the new technology (Tan & Teo, 2000).

Furthermore, Ndubisi & Sinti (2006) found that perceived risk (PR) can influence the use of information and communication technology. Kesharwani & Bisht (2012) also reported that PR negatively affects the behavioral intention to adopt such technology, with trust playing a role in reducing perceived risk. Researchers suggest that as perceived risk increases, interest in using information and communication technology decreases, and vice versa. The following hypothesis is proposed to test the relationship between perceived risk and the use of these services:

H2: Perceived risk (PR) has a negative effect on the utilization of information and communication technology among students.

Social Influence and Information and Communication Technology

The influence of social factors on technology acceptance behavior has garnered significant attention in academic discourse. Kesharwani and Bisht (2012) noted that many preceding studies primarily concentrated on subjective norms to elucidate the essence of social influence; however, the findings were often ambiguous, leading to inconsistencies regarding their impact on technology usage. Social influence (SI) exerts a notable effect on technology adoption, particularly when the use of such technologies is mandated. Conversely, its influence diminishes as users gain direct experience with the targeted system (Venkatesh & David, 2000).

Moreover, scholars such as Conner and Armitage (1998) and Terry and Hogg (2000) argue that the prevailing conceptualizations may be limited, as they focus disproportionately on the narrower aspect of trust while neglecting the broader societal context. Consequently, researchers emphasize the necessity for a more comprehensive exploration of the relationship between social influence and technology acceptance (Karahanna & Limayem, 2000).

In the realm of mobile-based online information and communication technology, it can be anticipated that recommendations from family, friends, or colleagues regarding the utility of such technologies will foster an individual's belief in the benefits of usage. This social influence is likely to cultivate a greater interest in employing information and communication technologies. Empirical evidence indicates that individuals are highly susceptible to the pressures of social norms as they seek to preserve a favorable personal and social image within their reference grouSI (Kesharwani & Bisht, 2012).

Reference grouSI, as defined by Schiffman and Kanuk, encompass any individual or collective deemed a benchmark for establishing values that guide behavior. Drawing upon research pertaining to diffusion and innovation, Moore and Benbasat (1991) conceptualized social image as a determinant in the adoption of innovations that are perceived to enhance an individual's status within a social framework. Venkatesh and David (2000) identified that subjective norms positively affect both personal and social image; thus, if a significant member of a social group advocates the use of a system, the likelihood of adoption increases, enhancing one’s social standing within that group.

In summary, the interrelationship between these concepts culminates in the formulation of the hypothesis that social influence will substantially affect an

individual's interest in utilizing specific mobile-based information and communication services or technologies.
H3: Social influence (SI) has a positive effect on the utilization of information and communication technology among students.

Perceived Ease of Use and Information and Communication Technology

According to Davis (1989), Perceived Ease of Use (PEU) is defined as the individual's evaluation of the mental effort required to utilize new technology. Venkatesh (2000) identified several determinants of PEU by integrating internal control factors (such as device efficacy) and external control factors (including supportive conditions) into the Model of Technology Acceptance (TAM). Subsequent studies (Davis, 1986, 1989) have demonstrated that PEUcan significantly influence Motivation to Perform (MP), as technologies that are perceived as easier to use are also considered more useful. In the realm of information and communication technology, research indicates a positive and significant relationship between PEU and MP (Wang et al., 2003; PhiliSI et al., 1994). As such, individuals are more inclined to accept internet-based information and communication technology services when they find these services easy to operate and navigate. This ease of use serves as a valuable tool in leveraging technology, contributing to cost reduction and enhanced performance (Kesharwani & Bisht, 2012). In alignment with previous studies, the following hypothesis is proposed:
H4: Perceived Ease of Use (PEU) positively influences on the utilization of information and communication technology among students.

Perceived Usefulness and Information and Communication Technology

Perceived Usefulness (PU) refers to the extent to which users believe that the adoption of a specific technology will enhance their performance (Davis, 1989). Within the realm of mobile-based online information and communication technology, indicators of a system's usefulness include the seamless execution of online activities, the ability to recharge mobile phone and cable television services, facilitate monetary transactions, engage in online shopping, transfer funds to credit cards, and book tickets (Shankar & Datta, 2018). Prior to the adoption of any new technology, users rigorously evaluate the benefits they anticipate receiving from its implementation. Kim et al. (2010) examined the impact of user-centered system characteristics on the utilization of information and communication technology services across various user demographics, concluding that PU significantly and positively influences the use of such technologies. Furthermore, PU has been empirically established as a critical factor influencing the intention to adopt new technologies (Apanasevic et al., 2016; Arvidsson, 2014; Duanne et al., 2014; Keramati et al., 2012; Kim et al., 2010; Chen, 2008). Consequently, the researcher posits the following hypothesis for empirical testing:
H5: Perceived Usefulness (PU) positively influences utilization of information and communication technology among students .

