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Article

Influence of region, experience, and subjective norm on the use of e-learning: Lesson from the insurance industry in Indonesia

Sancoko Sancoko[1,3,*], Lydia Freyani Hawadi[2,3], Lin Yola[3], Deni Danial Kesa[1]

[1] Vocational Education Program, Universitas Indonesia, West Java 16424, Indonesia
[2] Faculty of Psychology, Universitas Indonesia, West Java 16424, Indonesia
[3] School of Strategic and Global Studies, Universitas Indonesia, West Java 16424, Indonesia
*** Corresponding author:** Sancoko Sancoko, sancoko15@ui.ac.id

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Abstract: The effectiveness and efficiency of e-learning system in industry significantly depend on users' acceptance and adoption. This is specifically determined by external and internal factors represented by subjective norms (SN) and experience (XP), both believed to affect users' perceived usefulness (PU) and perceived ease of use (PEOU). Users' acceptance of e-learning system is influenced by the immensity of region, often hampered by inadequate infrastructure support. Therefore, this study aimed to investigate behavioral intention to use e-learning in the Indonesian insurance industry by applying Technology Acceptance Model (TAM). To achieve this objective, Jabotabek and Non-Jabotabek regions were used as moderating variables in all related hypotheses. An online survey was conducted to obtain data from 800 respondents who were Indonesian insurance industry employees. Subsequently, Structural Equation Model (SEM) was used to evaluate the hypotheses, and Multi-Group Analysis (MGA) to examine the role of region. The results showed that out of the seven hypotheses tested, only one was rejected. Furthermore, XP had no significant effect on PU, and the most significant correlation was found between PEOU and PU. In each relationship path model, the role of region (Jabodetabek and Non Jabodetabek) had no significant differences. These results were expected to provide valuable insights into the components of e-learning acceptability for the development of a user-friendly system in the insurance industry.

Keywords: e-learning; technology acceptance model; experience; subjective norm; region

1. Introduction

Business companies from various sectors, including the insurance industry, are currently facing a new era which promotes significant changes in the workplace. This is characterized by the depletion of natural resources, advances in science and technology, the presence of global markets, the expansion of the middle class, the integration of information and communication technology in the production process, along with influence of customers. Therefore, the use of technology and automation plays an essential role in augmenting production (Berawi, 2020; Cascio and Montealegre, 2016).

Influence of technology also affects the management of human resources, which specifically contribute skills, talents, energy, knowledge, and time to improve companies and support organizational objectives (Heathfield, 2021). In addition, financial improvements increase productivity, as shown in companies' reports. Human resource management is crucial in competitive companies as it affects the general growth of companies. Therefore, companies from various sectors, including the insurance industry, have invested in human resource development to promote efficiency and effectiveness, as well as retain productive employees to support organizational objectives (Barnes and Adam, 2017; Blaga, 2020). In Indonesia, insurance industries have invested in the development of e-learning applications to improve their human resources and adapt to technological transformation.

Various concepts, including the Theory of Planned Behavior (TPB), Theory of Reasoned Action (TRA), and Technology Acceptance Model (TAM), have provided an understanding of technology acceptance. TPB and TRA are specifically rooted in the disciplinary perspectives of psychology on human behavior, thereby limiting their application to certain contexts. Meanwhile, TAM, developed by Davis (1989), has been widely used in various contexts in private or public companies due to its robustness and parsimony (Kanwal and Rehman, 2017; Marikyan and Papagiannidis, 2023). This model focuses more on users' social behaviour derived from two indicators, namely perceived usefulness (PU) and perceived ease of use (PEOU) (Asvial et al., 2021). With defined external factors, TAM not only predicts technology adoption but also explains the reasons for the rejection of a particular system, thereby enabling academics and practitioners to take appropriate remedial measures. Abdullah and Ward (2016) summarized the conclusions of various studies that used modified TAM.

Table 1 shows that subjective norm (SN) and experience (XP) affected both PU and PEOU, with SN having a higher effect size. This study specifically used SN and XP indicators, which represented internal and external factors influencing changes in the behavior of e-learning users. A preliminary investigation by Venkatesh et al., (2003), focusing on demography such as gender and age as moderating variables, used region as a moderating variable in behavioral intention to use e-learning.

