Jurnal TAM (Technology Acceptance Model)
Jurnal TAM, Volume 14, Number 1, July 2023
E ISSN: 2579-4221; P ISSN: 2339-1103, pp. 19-30
Accredited SINTA 4 Number 225/E/KPT/2022
https://jurnal.ftikomibn.ac.id/index.php/index

ELUCIDATING THE IMPACT OF ELECTRONIC WORD OF MOUTH TO THE INTENTION TO USE LINKEDIN FOR ASEAN JOBSEEKERS: MODERATING ROLE OF GENDER

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Article history:
Received: April 22, 2023
Revised: June 3, 2023
Accepted: July 6, 2023

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Keywords:
eWOM;
LinkedIn;
TAM;
ASEAN

Abstract
LinkedIn is one of the most popular e-recruitment tools for job applicants. Although previous studies had explored the effectiveness of LinkedIn, the underlying cause of jobseekers' intention to use LinkedIn is still under-researched. This study examines the impact of Electronic Word of Mouth (eWOM) to the behavioral intention (BI) of jobseekers to use LinkedIn, using the Technology Acceptance Model (TAM) as the framework. The Partial Least Square Structural Equation Modelling (PLS-SEM) was applied to analyze 431 samples of ASEAN Jobseekers via SmartPLS 3. Findings show that eWOM positively influences the perceived ease of use (PEOU), Perceived Usefulness (PU), and Attitude (AT) of jobseekers, which consequently positively impacts the jobseekers' behavioral intention (BI) to use LinkedIn. The mediating role of PEOU, PU., and AT was also examined and shows that the three variables partially mediate the relationship between eWOM and BI. Theoretically, this study uncovers the significance of eWOM in new technology acceptance. Practically, managers can use this information to increase positive eWOM of their company's LinkedIn profiles to attract more decent talents to the company. To the authors' knowledge, this study is one of the first investigations into how external variables influence the TAM Model in e-recruitment which uses regional samples instead of specific country-wide samples.

1. INTRODUCTION

Recruitment is defined as "practices and activities carried out by the organization with the primary purpose of identifying and attracting potential employees" [1]. As technology emerges, the recruitment mode has shifted from conventional methods to e-recruitment [2], [3]. Tong and Sivanand (2005) describe e-recruitment to carry out, accelerate, or improve the recruiting process by utilizing information technology (IT). E-recruitment has transformed how jobseekers see and apply for jobs in organizations to attract incredibly talented individuals [5]. One such e-recruitment platform is LinkedIn, one of the most popular professional networking sites for recruitment and networking (J. Davis et al., 2020), with over 830 million members in more than two hundred countries worldwide [7].

Despite being widely used, e-recruitment is still under-researched, particularly regarding the underlying cause of using e-recruitment tools. Candra et al. (2020) have explored the acceptance of LinkedIn as a mode of recruitment among Indonesian jobseekers, using Technology Acceptance Model (TAM) developed by Davis (1989) as its framework. However, previous literature's approach has overlooked external factors that influence jobseekers' intention to adopt e-recruitment tools. One of the influencing factors is eWOM.

Azer and Alexander (2020) defined eWOM as "a statement via social media made by potential, actual, and former customers about products or services." eWOM has been extensively studied in the marketing literature [11]–[13]. Marketing constructs and theories have recently been applied in recruitment literature [14] since customers' purchase intention is like jobseekers' intention to apply a job for. Therefore, the recruitment literature has used eWOM to influence university selection [15] Or employer attractiveness [16]. Regardless of the abundance of eWOM research in recruitment, only Kaur & Kaur (2022) has explored the significance of eWOM on job seekers' intention to use e-recruitment tools using Indian samples. Their study, however, is limited to a country survey, which hinders a broader analysis of technology acceptance for a wider population.

The scope of this study is jobseekers from the ASEAN countries, which include Brunei Darussalam, Cambodia, Indonesia, Laos PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Viet Nam. This region has experienced massive growth in the economy over the past two decades from USD 0.6 Trillion in 2000 to almost USD 2.9 Trillion in 2020, amid the economic downturn in 2008-2009 and the Corona Pandemic in 2020 [17]. ASEAN's GDP is also the fifth largest in the World in 2020. In terms of population growth, ASEAN has an annual growth of 1.30% from 1980 to 2020, largely due to the newly joined countries in 1894 – 1999, but also due to the natural growth of birth in each country. Furthermore, the population of ASEAN has reached more than 600 million, making it the third-largest populated region after China and India. In addition to that, the majority population in ASEAN is the young generation which represented 33.1% of the ASEAN population [17].