Power Relationship Theory

The Power Relations Theory (PRT) is initially articulated in Michel Foucault's research (1982b) within his work titled, "The Subject and Power". Further elaboration can be found in Scott's (2007) study entitled, "Power After Hegemony". Drawing upon these seminal works, it can be asserted that interactions among various parties inherently involve the exercise of power. When one party possesses greater power, two potential outcomes emerge: hegemony and control.

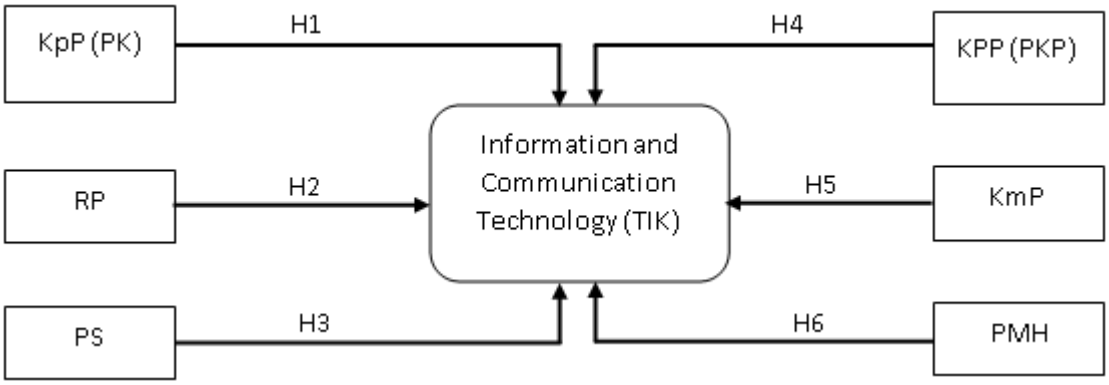
In accordance with PRT, it is posited that the behaviors exhibited by lecturers significantly influence the level of Information and Communication Technology (ICT) usage among students. From the students' perspective, lecturers are viewed as individuals possessing the requisite academic competence and capabilities that merit emulation. To facilitate this process of adoption and imitation, students require the utilization of ICT tools.

The influence exerted by lecturers can be articulated through their professional performance and moral hazard behavior (MHB). Lecturer performance reflects the quality of work produced in alignment with organizational standards, while moral hazard behavior denotes work attempted intentionally below these established standards. Based on this premise, the researcher formulates the following hypothesis:

H6: Moral hazard behavior (MHB) of Lecturers exerts a positive influence on utilization of information and communication technology among students.

Research Framework

Based on the literature review, the researcher can summarize various theories, arguments, reasoning, logic, and hypotheses in the form of a Research Framework, as shown in the following figure 1.



Source: Structural Equation Modelling (AMOS 26)

Figure. 1 Theoretical Framework

METHODOLOGY

The data utilized in this study comprise primary data. To acquire this primary data, the researcher meticulously crafted and employed a detailed and structured survey instrument. This instrument was administered to respondents with the support of the researcher. Respondents were selected through a combination of random selection (convenience sampling) and intentional

methods. All participants were accounting students who utilized Information and Communication Technology (ICT) in higher education institutions across Indonesia. A total of 313 accounting students participated in the study; however, the questionnaires that were completed and deemed suitable for analysis numbered 305. As part of the measurement tool, the researcher implemented a structured questionnaire comprising 19 items, employing a four-point Likert scale developed from an extensive literature review. Prior to distributing the questionnaire, respondents were provided with clear and accurate information regarding the items to mitigate confusion and minimize the potential for errors. Additionally, students contributed to defining the context of ICT usage and their respective domicile backgrounds.

RESULTS AND DISCUSSION

Demographic data

The data summary presented in Table 1 illustrates that the respondents are distributed across various regions of Indonesia, although representation from certain provinces and districts/cities is not comprehensive. The majority of respondents are located in Central Java province, while the fewest are found in the provinces of Banten, Bali, NTB, Central Kalimantan, and Aceh. In terms of gender demographics, the sample exhibits a higher proportion of women (62%) compared to men (38%). Additionally, the age distribution of the respondents predominantly falls within the range of 18 to 22 years. Further details are provided in the accompanying table.