Table 1. Summary of the use of subjective norm and experience variables.

Commonly used external factors of TAM	Effect size of the external factors	Two main constructs of TAM
SN	0.228	PEOU
XP	0.163	PEOU
SN	0.279	PU
XP	0.162	PU

The broadness of region was worth studying since one of the challenges to implementing e-learning was lack of network, as well as limited infrastructure and weak bandwidth (Qashou, 2022). The context of Indonesia as a vast country with administrative/formal and functional territorial divisions questions whether regional differences also influence differences in the acceptance of technology, specifically by e-learning users in the insurance industry. Therefore, this study focused on the concept of "regions" to foster companies in managing learning effectively through e-learning. The objectives included (1) validating the application of Extended TAM in the insurance industry to determine employees' behavioral intention to use e-learning and (2) confirming the role of region in moderating differences in all hypothesized relationships.

2. Literature review

2.1. E-learning

As the name suggests, e-learning has a different concept from other forms of learning, characterized by two attributes, namely electronic and learning. According to Sanderson and Rosenberg (2002), it is the distribution of learning materials through the internet to students in various locations. Furthermore, e-learning uses electronic technology to access educational curricula outside the traditional classroom. In most cases, it is applied in courses, programs, or degrees generally conducted online (Al-atabi and Al-noori, 2020). In a simple definition, e-learning is a learning method that uses electronic media, particularly information technology. It requires the use of formal methods, with a syllabus, learning materials or media, and a predetermined schedule, as well as informal methods with the use of email or a separate mailing list to share materials and have discussions (Koran, 2001). Therefore, e-learning can be applied through synchronous, asynchronous, and hybrid methods (Amiti, 2020). For synchronous, learning is conducted online through the use of virtual classrooms (VCR) applications like Zoom or Microsoft Team, where teachers and students are not required to be present in the same physical location and meetings can be recorded. For asynchronous, both parties are not obligated to be present in the same location or engage in simultaneous work. In this regard, teachers have the ability to capture video tutorials, accessible to students within a certain period (Aljawawdeh and Nabot, 2022). Meanwhile, the hybrid method combines both synchronous and asynchronous.

Distance learning through e-learning has several advantages. First, it is flexible, facilitating students to study at any location or time. Second, it reduces the costs incurred by students and teachers since they do not need to travel to specific locations. Third, it addresses communication barriers between both parties through chat forums (Arkorful and Abaidoo, 2014). However, the implementation of the system has various challenges. First, teachers often have very poor learning motivation and get bored easily due to the absence of cognitive and social aspects in distance learning. Second, e-learning requires a variety of more sophisticated supporting tools, such as computers, internet data or Wi-Fi, and a good internet network (Aboderin, 2015; Aini et al., 2020).

2.2. TAM

TAM, modified from TRA by Azjen and Fishben (1980), is the basis for users' behavior toward technology acceptance. The intention to do or "not to do" a specific activity is influenced by two factors, namely attitude and influence of social norms (SN) (Lai, 2017). In its premise, TAM proposes two constructs that determine individuals' behavioral intention to accept and use technology, namely PU and PEOU. PU refers to subjective perception regarding the potential of certain technology to improve work performance, while PEOU refers to the extent individuals believe that using a specific system will be effortless (Davis, 1989). Therefore, critical factors in adopting new technologies include users' attitudes and beliefs. Individuals with positive attitude toward information technology tend to show greater acceptance compared to those with negative attitude (Al-Alak and Alnawas, 2011). The first modified version of TAM is presented as follows.

Figure 1 shows that the supporting elements of TAM included PU, PEOU, attitude toward use, behavioral intention to use, and actual system use (Lu et al., 2003). The current study specifically used the latest version of TAM which removed the construct of attitude toward use, as it does not provide additional predictive power when preceded by PU and PEOU. According to Davis et al. (1989), attitude may not be a significant determinant of intentions to use technology in the workplace when other factors, such as usefulness, are considered independently (Yousafzai et al., 2007).