In the context of HR Practices, a literature review conducted by Do et al. (2020) on HRM practices in ASEAN countries revealed that there are research gaps between ASEAN and western countries, as well as other developed Asian countries. Secondly, the study found that most existing investigation ends at the corporate level of analysis. Lastly, the study also concluded that cross-comparative studies involving ASEAN members are still scarce.

This study aims to fill the gaps in the literature by extending the previous study by assessing the significance of eWOM on jobseekers' intention to use LinkedIn, as well as the moderating role of gender that influences it. Furthermore, this study expands the scope of samples, using regional samples instead of country-wide ones, allowing for a broader analysis of TAM in recruitment. Understanding the link between eWOM and jobseekers' intention to use LinkedIn will support companies in managing their eWOM on LinkedIn to attract potential jobseekers through the platform. This paper is structured as follows: Literature review on TAM, eWOM, and Demography profiles, the development of hypotheses, research methodology, description of results, practical implication of the study, limitation and recommendation, and conclusion.

II. LITERATURE REVIEW

The literature review of TAM and eWOM in the context of e-recruitment are presented in this section.

2.1. Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed by F. D. Davis (1989). It describes the willingness of an individual to accept new technology, influenced by several factors. Over time, TAM has evolved since it was first introduced. Lee et al. (2003) observations about TAM literature spanning from 1989 to 2003 show that TAM has been extended and elaborated since 1994 from its original form. This extension includes the introduction of external variables, relationships between TAM variables, and the addition of moderators' variables. Further, Lee et al. (2003) have applied in many contexts regarding Information Systems. This view is supported by Li et al. (2008), who discovered that TAM has matured with its adaptation and flexibility to be used in research.

There are four significant variables in TAM. The first is Perceived Ease of Use (PEOU), the user's perception of how much effort is required to use the technology [21]. Based on various studies [9], [21]–[23], PEOU significantly affects users' intention to use directly or indirectly via Perceived Usefulness (PU). The second primary variable is PU, which F. D. Davis (1989) defined PU as "the belief of users that the technology will improve their performance." Studies suggest [2], [9], [19] that PU is significantly affected by PEOU since the more straightforward the technology can be used, the more valuable it is from the users' perspective. Attitude (AT) is defined as individual characteristics that portray positive or negative behavior and reflect feelings and knowledge of a particular concept or subject [24]. Hussein (2017) suggests that AT significantly impacts students' intention to use E-Learning technology. This study is aligned with other works of literature that suggest AT drives, either positively or negatively, the intention to use new technologies [5], [23], [25]. The fourth variable of TAM is called Behavioral Intention (BI), which is the final dependent variable of TAM and is impacted by the other three variables [2], [20], [23]–[25]. On that note, Lunney et al. (2016) found that PU and PEOU did not directly impact BI but fully mediated the relationship between external variables and BI.

The use of e-recruitment tools depends on the easiness of use of the tech. The easier it is to use, the more job seekers perceive that tool to be useful [26]. Additionally, job seekers who perceived e-recruitment as easy to use lead to a positive attitude towards e-recruitment and actual use of the tools [20], [26]–[28].

F. D. Davis (1989) suggests that individuals will use a system if they believe technology will help them achieve their objectives. J. Kaur et al. (2021) confirmed this when they found that the e-banking application usefulness in India drives the samples to use the application. Another finding suggests that perceived usefulness in wearable fitness technology has a significant impact on MTurk workers' attitude toward the technology, which in turn has a positive impact on their Behavioral Intentions [22]

In the e-recruitment context, previous literature has shown that Attitude and Behavioral Intentions are predominantly affected by Perceived Ease of Use and Perceived Usefulness [8], [29], [30]. The attitude is proven to be the driver of Behavioral Intentions to use e-recruitment tools [28], [30].

PU, PEOU, and Attitude have been shown to mediate between external factors and the BI of users [20], [25], [28]. Furthermore, eWOM is proven a reliable source of information for jobseekers regarding minimizing information asymmetry [16]. D. Kaur & Kaur (2022a) tested the mediating effect of PU, PEOU, and attitude to the relationship between eWOM and BI. The result showed that PEOU did not have a significant mediating effect.