Tabel 1. Respondents Demographic Information

Province		Regency/City				
BANTEN	1%	Tangerang	Tangerang Selatan			
JABAR	8%	Cilegon	Bogor	Bekasi	Bogor	Kota Bekasi
		Kota Bandung	Cirebon	Kota Cirebon	Kota Depok	Bandung
JAKARTA	4%					
JAMBI	3%	Kota Jambi				
JATENG	57%	Kota Semarang	Semarang	Pati	Purworejo	Purwodadi
		Sragen	Salatiga	Surakarta	Batang	Sragen
		Sukoharjo	Pekalongan	Demak	Kudus	Cilacap
		Rembang	Wonosobo	Purwokwerto	Wonosobo	Boyolali
		Grobogan	Pemalang	Temanggung	Blora	Wonogiri
		Jepara	Tegal	Karanganyar	Klaten	
JATIM	13%	Blitar	Nganjuk	Jombang	Madiun	Kendal
		Sidoarjo	Kediri			
RIAU	2%	Siak	Pekanbaru			

SUMUT	3%	Kota Medan	Dairi	Simalungun	
Yogyakarta	6%	Sleman			
BALI	1%	Bangli			
KALTENG	1%	Pangkalan Bun	Banjarbaru		
NTB	1%	Sumba	Lombok		
ACEH	1%	Sabang			
305	100%				
Male	38%	117			
Female	62%	188			
Age	18 - 22 years old				

Source: Instrument Survey

Reliability and Validity Analysis

Researchers employ composite reliability (CR) and average variance extracted (AVE) values to assess the reliability of data. As indicated in Table 2, all CR values for each variable exceed the threshold of 0.70. This finding leads to the conclusion that the data utilized in this research are reliable (Henseler et al., 2009; MacKinnon, 2008; Hair et al., 1998; Fornell & Larcker, 1981).

Tabel 2. Composite Reliability

Faktor (Variabel)	CR	AVE
PT	0,830	0,620
PR	0,909	0,769
SI	0,891	0,731
PEU	0,863	0,678
PU	0,838	0,632
MHB	0,829	0,621
UICT	0,860	0,628

Source: IBM Statisics SSIS 25

The validity test, as referenced by Hair et al. (2014), indicates that a convergent validity is considered acceptable when the Average Variance Extracted (AVE) value is greater than 0.5. For assessing discriminant validity, the researcher follows the methodology outlined by Fornell and Larcker (1981), which involves comparing the AVE value with the correlation values of other variables. According to Hair et al. (2014), the square root of the AVE should exceed the correlation values between different variable constructs. The results for discriminant validity are shown in Table 3, where it is evident that each factor meets the recommended criteria.

Table 3. Discriminant Validity

	UICT	PT	PR	SI	PEU	PU	MHB
UICT	0,792**						
PT	0,200	0,787***					
PR	0,042	0,042	0,877**				
SI	0,300	0,146	-0,066	0,855*			
PEU	0,406	0.186	0,099	0,332	0,823**		
PU	0,453	0,059	0,088	0,246	0,454	0,795*	
MHB	0,397	0,102	0,067	0,314	0,393	0,384	0,883***

Source: IBM Statisics SSIS 25

Data Normality

According to Tabachnick and Fidell (2001), the criteria for skewness and kurtosis values for each item are deemed satisfactory within the range of -4 to +4. The findings presented in Table 4 indicate that all data exhibit a normal distribution. Furthermore, the kurtosis values in Table 4 surpass the threshold of 3.3, as identified by Sposito et al. (1983), thereby confirming the normality of the research data.

Table 4. Normality Data

Factor	Items	N	Mean	Std. Deviation (Statistic)	Skewness (Statistic)	Kurtosis (Statistic)
PT	PT1	305	2,94	1,021	-0,025	-0,371
	PT2	305	3,04	1,061	-0,041	-0,685
	PT3	305	3,15	1,026	-0,304	-0,168
PR	PR1	305	3,29	1,034	-0,455	-0,231
	PR2	305	3,38	1,079	-0,284	-0,21
	PR3	305	3,31	1,071	-0,34	-0,533
SI	SI1	305	3,15	1,033	-1.097	1.423
	SI2	305	3,29	1,094	-0,473	0,318
	SI3	305	3,43	1,056	-0,671	0,632
PEU	PEU1	305	3,46	1,046	-1.157	0,355
	PEU2	305	3,34	1,072	-0,78	-0,387
	PEU3	305	3,46	1,032	-0,475	-0,734
PU	PU1	305	3,26	1,056	-0,944	0,406
	PU2	305	3,22	1,039	-0,566	-0,312
	PU3	305	3,38	1,012	-0,916	0,35
UICT	UICT1	305	3,24	1,023	-0,214	-0,584
	UICT2	305	3,44	1,014	-0,214	-0,584
	UICT3	305	3,24	1,031	-0,214	-0,584
	UICT4	305	3,14	1,021	-0,214	-0,584
MHB	MHB1	305	33,33	24,73	-0,42	1,06