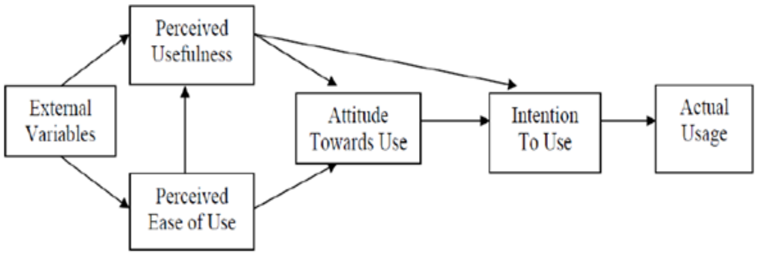

Figure 1. TAM developed by Davis
Source: Lai, 2017.

2.3. External variables and hypotheses

This study used two external variables, namely Subjective Norm (SN) and Experience (XP), with the following explanation. Igbaria et al., (1995) Igbaria (1995) found that computer XP, as an external variable had, a direct effect on system acceptance. In addition, XP can have an indirect impact through PU and PEOU. These results were supported by Purnomo and Lee (2013), where XP had a significant impact on PU and PEOU, with PEOU being influenced more strongly. Based on discussions, the following hypotheses were proposed:

H1: XP has a significant and positive influence on PU.

H2: XP has a significant and positive influence on PEOU.

SN are individuals' feelings or assumptions of expectations to exhibit certain behavior. According to Ajzen (1991), it is the perception of social pressure to show or not show a behavior. In this context, social pressure can come from parents, teachers and friends in a school environment, or coworkers and superiors at work. Venkatesh and Davis (2000) argued that individuals tend to dictate certain system as appropriate for coworkers. In developing TAM concept, Buabeng-Andoh (2018) reported that SN can affect PU. Comparatively, Teo (2009) with teachers and students as study objects showed that SN had a significant influence on PU and PEOU. Based on discussions, the following hypotheses were proposed:

H3: SN have a significant and positive influence on PEOU.

H4: SN have a significant and positive influence on PU.

PEOU is defined as the extent individuals believe an information technology system is easy to understand and use. Users tend to have a positive response and intention to use a system when it is perceived to be easy to understand, learn, and operate (Kustono, 2021). On the other hand, PU is the extent individuals believe a particular technology can improve work performance. Meanwhile, behavioral intention is the extent individuals consciously plan to "do or not do" an activity in the future (Kalayou et al., 2020). Numerous tests using TAM, TAM2, and TAM3 have proven that PU and PEOU both have a significant effect on BI, while PEOU has a significant effect on PU (Baleghi-Zadeh et al., 2014; Lee, 2013). Based on discussions, the following hypotheses were proposed:

H5: PEOU has a significant and positive influence on PU.

H6: PEOU has a significant and positive influence on behavioral intention to use.

H7: PU has a significant and positive influence on behavioral intention to use.

2.4. Region and study model

Region has several different definitions depending on the perspective. There are three types of regions in geography, namely physical, political, and economic (Van Langenhove, 2013). According to Ritter (1852), region is an entirely perfect structure where unity exists between nature and humans. Furthermore, it is a chronological unit consisting of a defined geographic area and its contents. The Earth's surface is heterogeneous and comprises many regions, each of which develops in the process of human adaption, is organized in society, and subject to specific environmental conditions (Vukovic and Kochetkov, 2017). There are two forms of region, namely formal and functional. A functional region (FR) is a territorial area with significant frequency of intraregional connections. Within this framework, connections may be in the form of economic exchanges, financial and information flows, or individuals mobility (Drobne et al., 2020).

In the context of Indonesia, region can be formed formally and functionally or both. **Figure 2a** presents Indonesia's administrative region, comprising 34 provinces regulated by law. Meanwhile, **Figure 2b** describes the FR on, "Jakarta, Bogor, Depok, Tangerang, and Bekasi" (Jabodetabek). Jabodetabek is one of the most FR in Indonesia, having interconnected activities centered in Jakarta. In 2022, Jakarta and its peripheral areas became region with the highest internet penetration in Indonesia.

Figure 2. Two types of regions **(a)** The map of Indonesia taken from pinterest.com; **(b)** The Jabodetabek regions obtained from wikipedia.org.