2.2. Electronic Word of Mouth

Word of Mouth is defined as the intercommunication behavior between consumers about a product, service, or brand [31]. Typically, word-of-mouth behavior is related to marketing activities, which can improve the public's awareness of products or services. It effectively increases sales because the information is exchanged between people who know each other [31]. As technology advances, consumer communication has moved through the internet, called Electronic Word of Mouth (eWOM) [12], [15], [32]. In formal definition, Litvin et al. (2008, p. 461) defined eWOM as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers."

In marketing literature, eWOM has been mentioned as influential towards pre-purchasing behavior [34], improving customer service quality [35], and improving purchase intentions of customers through Social Networking Sites (SNS) [36]. In this literature, consumers seek information about the products and services on the internet, affecting their perceived usefulness of technology and purchase intention. In e-recruitment, eWOM has a high impact on increasing employee attractiveness [16], [37]. In previous e-recruitment literature, jobseekers use SNS to find employer profiles and posts, hence improving the perspective of the technology's usefulness. Furthermore, the emergence of SNS has made information more accessible. Consumers, for instance, can look for their desired products quickly on SNS Websites and gain a better understanding of the products and the websites' system through eWOM [11]. The same is valid with jobseekers, who can access a wide variety of skills on the internet for their desired job, and through eWOM, can gain a better understanding of the job and the company [5]. Other findings suggest that the type of eWOM, either positive or negative, can influence the users' Attitude and Behavioral Intentions in using the system. For instance, Filieri et al. (2021) found that highly positive and negative EWOM significantly impact travelers' attitudes to a specific website. Furthermore, eWOM also affects the attitude and intention to travel based on website customer reviews about the destination [12]. Therefore, eWOM can also affect the attitude and Behavioral Intentions to use e-recruitment technology.

2.3. Gender, Nationalism, Age, and Education Level

An exploration of the literature shows that respondents' demographical profiles also affect the relationship between variables. Bem (1981) proposed the Gender Schematics theory, which sees gender as a social construct rather than biological sex. Therefore, using this theory as a basis, this study defines gender as the decision-making process of people of different sex that conforms their identity to their gender schema. Previous literature has shown that males and females have different decision-making mechanisms [40], [41]. Moreover, Li et al. (2008) found that control variables significantly impact the forecasting capabilities of a research model. Samples' demographic profiles, i.e., age and education level, are most often used as the control variables in previous technology acceptance literature [24], [42].

The gender schematics theory developed by Bem (1981) drives research institutions to discover the effect of gender on technology acceptance. For instance, men and women perceive their technological capabilities differently [43]. Gender affects attitude and persistence in online learning (Lakhal & Khechine, 2021). Men tend to have a high level of technological complexity, while women are more inclined towards moderate technology [40]. Other findings suggest that gender moderates the relationship between service satisfaction and word of mouth [45] and that the impact of anxiety on review helpfulness is also moderated by reviewer gender [46].

III. METHODOLOGY

3.1. Data Collection and Measurement Instrument

This study adopted a quantitative approach and used a survey to collect data. Data were collected by a questionnaire which has a seven-point Likert scale in each statement, in which 1 = "Strongly Disagree," and 7 = "Strongly Agree." This study targets ASEAN jobseekers who have used or are at least aware of LinkedIn, and the survey is depicted in table 1. Four eWOM constructs were adopted from Jalilvand & Samiei (2012) and D. Kaur & Kaur (2022a). The TAM constructs measurement is mainly adopted from Davis (1989) and other studies conducted in more recent times. Four items to measure PEOU and PU are adopted from Irawan et al. (2021), while five items to measure AT are adapted from D. Kaur & Kaur (2022a) and Rodrigues Pinho & Soares (2011). Finally, BI is measured through four items adapted from Brahmana & Brahmana (2013).

In a more recent study, Uakarn et al. (2021) compared various formulas to estimate the sample size. The results show that Cochran's Formula, developed in 1967 [49], is most suitable when dealing with a sizeable unknown population and unknown proportion.

Based on the formula, this study's required number of samples is 385 ASEAN jobseekers. This study gathered 431 respondents from the ASEAN Countries, so the number of respondents in this study is sufficient.