Source: IBM Statisics SSIS 25

Model Evaluation

Exploratory Factor Analysis (EFA)

To evaluate Exploratory Factor Analysis, four primary assumptions are established (Field, 2000; Hair et al., 1998). These assumptions consist of: (1) sample adequacy, (2) the minimum Eigenvalue associated with each factor, (3) sample size, specifically requiring a factor loading threshold of 50% for each item, and (4) the implementation of varimax rotation for factor intePRretation (Field, 2000). The analysis can be conducted when the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity yield significant results.

As indicated in Table 5, the KMO measurement index (overall MSA = 0.793) satisfies the recommended threshold of 0.5 (Hair et al., 1998), and Bartlett's Test of Sphericity has shown significant results (p = 0.000). Following the examination of the AFE matrix patterns for each question indicator, the findings reveal that each indicator maintains a factor loading value exceeding 0.5, indicating a high level of significance (Hair et al., 2010). The lowest recorded factor loading (FL) was 0.793, while the highest was 0.914. Furthermore, the reliability coefficient (Cronbach's Alpha) for each factor was greater than 0.7, demonstrating a high level of reliability as per the standards set by Nunnally and Bernstein (1994).

Table 5. Exploratory Factor Analysis (EFA)

Factor	Items	FL	AFE	Alpha
PT	PT1	0,845		
	PT2	0,901		
	PT3	0,824	0.87	0.912
PR	PR1	0,815		
	PR2	0,834		
	PR3	0,834	0.83	0.896
SI	SI1	0.817		
	SI2	0,793		
	SI3	0,871	0.72	0.902
PEU	PEU1	0.857		
	PEU2	0,798		
	PEU3	0,875	0.81	0.879
PU	PU1	0,914		
	PU2	0,866		
	PU3	0,906	0.84	0.902
UICT	UICT1	0,842		
	UICT2	0,821		
	UICT3	0,901		
	UICT4	0,814	0.91	0.894
MHB	MHB1	0,842	0.78	0.891
Kaisers Mayers-Olkin (KMO) – 0,793				
Barlett’s Test of Spericity = Sig 0,000				
DF =190				

Source: IBM Statistic SSIS 25

The results of the EFA test indicate that factor analysis has met the established criteria. According to the Eigenvalue greater than 1 (see Table 6), the seven-factor model identified explains 74.40% of the total variance in the data. These findings suggest that the model has the explanatory power to predict students' interest in using uict. Overall, the data has successfully passed the factor analysis test and is ready for further testing, specifically Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

Table 6. Total Varians *Explained*

EV	PV (%)	CV (%)
5.894	29.5	29.5
2.477	12.4	41.9
1.945	9.7	51.6
1.818	9.1	60.7
1.527	7.6	68.3
1.217	6.1	74.4
1.323	6.7	52,3

EV = Eigen Value
PV = Percent of Variance
CV = Cumulative Variance

Sumber: IBM Statisics SSIS 25

Confirmatory Factor Analysis (CFA)

Table 7 below presents the Confirmatory Factor Analysis used to verify the factor structure of a set of observed variables.

Table 7. Confirmatory Factor Analysis (CFA)

GFI	Value	Acceptance Level	References
Chi-square/df	2,214	<5,0	Marsh & Hocevar (1985)
CFI	0,981	>0,90	Bentler (1990)
RMR	0,062	<0,08	Hu & Bentler (1999)
GFI	0,910	>0,90	Joreskog&Sorbom (1993)
AGFI	0,862	>0,85	Anderson & Gerbig (1984)
RMSEA	0,067	<0,08	Browne &Cudeck (1993)
SRMR	0,061	<0,08	

CFI = Comparative Fit Index
RMR = Root Mean Residual
GFI = Goodness of Fit Index
AGFI = Adjusted Goodness of Fit Index
RMSEA = Root Means Square Error of Approximation
SRMR = Square Root Mean Residual

Source: Structural Equation Modelling (AMOS 26)

The CFA methodology enables researchers to verify the correlation of existing variables with their respective factors. The Chi-Square value of 2.214, which is less than the threshold of 5.0, indicates that the model is a suitable fit (Marsh & Hocevar, 1985). Additionally, the Goodness of Fit Index (GFI) of 0.910

suPRasses the required threshold of 0.90 (Joreskog & Sorbom, 1993), reinforcing the model's adequacy. Collectively, the indicators suggest that the model exhibits a commendable fit (Goodness of Fit / GoF).