In this study, Jabodetabek was chosen in comparison with other regions (non Jabodetabek) due to its high human development index, which is measured through residents' level of knowledge. It is assumed that individuals who engage in e-learning activities in Jabodetabek are more accepted than those outside region. Two categories of region (Jabodetabek and Non Jabodetabek) were specifically used as moderating variables for all related hypotheses.

In addition to the hypotheses on the structural model, seven other hypotheses (H8-H14), regarding the differences in the use of region variable in all path analyses, were proposed. Examples include H8 "there is a significant difference in the relationship between XP and PU based on respondent region," and H9 "there is a significant difference regarding the relationship between XP and PEOU based on respondent region." The hypothesis model is presented as follows (**Figure 3**).

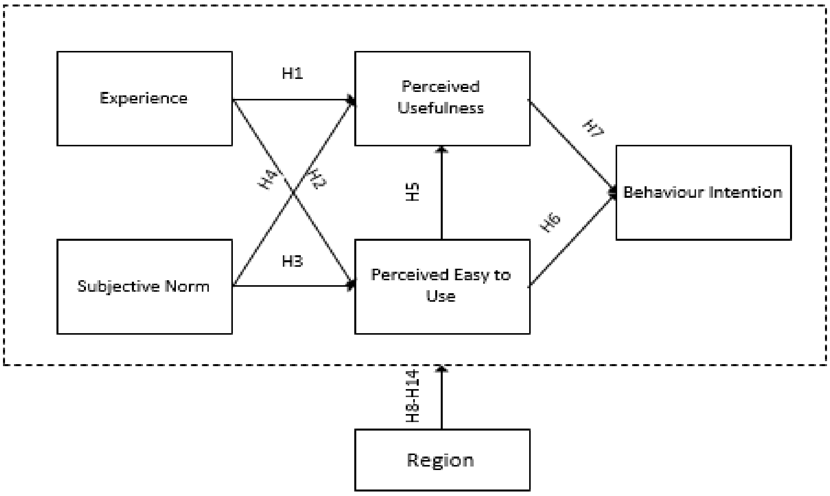

Figure 3. Study model.

3. Methods

3.1. Study design

This study used a quantitative method to address the relationships between variables by explaining or forecasting a social phenomenon. The method helped in drawing conclusions about a population based on existing samples (Mohajan, 2020). To achieve this objective, a cross-sectional survey was conducted at a specific point in time and limited period. In this study, a Google form link was shared to survey personnel who applied e-learning in insurance industry.

The notion of the question was evaluated through Likert scale, which is often used in education and social sciences studies, since it measures individuals' attitudes or perceptions (Sullivan and Artino, 2013). To avoid respondents' uncertainty, only four scales were used, namely 1 (strongly disagree), 2 (disagree), 3 (agree), and 4 (strongly agree).

Furthermore, structural equation modeling (SEM) was used, a statistical method for analyzing the relationships between observed and latent variables (Khine, 2013). Two categories of SEM were subsequently established, namely co-variance and variance-based. Variance-based SEM was specifically chosen as the study model focused on indicator prediction, and normal data distribution was not required. Region was included as a "new variable" to predict differences in e-learning acceptance. Variance-based SEM was introduced using SMARTPLS 3, with three phases of examination, namely measurement model, structural model, and multi-group analysis (MGA).

Measurement model was used to measure latent variables and indicators to ensure validity and reliability. To assess this model, Convergent Validity, Construct Reliability, and Discriminant Validity were conducted. Structural model focused on assessing the inter-relationship between latent variables through coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), model fit, and statistical significance. Lastly, MGA was carried out using region (Jabodetabek and non Jabodetabek) as a moderating variable to examine differences in all paths of the structural model. This study applied extended TAM comprising five constructs, namely BI, PU, PEOU, SN, and XP.

3.2. Participants

The participants included employees in the insurance industry throughout Indonesia. The demographic data are presented as follows:

Table 2. Respondents profile.