Table 1 Measurement Instrument

Constructs	Items
1st Section: Demographics Profile	
Gender	*Male* *Female*
Age	*18 – 22* *23 – 27* *28 – 32* *33+ Years*
Education Level	*High School / Vocation School* *Associate Degree / Diploma* *Bachelor's Degree* *Master's Degree* *Ph.D. / Doctorate Degree*
2nd Section: Statements about Jobseekers' AT and BI towards E-Recruitment	
eWOM	*1. I refer to online reviews to know whether LinkedIn made a good impression on jobseekers* *2. I frequently gather online reviews of LinkedIn from various sources before signing up* *3. The information I can get online is crucial to me* *4. I often consult with my friends online before signing up to LinkedIn*
PEOU	*1. LinkedIn is simple to use in my opinion* *2. I can easily understand how I interact with LinkedIn* *3. The registration and data uploading process to LinkedIn is easy in my experience* *4. I find it simple to fix errors when using LinkedIn*
PU	*1. When submitting Curriculum Vitae (CV) and Resume, using LinkedIn sites saves me time compared to conventional method* *2. Using LinkedIn allows me to apply for more jobs than would otherwise be possible* *3. My chances of finding an appropriate job are increased thanks to using LinkedIn* *4. In general, LinkedIn is useful to look for a job*
AT	*1. I enjoy using LinkedIn* *2. I love the idea of using LinkedIn to find an appropriate job* *3. People are usually impressed about how I use LinkedIn* *4. My experience in using LinkedIn is mostly positive* *5. I believe that using LinkedIn is desirable for job searching*
BI	*1. I intend to register myself on LinkedIn* *2. I intend to use LinkedIn for job searching* *3. I intend to upload my CV and resume to LinkedIn* *4. I believe that the probability of me using LinkedIn for job searching is most likely*

3.2. Demography of Respondents

Table 2 shows the respondents' demography of the data collected. Of 431 respondents, 212 were male (49.2%), and 219 were female (50.8%). This distribution is pretty much even, considering there is only a 1.6% difference. This figure is vital since Gender is the moderator variable of the operational model, which may or may not influence the relationship between latent variables.

Regarding age, most respondents are people in the age range of 28 – 32 years old, with 26.9% out of the total 431 respondents. The second most respondents are 18 – 22 years old, with 26.0%. 23.7% of respondents come from the 33 years old and up group, while the rest 23.4%, are between the ages of 23 – 37. The respondents' dominant education level is bachelor's degree graduates (26.9%), followed by Associate degree and High School (24.1%). The amount of master's degree graduates (16.7%) is higher than the amount of Doctorate Degree graduates (8.1%). Regarding nationalities, most respondents come from Indonesia (15.5%), followed by Brunei Darussalam, Cambodia, and Vietnam (10.2%). Other ASEAN countries are represented in the data, with the least respondents coming from Thailand, with 7.7% of the total respondents.

Further details regarding respondents' age, gender, education level, and nationalities can be seen in Tables 4.4 and 4.5. As shown in Table 4.4, most high school and Associate degree graduates come from the 18 – 22 years old group, with 42.30% and 35.57% out of 104 respondents, respectively. 31.03% of respondents with bachelor's degrees are in the age range between 23 – 27 years old, followed by the age group between 18 – 22 years old with 26.72%. for master's graduates, the distribution is even for the 23 – 27, 28 – 32, and 33+ years old group, with 33.33%, 31.94%, and 34.72%, respectively. Lastly, there are no 18 – 22 and 23 – 27 years old groups with Doctorate, so the respondents with the highest education level came from the later groups of age, with 60% the 28 – 31 years old and the rest 40% coming from the 33+ years old.

3.3. Common Method Bias

According to F. Kock et al. (2021), when the independent and dependent variables data are collected from the same questionnaire, there is a possibility of bias in the data. We employed Harman's Single Factor Exploratory Factor Analysis on SPSS to check the bias [51]. Multicollinearity testing is used to ensure that no two or more constructs are correlated to each other [52]. According to Hair et al. (2019), the Variance Inflation Factor (VIF) is one reliable way to test for Multicollinearity and Common Method Bias. The results showed that there is no multicollinearity between constructs. Harmans's Single Factor Exploratory Factor show that no common method bias in the data set.

IV. RESULTS

PLS-SEM method was used in this study to evaluate the reliability and validity of measurement items, evaluate the measurement model, as well as to analyze the mediating and moderating variables.