Table 7 delineates the results of the CFA test, which serves as a prerequisite for establishing a default model for GoF. The Adjusted Goodness of Fit Index (AGFI) value reported in Table 7 is 0.862, exceeding the acceptable benchmark of 0.85 (Anderson & Gerbig, 1984). Furthermore, the Comparative Fit Index (CFI) value of 0.981 is also above the cut-off value of 0.9 (Bentler, 1990). The results of the CFA test demonstrate a Root Mean Residual (RMR) value of 0.062, which is below the threshold of 0.08 (Hu & Bentler, 1999). Moreover, the Root Mean Square Error of Approximation (RMSEA) value of 0.067 is less than 0.08 (Browne & Cudeck, 1993). Finally, the Square Root Mean Residual (SRMR) index is reported at 0.061, which remains under the 0.08 threshold (Browne & Cudeck, 1993). In conclusion, all GoF indices satisfy the criteria indicative of a good fit, thereby affirming that the model is both good and acceptable for analysis.

Collinearity Test

To determine whether multicollinearity is present, the tolerance values and the variance inflation factor (FIV) were calculated, as shown in Table 8. The results indicate that the FIV values are all below 10, with a maximum FIV of 1.389, suggesting that multicollinearity is not a concern. According to Hair et al. (1998), a FIV of 1 indicates no correlation, a value between 1 and 5 indicates sufficient correlation, and a value greater than 5 indicates a high level of correlation.

Table 8. Variance Inflation Factor and Tolerance in Multicollinearity

	Tolerance	FIV
PT	0,955	1,047
PR	0,974	1,026
SI	0,859	1,164
PEU	0,720	1,389
PU	0,779	1,283
MHB	0,863	2,102
UICT	0,784	1,193

Source: IBM Statisics SSIS 25

Common Method Bias (CMB)

The results of the Common Method Bias (CMB) as indicated by Harman's single factor test, presented in Table 9, reveal that the percentage of variance attributable to a single factor was less than 50%, specifically at 26.4%. This outcome suggests the absence of bias (Aguirre-Urreta & Hu, 2019). Such a percentage implies that a single factor does not account for the majority of the observed variance. Harman's single factor test serves as a useful method for assessing whether a predominant single factor can explain the majority of variance in the dataset.

Tabel 9. Common method bias test

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.894	29.468	29.468	5.288	26.442	26.442

Source: IBM Statisics SSIS 25

Structural Model

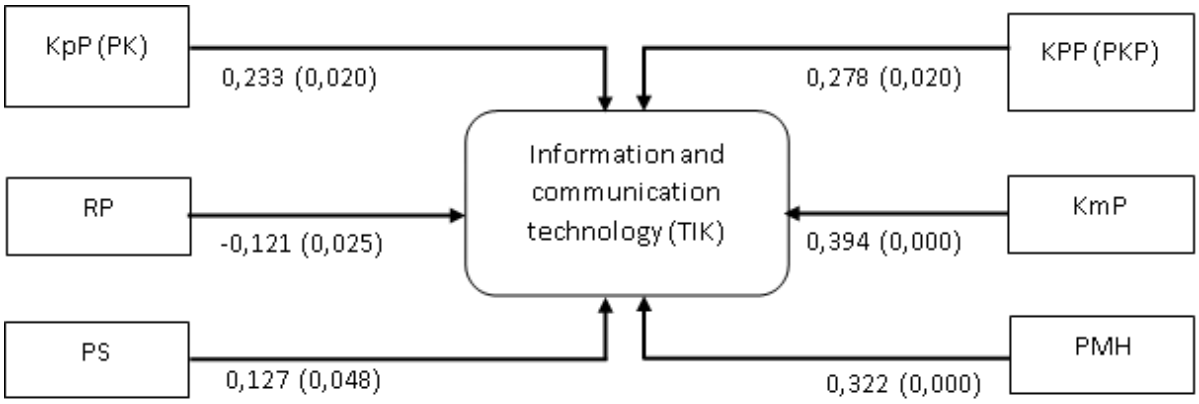
This study employs multivariate analysis techniques, specifically covariance-based structural equation modeling, to assess the effects of six identified factors on the utilization of Information and Communication Technology (UICT). The findings from the statistical tests are detailed in Table 10, which includes structural parameter estimates as well as the outcomes of hypothesis testing. In accordance with the criteria established by Hair et al. (2014), a Probability value (P-value) of less than 0.05 is indicative of a significant relationship between variables, while a P-value greater than 0.05 suggests that the relationship is not significant.