Category		Freq	Percent
Gender	Male	430	54%
	Female	370	46%
Level Education	S2/Master	91	11%
	S1/Bachelor	636	80%
	D3/ Associate	63	8%
	SMA/High School	10	1%
Job Position	Manager	97	12%
	Supervisor	52	7%
	Staff	630	79%
	Others	21	2%
Region	Jabodetabek	116	14%
	Non Jabodetabek	684	86%

Table 2 shows that 430 respondents (54%) were male while 370 were female (46%). Based on education level, 636 respondents had bachelor's degrees (80%), 91 had master's degree (11%), 63 with associate's degree (8%), and 10 with high school diploma (1%). A total of 630 respondents (79%) were at staff level, 97 (12%) at management level, 52 (7%) were at supervisor level, and 21 (2%) were in other positions. Meanwhile, based on region, 684 respondents worked outside Jabodetabek and 116 (15%) were in Jabodetabek.

4. Results and discussion

4.1. Measurement model

Convergent validity test with Outer Loading and Average Variance Extracted (AVE) was carried out to determine the validity of the relationships between indicators and constructs. AVE value was used to assess the convergent validity of a construct using reflecting indicators to meet the discriminant validity requirements. To consider the validity of constructs, the Outer Loading value should be greater than 0.70 and AVE value should be greater than or equal to 0.5 (Fornell and Larcker, 1981; Hair et al., 2021).

Construct reliability can be assessed through Composite Reliability (CR), which is considered better for estimating the internal consistency of a construct. The other measures that describe internal reliability consistency are Cronbach's Alpha and rho_A. Cronbach's Alpha value often produces a lower reliability value while CR value is considered too high. Rho_A test was conducted as an alternative, with the value falling between Cronbach's Alpha and CR.

Based on **Table 3**, Outer Loading, Cronbach's alpha, and CR values all exceeded the threshold of >0.70, while AVE exceeded the threshold of >0.50. This confirmed the constructs met the reliability and convergent validity requirements.

Table 3. Measurement model.

Construct	Item	Loading	Cronbach's Alpha	rho_A	CR	AVE
XP	Exp1	0.923	0.819	0.849	0.894	0.741
	Exp2	0.927				
	Exp3	0.717				
SN	SN1	0.897	0.882	0.881	0.920	0.742
	SN2	0.900				
	SN3	0.885				
	SN4	0.755				
PU	PU1	0.793	0.901	0.904	0.927	0.719
	PU2	0.869				
	PU3	0.881				
	PU4	0.888				
	PU5	0.803				
PEOU	PEOU1	0.891	0.916	0.919	0.938	0.751
	PEOU2	0.890				
	PEOU3	0.885				
	PEOU4	0.883				
	PEOU5	0.779				
Behaviour Intention	BI1	0.786	0.882	0.888	0.919	0.740
	BI2	0.883				
	BI3	0.873				
	BI4	0.895				

Discriminant validity tests were carried out to ensure that a reflective construct had the most significant relationship with its indicators. In addition, discriminant validity was assessed using Cross Loadings and the Fornell-Larcker criterion. Cross-loadings was carried out to confirm that the correlation of the construct with the measurement item was greater than the other constructs. **Table 4** shows that the cross-loadings value exceeded the loading values of other constructs, confirming the indicators could be interchanged.

Fornell-Larcker Criterion is used for comparing the root value of AVE with the correlation value between latent variables. The square root value of AVE for each construct should be greater when compared to other constructs in the model. **Table 5** shows that the root value of AVE (Fornell-Larcker Criterion) for each construct exceeded the relationship with other variables, confirming discriminant validity.

Table 4. Discriminant validity (cross loadings).

	BI	Exp	PEOU	PU	SN
BI1	0.786	0.519	0.552	0.581	0.541
BI2	0.883	0.541	0.655	0.678	0.646
BI3	0.873	0.495	0.597	0.676	0.620
BI4	0.895	0.569	0.651	0.707	0.679
Exp1	0.580	0.923	0.589	0.499	0.563
Exp2	0.560	0.927	0.583	0.483	0.551
Exp3	0.443	0.717	0.442	0.375	0.512
PEOU1	0.640	0.554	0.891	0.682	0.601
PEOU2	0.613	0.527	0.890	0.650	0.559
PEOU3	0.647	0.508	0.885	0.669	0.569
PEOU4	0.643	0.612	0.883	0.665	0.557
PEOU5	0.549	0.527	0.779	0.578	0.520
PU1	0.603	0.442	0.563	0.793	0.582
PU2	0.674	0.494	0.650	0.869	0.603
PU3	0.672	0.466	0.663	0.881	0.589
PU4	0.689	0.459	0.644	0.888	0.587
PU5	0.621	0.380	0.656	0.803	0.538
SN1	0.657	0.525	0.555	0.607	0.897
SN2	0.618	0.530	0.524	0.554	0.900
SN3	0.601	0.561	0.541	0.578	0.885
SN4	0.609	0.537	0.600	0.602	0.755

Table 5. Discriminant validity (Fornell-Larcker criterion).