Table 2 Respondents' Demography

Characteristics	**Frequency (n = 431)**	**%**
Gender		
Male	212	49.2%
Female	219	50.8%
Age		
18 - 22 Years Old	112	26.0%
23 - 27 Years Old	101	23.4%
28 - 32 Years Old	116	26.9%
33 Years and Up	102	23.7%
Education Level		
High School	104	24.1%
Associate Degree	104	24.1%
Bachelor's Degree	116	26.9%
Master's Degree	72	16.7%
Doctorate Degree	35	8.1%
Nationality		
Brunei Darussalam	44	10.2%
Cambodia	44	10.2%
Indonesia	67	15.5%
Lao PDR	42	9.7%

Malaysia	40	9.3%
Myanmar	43	10.0%
Philippines	36	8.4%
Singapore	38	8.8%
Thailand	33	7.7%
Viet Nam	44	10.2%

4.1. Assessment of Measurement Model

The measurement model reliability and validity are calculated via SmartPLS 3 [51]. The result of reliability and validity is depicted in Appendix A. The reliability is measured by Cronbach's Alpha (α) and rho alpha (ρA), where these values should be greater than 0.7 to be deemed acceptable. The results satisfied this condition in which all constructs value ranges from 0.720 to 0.735 for α and between 0.757 to 0.768 for ρA. The validity of the questionnaire is indicated by outer loadings (≥ 0.5), Composite Reliability (CR; ≥ 0.7), and Average Variance Extracted (AVE; ≥ 0.5). The outer loadings range from 0.711 (EWOM3) to 0.806 (PEOU4). These outer loadings are then used to calculate AVE and CR, and the values have also fulfilled the criteria. The CR ranges from 0.823 to 0.856, while the AVE ranges from 0.538 to 0.586.

4.2. Assessment of Structural Model

The overall result of the structural model is depicted in figure 2, while the hypotheses evaluation is summarized in table 3. The structural relationship confirms that eWOM positively influences TAM variables. eWOM affects PU (β = 0.275; t =5.709; and p = 0.000), PEOU (β = 0.563; t = 17.149; and p = 0.000), AT (β = 0.191; t = 4.310; and p = 0.000), and BI (β = 0.192; t = 4.401; and p = 0.000), which confirms H1, H2, H3, H4, respectively. Meanwhile, the relationship between TAM variables is confirmed by the results. The relationship between PU and BI (β = 0.225; t = 4.630; and p = 0.000), as well as AT and BI (β = 0.311; t = 6.279; and p = 0.000) support H9 and H10, respectively. These findings indicate that the intention to use LinkedIn in ASEAN job seekers is dependent upon their perceived usefulness and attitude (H9 and H10 supported). In addition, PU affects AT significantly (β = 0.287; t = 5.837; and p = 0.000), which indicates that ASEAN jobseekers' attitude is dependent upon their perceived usefulness. Furthermore, PEOU has a significant effect on the other TAM variables: PEOU and PU (β = 0.472; t = 10.110; and p = 0.000), PEOU and AT (β = 0.423; t = 8.909; and p = 0.000), as well as PEOU and BI (β = 0.200; t = 3.765; and p = 0.000), which supports H5 through H7. This result indicates that PEOU is LinkedIn's critical factor regarding ASEAN jobseekers' Behavioral intention to use the platform. Finally, the model incorporated control variables, i.e., Nationality, Age, and Education Level. However, none of the control variables included in the model affect BI significantly.