Table 10. Regression Weights: (Group number 1 - Default model)

Relation	Hypothesis	Estimate	S.E	C.R	P	Label
UICT ← PT	H1	0,233	0,221	2,320	0,020	Supported
UICT ← PR	H2	-0,121	0,051	2,221	0,025	Supported
UICT ← SI	H3	0,127	0,064	1,981	0,048	Supported
UICT ← PEU	H4	0,278	0,119	2,327	0,020	Supported
UICT ← PU	H5	0,394	0,109	3,606	0,000	Supported
UICT ← MHB	H6	0,322	0,092	2,906	0,000	Supported

Sumber: Structural Equation Modelling (AMOS 26)

The findings of the study indicate that the five factors, PT, SI, PEU, PU, and MHB—exhibit P-values below 0.05. This suggests that they have a positive and statistically significant impact on the use of information and communication technology (TIK), thereby supporting hypotheses H1, H3, H4, H5, and H6. Conversely, the PR factor presents a P-value less than 0.05, indicating a negative correlation, which supports hypothesis H2. These influences are illustrated in Table 10 and further represented in the structural equation model depicted in Figure 2.



Source: Structural Equation Modelling (AMOS 26)

Figure 2. Structural equation modeling

CONCLUSIONS AND RECOMMENDATIONS

The findings of the study demonstrate that Perceived Trust (PT) exerts a significant positive influence (β = 0.233, CR = 2.320, p = 0.020) on utilization of Information and Communication Technology (UICT) within the context of Indonesian education. This outcome is consistent with prior research conducted by Shankar and Datta (2018), Zhou (2013), Lu et al. (2011), and Srivastava et al. (2010). The second factor, Perceived risk (PR), displays a significant negative effect on UICT (β = -0.121, CR = 2.221, p = 0.025) in Indonesian educational settings. This finding aligns with the studies performed by Kesharwani and Bisht (2012) and Cho (2004).

Additionally, the third factor, Social influence (SI), has a notable positive impact on the utilization of ICT, as indicated by the results (β = 0.127, CR = 1.981, p = 0.048). This finding is corroborated by the research of Kesharwani and Bisht (2012) and Vankatesh and Davis (2000). Moreover, the fourth factor, Perceived Ease of Use (PT), significantly and positively influences ICT usage among Indonesian education students (β = 0.278, CR = 2.327, p = 0.020), consistent with previous studies by Kesharwani and Bisht (2012) and Wang et al. (2003).

The fifth factor, Perceived Usefulness (PU), also has a significant positive impact on the adoption and utilization of ICT (β = 0.394, CR = 3.606, p = 0.000), echoing findings from Apanasevic et al. (2012) and Kim et al. (2010). Finally, this study highlights that the moral hazard behavior of lecturers (MHB) in Indonesia significantly and positively influences ICT usage, as evidenced by the results (β = 0.322, CR = 2.906, p = 0.000).

Considering the substantial influence of lecturer moral hazard behavior alongside the constructs of the Technology Acceptance Model (TAM) on students' utilization of Information and Communication Technology (ICT), future research is advised to broaden the scope of analysis beyond accounting students by involving diverse academic disciplines and educational levels. Longitudinal approaches and mixed-method designs are also recommended to capture temporal dynamics and contextual depth. Furthermore, investigating potential moderating variables—such as digital literacy, institutional trust, and organizational culture—may enrich the explanatory power of the model. The

integration of alternative theoretical frameworks, including Institutional Theory or Actor-Network Theory, is suggested to deepen the understanding of the complex interactions between technology adoption, power dynamics, and institutional structures, particularly within the context of developing countries.

FURTHER STUDY

This study provides an initial exploration of how lecturers' moral hazard behavior may influence the utilization of students' Information and Communication Technology (ICT) in Indonesian education.

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