	BI	Exp	PEOU	PU	SN
BI	0.860				
Exp	0.617	0.861			
PEOU	0.715	0.630	0.867		
PU	0.770	0.529	0.750	0.848	
SN	0.725	0.628	0.648	0.684	0.861

4.2. Structural model

The R Square values in **Table 6** showed the strength of the effect of the exogenous construct. Chin (1998) classified R Square values of 0.67, 0.33, and 0.19 as strong, moderate, and weak (Ghozali and Latan, 2015). Furthermore, the R^2 value for BI as an endogenous construct was 0.636, confirming exogenous constructs (PU and PEOU) moderately explained the variance of the endogenous construct (BI) by 63.6%.

PU had an R^2 value of 0.631, meaning PEUO, XP, and SN moderately explained PU by 63.1%. Meanwhile, PEOU had an R^2 value of 0.502, meaning XP and SN moderately explained PU by 50.2%.

The *Q* Square was obtained through a blindfolding procedure to measure whether the model had predictive accuracy, where a value greater than 0 means exogenous variable has predictive relevance to the endogenous variables. Based on **Table 6**, the Q^2 values were greater than 0, confirming predictive relevance.

Table 6. *R* Square.

	R^2	Q^2
BI	0.636	0.466
PEOU	0.502	0.373
PU	0.631	0.449

The f^2 value described the magnitude or strength of the relationships between latent variables. Hair et al. (2021) and Henseler (2009) classified this value into 0.02 (small), 0.15 (medium), and 0.35 (large) (Hair et al., 2021; Henseler et al., 2009). Therefore, the effect size, as presented in **Table 7**, was large (0.397) for H5 and small (0.002) for H1. Meanwhile, the outside of the two paths had a medium effect size.

According to Henseler et al. (2016), the standardized root mean square residual (SRMR) is the only approximate model fit criterion for evaluating PLS models, with an SRMR value below 0.08 confirming a fit model. Karin Schermelleh et al. (2003) also stated that an SRMR of less than 0.10 could be considered acceptable fit (Fornell and Larcker, 1981; Hair et al., 2021). Therefore, the SRMR value presented in **Table 7** confirmed the validity and reliability of the model.

T-value was used to test the hypotheses. According to Holmes-Smith (2001), a parameter with a *t*-value greater than 1.96 and sig = 0.05 can be considered a significant and valid indication (as cited in Ichwan and Nursyamsiah, 2019). Based on the hypotheses testing (**Table 7**), six hypotheses had a value greater than 1.96, while only one had a value less than 1.96.

Table 7. Structural model test.

H	Path	β	*t* value	*p* Values	Result	f^2	Item	Value
H1	Exp → PU	-0.034	0.927	0.355	Reject	0.002	**SRMR**	0.063
H2	Exp → PEOU	0.367	8.256	0.000	Accept	0.164		
H3	SN → PEOU	0.418	10.282	0.000	Accept	0.212		
H4	SN → PU	0.353	9.359	0.000	Accept	0.169		
H5	PEOU → PU	0.543	14.495	0.000	Accept	0.397		
H6	PEOU → BI	0.314	8.149	0.000	Accept	0.118		
H7	PU → BI	0.534	14.016	0.000	Accept	0.342		

The Table shows that H1 was rejected with a *t*-value of 0.927, which was lower than 1.96, and a negative path coefficient value ($\beta = -0.034$, $p > 0.05$). Meanwhile, H2, H3, H4, H5, H6, and H7 were all accepted, with *t*-values of 8.256, 10.282, 9.359, 14.495, 8.149, 14.016, and positive path coefficient values of ($\beta = 0.367$, $p < 0.01$), ($\beta = 0.418$, $p < 0.01$), ($\beta = 0.353$, $p < 0.01$), ($\beta = 0.543$, $p < 0.01$), ($\beta = 0.314$, $p < 0.01$), and ($\beta = 0.534$, $p < 0.01$), respectively.