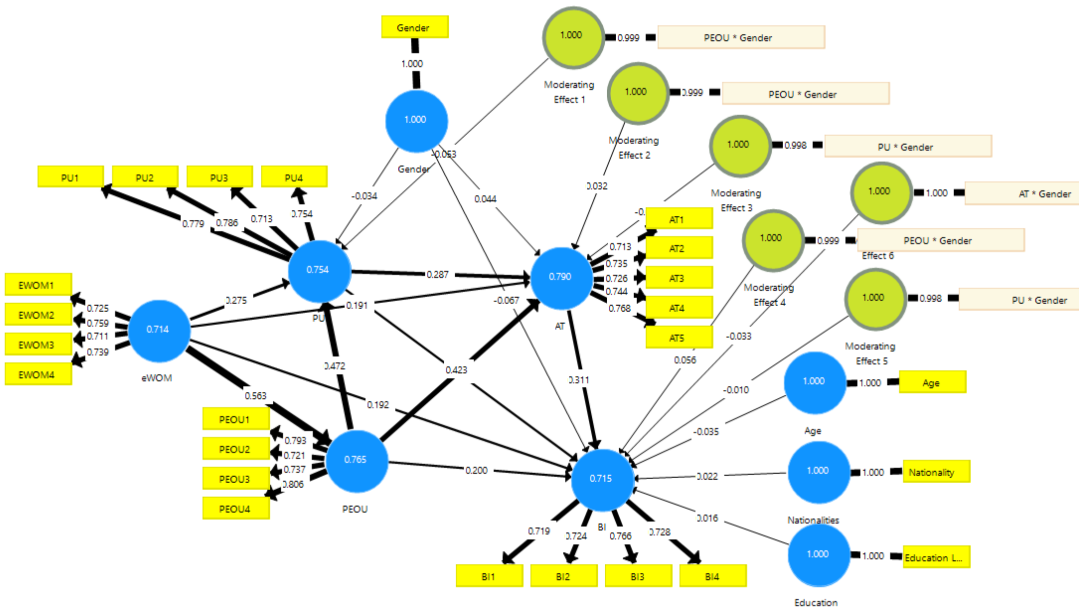

Figure 1 Path Coefficient Result

Table 3 Path Coefficients Result

Hypothesis	Path Relationship	Path Coefficient	t-statistics	p-values	Results
H1	eWOM -> PU	0.275	5.709	0.000	Supported
H2	eWOM -> PEOU	0.563	17.149	0.000	Supported

H3	eWOM -> AT	0.191	4.310	0.000	Supported
H4	eWOM -> BI	0.192	4.401	0.000	Supported
H5	PEOU -> PU	0.472	10.110	0.000	Supported
H6	PEOU -> AT	0.423	8.909	0.000	Supported
H7	PEOU -> BI	0.200	3.765	0.000	Supported
H8	PU -> AT	0.287	5.837	0.000	Supported
H9	PU -> BI	0.225	4.630	0.000	Supported
H10	AT -> BI	0.311	6.279	0.000	Supported

The value of the coefficient of determination is depicted in table 4. It shows that job seekers' BI to use LinkedIn is the proposed model that can explain 62.9%. R^2 value of AT is 0.598, which means PEOU, PU, and eWOM can explain 59.8% of the variation in job seekers' attitudes toward LinkedIn. Respondents' PU variation is 45.0% affected by PEOU and eWOM, while 31.7% in PEOU is affected by eWOM. On the right-most column of table 4.8 is the p-values of R^2, resulting from the bootstrapping algorithm. Based on this column, it is concluded that the R^2 is deemed significant since its value is lower than the significant level of 0.05.

Table 4 Coefficient of Determination Results

Constructs	Coefficient of Determination (R^2)	Evaluation	p-values
AT	0.598	Medium explanatory Power	0
BI	0.629	Medium explanatory Power	0
PEOU	0.317	Weak explanatory Power	0
PU	0.450	Weak explanatory Power	0

The effect size result is shown in table 5. In general, most path relationships have minor effects on each other by looking at its f^2 in which it is above 0.02 but below 0.15. PEOU has the most significant effect among all variables, especially when it comes to affecting PU (f^2 = 0.275; p = 0.000) and AT (f^2 = 0.237; p = 0.000). These effect sizes of PEOU on PU and AT are categorized as Medium Effect since its f^2 is between 0.15 and 0.34. One notable path relationship is eWOM and PEOU, which resulted in $f^2 = 0.465$. This result indicates eWOM has the largest influence on jobseekers' perception of LinkedIn's ease of use, which also impacts PU and AT. In contrast, PEOU has a negligible effect on BI (f^2 = 0.0.046; p = 0.076), which means LinkedIn's ease of use does not significantly influence jobseekers' attention directly.

Table 5 Effect Size Results

Path Relationships	Effect Size (f^2)	P Values	Results
EWOM -> PU	0.093	0.008	Small effect
EWOM -> PEOU	0.465	0.000	Small effect
EWOM -> AT	0.056	0.041	Small effect
EWOM -> BI	0.058	0.038	Small effect
PEOU -> PU	0.275	0.000	Small effect
PEOU -> AT	0.237	0.000	Small effect
PEOU -> BI	0.046	0.076	No effect
PU -> AT	0.112	0.009	Small effect
PU -> BI	0.067	0.032	Small effect
AT -> BI	0.104	0.004	Small effect

Aside from PEOU, eWOM has a small effect on the other variables. For instance, eWOM has a small effect on AT (f^2 = 0.056; p = 0.041), which indicates that eWOM, either positive or negative, influences ASEAN jobseekers' attitudes towards LinkedIn rather modestly. The same is true for the eWOM effect toward PU (f^2 = 0.093; p = 0.008), and BI (f^2 = 0.058; p = 0.038). Meanwhile, PU has a relatively small effect on AT (f^2 = 0.112; p = 0.009) and BI (f^2 = 0.067; p = 0.032), which is aligned with the path coefficient results. For AT, the effect size results show the same consistency as the path coefficient results, in which AT has a small effect on BI (f^2 = 0.104; p = 0.004).

