Development and Validation of The Technology Acceptance Model (TAM) for Information Technology (IT) Job Seekers In KualaLumpur using Exploratory and Confirmatory Factor Analysis

Yee Chin Yip
Fakulti Pengajian Bahasa Utama
Universiti Sains Islam Malaysia

Ng Siew Yin
Putra Business School
Universiti Putra Malaysia

Corresponding Author's Email: cyyee_cool@yahoo.com

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Abstract

The Technology Acceptance Model (TAM) has been pivotal in assessing the effectiveness of intentions to use e-recruitment (ER), which emerged as the primary job-searching mechanism during the Covid- 19 crisis and the ongoing digital era. In Malaysia, ER has completely supplanted traditional job application methods, presenting new avenues for interaction and communication between employers and potential employees. Despite these advancements, the adoption and intention to use ER among IT job seekers in Kuala Lumpur require enhancement. Originating from the Theory of Reasoned Action (TRA)-a psychological theory that elucidates the relationship between attitudes and behaviours-TAM was employed to develop a measurement instrument aimed at investigating this issue more deeply. A pilot test in this cross-sectional study garnered 126 responses from the IT industry, which were subjected to exploratory factor analysis (EFA) using SPSS. The EFA results indicated that all items should be retained. Subsequently, the actual data collection for the study yielded 366 responses from IT employees, which underwent confirmatory factor analysis (CFA) with AMOS. The results validated the TAM model's criteria, confirming its effectiveness in evaluating job seekers' intentions to use e-recruitment (ER). TAM's insights are not only theoretical but also offer practical implications for system design enhancements to boost job seekers' technology adoption and use. Furthermore, the model may suggest additional strategies to raise awareness about the intention to use e-recruitment, thus potentially increasing the efficacy of job search efforts.

Keywords: *Technology Acceptance Model (TAM), Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), Kuala Lumpur (KL), intentions to use e-recruitment (ER)*

Introduction

In the realm of Human Resource Management (HRM), recruitment plays a vital role as the conduit through which companies attract and secure the right talent for their open positions. A strategic recruitment program is essential to entice competent candidates. Before 2021, traditional in-person

interviews were standard in candidate selection. Yet, the COVID-19 pandemic's emergence necessitated a pivot to digital recruitment strategies. In response to Malaysia's Movement Control Orders (MCO), companies swiftly shifted to online recruitment to find candidates, ensuring business continuity while complying with health protocols. Despite the easing of these orders, digital recruitment has solidified its place as the contemporary standard in talent acquisition (Wijaya et al., 2022). Known variously as e-recruitment, cyber recruiting, or internet recruiting, this modern approach to sourcing candidates through the internet has gained global traction (Galanaki, 2002).

Nevertheless, in Malaysia, it's still a burgeoning practice (Reddy et al., 2019). While an increasing number of Malaysian companies are starting to realize the benefits of e-recruitment, the degree to which these online platforms are understood, accepted, and utilized differs widely among them. The e-recruitment landscape in the country shows varied levels of adoption among organizations; some are pioneers in this digital transition,while others are just starting to embark on it. In simpler term, the adoption or implication of e- recruitment is still nascent and falls short of the progress seen in Western nations (Ekanayaka, 2019).

The task of shifting mindsets and behaviors towards innovative e-recruitment strategies is crucial. Traditionally, employers have relied on methods such as physical banners, newspaper advertisements, and face-to-face interviews, which continue to have a strong presence in the job-seeking landscape. This adherence to tradition is especially common among candidates who are not well-versed in digital technologies or view modern methods with skepticism (Galhena & Liyanage, 2014). Reluctance to adopt e-recruitment may arise from various concerns: inappropriate of information or contains, discomfort with or lack of experience in digital platforms, fears regarding the security and privacy of personal data shared online, or simply the inertia of long-standing habits (Tanya, 2009: Stephanie & Gail, 2012; Mirza et al., 2022). In an era of swift digital advancement, a confluence of factors contributes to a reluctance within sectors of the job market to fully acknowledge or embrace the comprehensive benefits of transitioning to digital recruitment. Consequently, it becomes imperative to undertake studies that unpack these issues and foster a deeper understanding of the barriers to acceptance.

In light of these trends, the present study undertakes to delve into the intricacies of the Technology Acceptance Model (TAM) as it relates to e-recruitment, scrutinizing its validity, suitability, workability and reliability in the context of factors influencing IT job seekers' intent to use digital platforms (e- recruitment). This research aims to enrich academic discourse while simultaneously providing actionable insights for organizations aiming to refine their recruitment methodologies within the evolving digital milieu.