4.3. Results of the MGA

A total of 684 respondents (85%) lived outside of Jabodetabek, while 116 (15%) resided within region. The moderating role of region (Jabotadetabek and Non-Jabodetabek) was examined through MGA.

MGA results (**Table 8**) showed that region had no significant impact on most predictors of exogenous constructs, confirming the rejection of all hypotheses. For example, the *p*-value of the difference in the relationship between XP and PU was insignificant ($\beta = 0.162$; $p = 0.059$), confirming the rejection of H8. The difference in the path coefficient between both variables was also insignificant ($\beta = 0.012$; $p = 0.059$), confirming the rejection of H9. However, there were significant differences in individual groups for H8, namely $\beta = -0.170$; $p = 0.024$ for Jabodetabek and $\beta = -0.07$; $p = 0.856$ for non-Jabodetabek. The Jabodetabek group in H8 had a significant and negative relationship.

Table 8. MGA results regarding all paths based on region (Jabodetabek and Non Jabodetabek).

H	Path	*β* (Jabo detabek)	*β* (Non_Jabo detabek)	*p* Jabo detabek	*p* Non Jabo detabek	*β* (Jabo detabek-Non Jabo detabek)	*p* Jabo detabek-non
H8	Exp → PU	−0.170	−0.007	0.024	0.856	−0.162	0.059
H9	Exp → PEOU	0.357	0.370	0.001	0.000	−0.012	0.915
H10	SN → PEOU	0.486	0.407	0.000	0.000	0.079	0.362
H11	SN → PU	0.291	0.357	0.000	0.000	−0.066	0.465
H12	PEOU → PU	0.695	0.519	0.000	0.000	0.176	0.061
H13	PEOU → BI	0.275	0.323	0.000	0.020	−0.049	0.696
H14	PU → BI	0.544	0.533	0.000	0.000	0.012	0.921

5. Discussion

Based on analysis, H1 and H2 showed difference significant results, where experience, which was statistically rejected, had no effect on PU. On the other hand, XP significantly influenced PEOU. These results (**Table 7**) contradicted Purnomo (2013), focusing on employees in the banking industry in Indonesia, as well as Mailizar (2021), where XP influenced PU and PEOU (Mailizar et al., 2021; Purnomo and Lee, 2013).

Based on experience, the comparison of e-learning training with traditional training led to different results. E-learning training has several limitations. First, students reported an increase in study load. Second, there were perceptions that e-learning promoted isolation, as it required spending a significant amount of time on computer. Third, there was no interaction between students, which is an integral part of job skills (Maatuk et al., 2022). The more often individuals take part in e-learning, the less favorable the perception of its usefulness. Online learning participants often losses due to the inability to travel to various places and lack of stipends.

E-learning training was also considered to be ineffective due to the inability to improve knowledge, skills, and attitudes. According to Kirkpatrick (1998), learning can be defined as the extent individuals change attitudes, improve knowledge and skills as a result of participating in a program. There are four methods for evaluating the outcomes of training, one of which is learning evaluation through post-test and pre-test (Pateda et al., 2020). According to Munajatisari (2014) investigation at the Education and Training Center of the Ministry of Finance of the Republic of Indonesia, classical training (mean = 75.363) was more effective compared to e-learning training (mean = 66.450). Furthermore, the lack of significant correlation between XP and PU could be attributed to limited information, and communication technology (ICT) skills among insurance employees. ICT skills are projected to be in high demand, regardless of whether applicants have IT background. An investigation conducted in Bangladesh on students' acceptance of e-learning showed that individuals with advanced ICT skills preferred online learning (Alam and Ogawa, 2024).