4.3. Mediation Analysis

The mediation analysis explains how the direct relationship between eWOM, and BI has a rather small value compared to the other eWOM path coefficients, depicted in table 6. Firstly, in the absence of all other variables, eWOM has a more significant effect on BI than when all variables are present ($R^2 = 0.373; p_{R^2} = 0.000; \beta = 0.611; p_\beta = 0.000;\ f^2 = 0.595; p_{f^2} = 0.000$). However, this relationship becomes less significant in the presence of other constructs.

Table 6 Mediation Analysis Results

Hypotheses	Path Relationships	Path Coefficients	P Values	Results

H11a	eWOM -> PU -> BI	0.062	0.000	Supported
H11b	eWOM -> PEOU -> BI	0.114	0.000	Supported
H11c	eWOM -> AT -> BI	0.059	0.000	Supported
Total Indirect Effect			**0.234**	
Direct Effect eWOM -> BI			**0.192**	
Total Effect			**0.608**	
VAF (Total Indirect / Total Effect)			**38.49%**	

Based on table 6, all hypothesized constructs have significant mediating effects on the relationship between eWOM and BI, with PEOU having the most mediating effect of all ($\beta = 0.114; p = 0.000$). In addition, PU has a 6.2% mediating effect, while AT has a 5.9% mediating effect on the relationship between eWOM and BI. These results support hypotheses 11a through 11c. The total indirect effects are summed, and it is added by the direct path coefficient of eWOM and BI ($\beta = 0.192$) to determine the size effect of PEOU mediation. The total indirect effect is then divided by the total effect to form the Variance Accounted For (VAF), which results in 38.49%. Since the VAF is between 0.20 and 0.80, it can be concluded that PEOU, PU, and AT partially mediates the relationship between eWOM and BI.

4.4. Moderation Analysis

The moderation effect results of Gender on the TAM variables are depicted in table 7. It shows that the p-values for all moderating relationships are above the confidence level interval, and therefore, H12a through H12f are rejected. In other words, Gender does not moderate the relationship of the TAM variables, in the context of LinkedIn acceptance for ASEAN Jobseekers.

Table 7 Moderation Analysis Results

Hypothesis	IV	MoV	DV	Path	t-values	p-values	Results
H12a	PEOU	Gender	PU	-0.053	1.528	0.127	Not Supported
H12b	PEOU	Gender	AT	0.032	0.710	0.478	Not Supported
H12c	PEOU	Gender	BI	0.056	1.080	0.280	Not Supported
H12d	PU	Gender	AT	-0.005	0.100	0.920	Not Supported
H12e	PU	Gender	BI	-0.010	0.213	0.831	Not Supported
H12f	AT	Gender	BI	-0.033	0.671	0.502	Not Supported

4.5. Discussion

This study found that eWOM influenced ASEAN jobseekers' intention to use LinkedIn, both directly and indirectly. The significant relationship between eWOM and BI of ASEAN Jobseekers towards LinkedIn acceptance confirmed hypothesis number four as well as answered research question number four. This finding is different to the finding of D. Kaur & Kaur (2022a) where eWOM did not have a significant direct relationship with BI. The difference may be caused by a more diverse sample or cultures that might influence why eWOM can influence BI directly. Nevertheless, further investigation is needed on whether culture might moderate the connection between eWOM and BI.

Another notable result is the connection between eWOM and PEOU. This finding suggests that PEOU is the most affected by eWOM in ASEAN Jobseekers. Positive eWOM affects positively how ASEAN Jobseekers perceived LinkedIn as easy to use. This finding supports the study by Tóth et al. (2022), in which eWOM affects customers' perceived usefulness on Alibaba websites. Although there is a difference in management fields, both studies empirically proved that eWOM influences users' perceived ease of use towards new technology. With these results, the significant influence of eWOM on PEOU answers the first research question of the study and supported the second hypothesis of the study.

eWOM also significantly influences PU in the results of this study, confirming hypothesis one and answering research question two. This finding is consistent with Amani (2022) who empirically discovered that university students choose their respective academic institutions following the recommendations they receive from the people whom they believe the most. Therefore, in both cases, eWOM and WOM have significant impacts on the perceived usefulness of the users, either job seekers or university students.

The results of this study also showed that eWOM affected AT significantly among ASEAN Jobseekers. Positive eWOM leads to a positive attitude toward the use of LinkedIn and in turn leads to a positive behavioral intention to use LinkedIn among ASEAN Jobseekers. This result is consistent with Hussein (2017) and Jalilvand & Samiei (2012), in which eWOM was associated directly with users' attitudes towards e-learning and tourism destinations, respectively. These results confirmed the third hypothesis and answered research question three.The hypotheses regarding the connection among the TAM variables are all supported by the results (H5 through H10). These results confirm the maturity of TAM to be used for knowing the intention of users toward new technology. In the context of LinkedIn acceptance, the PEOU of jobseekers towards the technology heavily affected their PU, which in turn, influence their AT and BI. These results also confirm the study conducted by Candra et al. (2020), in which Indonesian Jobseekers' PEOU heavily influences PU toward the intention and acceptance of LinkedIn. In addition, perceived ease of use, perceived usefulness, and attitude were empirically proven to mediate the relationship between eWOM and behavioral intention by 38.49%, confirming hypotheses 11a through 11c.

Lastly, we hypothesize gender as a moderator variable, following the study of D. Kaur & Kaur (2022b). However, the results of this study did not prove that gender moderates the relationship among TAM variables (PEOU, PU, AT, and BI), and thus hypotheses 12a through 12f were rejected. This result contradicts the results of D. Kaur & Kaur (2022b), in which gender moderates the relationship among TAM variables in Indian Jobseekers. This implies that ASEAN job seekers' perception of LinkedIn recruitment is not associated with their gender. The author speculates that this might be due to different cultures and norms among ASEAN and Indians, but this will need further investigation to be confirmed, regardless.

V. CONCLUSION

This study investigates whether eWOM is a substantial factor affecting ASEAN jobseekers' intention to use LinkedIn for job seeking. Specifically, the operational model of this study empirically explored how eWOM affects LinkedIn adoption among ASEAN Jobseekers through the lens of the TAM model. Furthermore, this study examines how PEOU, PU, and AT mediate the connection between eWOM and BI. Lastly, this study also examined how gender moderates the TAM Model in the context of LinkedIn adoption among ASEAN Jobseekers.

This study found that eWOM significantly affect ASEAN jobseekers' behavioral intention towards the use of LinkedIn, both directly and indirectly. Directly, eWOM influences the behavioral intention of jobseekers by 19.2%, while indirectly, eWOM influences behavioral intention by 41.6%. Out of the total indirect effect between eWOM and BI, 38.49% was influenced by the Perceived Ease of Use, Perceived Usefulness, and Attitude mediation effect. Furthermore, the TAM model was proven to be a robust model to explain users' behavioral intention to use new technology, consistent with previous studies. However, this study did not discover that gender had any moderating role in any of the TAM's variables relationship.

This study contributes to the literature by finding that eWOM affects the TAM framework in the e-recruitment context and considering eWOM in the acceptance of HR-related technology. The TAM model is proven to be a robust model to discover the influence of users' intentions toward new technology. Furthermore, eWOM influence the attitude of jobseekers, both directly and indirectly through the aid of the TAM model. The practical significance of this study is that recruiters can encourage past applicants to give feedback on their platform, with the agenda of increasing eWOM throughout their LinkedIn pages and posts. Another practical implication of this study is that managers can increase the trustworthiness of the company through positive eWOM about the company's LinkedIn pages and popularity.

Convenient sampling was used in this research. Although the results showed that there is no common method bias in the data, the sample lacks clear generalizability. Therefore, we suggest repeating the survey to verify the results. In regard to the role of moderation of gender, it would be interesting to see further investigate whether this was true. Therefore, re-evaluating the model in other regional areas such as the EU or American Latin would conform to the results presented in this study. Furthermore, this study did not consider nationalities or culture as a moderator variable. It would be interesting to see how nationality or culture interacts with the research model. Lastly, there was only one external variable considered in this study. It would be interesting to add other variables that might affect jobseekers' intention in using LinkedIn, such as trustworthiness and perceived playfulness.

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