H3 and H4 with the SN variable were statistically supported in this study, where SN predicted PEOU ($\beta = 0.610$) more accurately than PU ($\beta = 0.294$). This resonated with Lee (2011) on Taiwanese workers, where SN was the most significant predictor of PEOU than PU in the use of e-learning (Lee et al., 2011). SN, derived from TRA, is usually influenced by coworkers, managers, consumers, or companies' values. In this regard, positive attitudes toward e-learning system could be attributed to encouragement from supervisors and coworkers.

Individuals are affected by social influences through three mechanisms, namely compliance, internalization, and identification. As a reaction to social influences, compliance mechanism can alter preferences. For instance, individuals tend to respond to those who can impose penalties or provide rewards. This includes concurring with leaders or coworkers who claim the usefulness of e-learning, despite the perception to disagree (Venkatesh and Davis, 2000). The following strategies can be used to increase employees use of e-learning system: (1) employees are expected to attend training on the use of e-learning system; and (2) the usage of the system should be supported by necessary resources (Lee et al., 2011).

H5 and H6 with PEOU were statistically supported in this study, as PEOU had a significant effect on PU and BI. This variable represented users' perception that the system was easy to understand, master, and operate. Employees who find e-learning as easy to use tend to have good attitude toward consistent usage, perceiving the system to be beneficial for improving knowledge. Both PEOU and PU simultaneously influenced BI, with PEOU having a lower predictor value. These results were in line with Purnomo and Lee (2013) and Venkatesh and Davis (2000), where PU served as the main predictor of BI. In other words, PU was the primary determinant of technology adoption, specifically e-learning in the insurance industry of Indonesia (Purnomo and Lee, 2013; Venkatesh and Davis, 2000).

For H7, PU had a significant effect on BI, with the effect size (β value) confirming that e-learning system created by the insurance industry met the usability level. According to ISO 9241–11 (1998), the usability of a product by users should meet certain levels of effectiveness, efficiency, and satisfaction. The efficiency aspect is related to how quickly users can achieve their objectives when using e-learning product. Meanwhile, effectiveness reflects the level of effectiveness achieved in relation to resources, specifically time and costs. Satisfaction specifically measures the extent users are free from discomfort when using e-learning product (Alfidella et al., 2015; Sukma et al., 2020). With organization's mandatory implementation of e-learning, students believe that the system helps improve knowledge and provide relevant exam materials.

For H8, MGA (**Table 8**) showed XP had a significant effect on PU, with region (Jabodetabek) as a negative moderating variable. Therefore, a point increase in XP could decrease PU by 0.17 points. This negative trend could be attributed to respondents in region having better knowledge or system developed by the insurance industry, making the e-learning training useless. The e-learning system is no better than the existing systems, such as Ruangguru, Coursera, Udemy, and others.

Another premise among users from outside Jabodetabek is the disparity in infrastructure support, such as network, internet, which remains to be addressed. These results were in line with previous studies, confirming adequate infrastructure as crucial for e-learning success. For example, in an investigation of e-learning among students in Bangladesh, while internet was accessible, 73.5% reported that the connection was not fast and stable. Interviews also emphasized that poor internet network constraints made it difficult for students to access, use, and learn effectively (Alam et al., 2023; Basar et al., 2021; Dhawan, 2020).

6. Conclusion

In conclusion, this study showed perceived usefulness and perceived ease of use had a significant effect on behaviour intention to use e-learning in the insurance industry, with perceived usefulness serving as the main predictor. While the use of experience as an external factor had no significant effect on PU, several studies have shown its impact on both PU and PEOU. Based on MGA, there was no significant difference in the role of region in moderating all path analyses.

Further investigations on employees of the insurance industry were expected to examine why experience had no effect on PU by using the modified TAM with other moderating variables such as self-efficacy, computer anxiety, and management support. In addition, the use of "region" as a moderating variable was expected to expand to different contexts, namely higher education or state archipelago. Studies in different field or countries with similar problems could help institutions in adopting appropriate policies.

For instance, longitudinal studies conducted on employees in Indonesia provided insights into the adoption and acceptance of e-learning in various countries. Therefore, the insurance industry in Indonesia should provide a pleasant e-learning environment and adequate support for students. For those who were eligible to participate, support could be provided in the form of finances, equipment, and rewards. This would increase the motivation to use and recognize the benefits of the system. It was also crucial to provide adequate network coverage for lacking regions.

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