Literature Review

The Technology Acceptance Model (TAM), proposed by Davis in 1989, has been extensively applied across various industries to understand and interpret technology acceptance among job seekers, employers, and other stakeholders. Within the context of HRM, TAM provides insights into the factors

influencing the adoption and use of technologies, as well as individuals' attitudes and intentions toward technology in job searching. However, there have been debates and discussions regarding its validity and reliability, leading some researchers to highlight limitations and potential issues with TAM.

According to Howard & Melloy (1990), the researcher has scrutinized the adequacy of the Technology Acceptance Model (TAM) in encapsulating the intricacies of e-recruitment behavior. Their research proposed that the existing model may not be sufficiently comprehensive to grasp the subtle and complex factors influencing individual behaviors toward electronic recruitment systems. They suggested that while TAM provides a foundational framework for understanding technology acceptance, it falls short in addressing the specific challenges and considerations inherent to the e-recruitment context (Tarhini et al., 2013). Such challenges may include individual resistance to technological change, the influence of organizational culture on technology adoption, and the unique attributes of e-recruitment platforms that affect user experience. Howard & Melloy argued for a more tailored approach, advocating for the inclusion of additional, context-specific constructs that would enhance the model's predictive power and relevance to e-recruitment practices.

The study by Legris et al. (2003) rigorously tested the Technology Acceptance Model (TAM) through both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to evaluate its psychometric properties. Although results demonstrated that TAM met and even exceeded the baseline criteria for model fitness, these outcomes also hinted that its universal applicability might be questionable without contextual modifications. The research revealed psychometric issues, such as potential limitations of the original TAM items to capture all factors influencing technology acceptancein different scenarios (Chuttur, 2009; Gahtani, 2011; Tarhini et al., 2013). It implies that researchers should contemplate adding context-specific items or refining the existing ones by incorporating aspectslike user trust, social influence, or system compatibility. These adjustments would improve the TAM's capacity to identify the distinct drivers of user acceptance in various environments, thus bolstering the model's predictive precision and reliability across different technological domains (Wu & Wang, 2005). Furthermore, Lee et al. (2003) endorsed the notion of context-tailored modifications to the TAM, recognizing that without these critical refinements, the model could fail to address subtle psychometric concerns such as construct validity and reliability in diverse contexts. Their findings underscore the risk of misinterpreting TAM's predictive capability if applied indiscriminately, without due consideration for unique user interactions and cultural factors. This iterative approach to validation underscores the dynamic nature of TAM and its potential for customization to fit particular research needs or practical applications.

Additionally, Venkatesh and Davis (2000) conducted a longitudinal study to examine the construct validity and reliability of the Technology Acceptance Model (TAM) over extended periods. Their research highlighted that while the TAM exhibits strong validity and reliability in initial measurements,these psychometric properties can fluctuate with time, as user familiarity and environmental factors evolve. This finding draws attention to the fact that the perceived ease of use and perceived usefulness

which are core elements of TAM, it may not maintain consistent levels of influence on user acceptance and intention to use an advance technology system. These temporal variations underline the importance of regularly reassessing the TAM constructs to ensure their ongoing relevance and to adjust for potential validity and reliability issues that could arise as users' attitudes and behaviors change over time.

Moreover, Bagozzi's (2007) research shed light on the inconsistencies in the psychometric properties of the Technology Acceptance Model (TAM), suggesting its reliability might be contingent upon the context, thereby influencing its generalizability across different job markets or industry. Methodological critiques also emerge from common research practices, like reliance on cross-sectional data and self- reporting measures, which can potentially overstate the model's validity and reliability (King & He, 2006). Despite these concerns, TAM's straightforwardness and user-friendliness sustain its popularity among scholars and industry professionals. Looking ahead, integrating TAM with additional behavioral theories is anticipated to enrich the comprehension of the dynamics underpinning e-recruitment technology adoption, guiding the development of more refined, user-focused recruitment platforms (Venkatesh et al., 2003). In addditional, as technology evolves and new contexts emerge, the model's one-size-fits-all approach may not capture all the nuances of specific environments (Yousafzai et al., 2007). Based on Colesca's study (2009), she highlights this by suggesting that while TAM's core components—perceived ease of use and perceived usefulness are widely applicable, the model's validity,reliability, and suitability might require adjustments when applied to particular settings. Even, Colesca (2009) argued that certain elements within the TAM need refinement to align with specific user groupsor technologies. This could mean adding new constructs or modifying existing ones to reflect unique user experiences or expectations within a distinct context, such as e-recruitment. For example, factors like trust in technology, user experience, and personal innovativeness in IT could be pivotal in some scenarios and would thus necessitate customization of the TAM to accurately predict user acceptance and usage behavior.

Recently, Dwivedi et al. (2019) conducted a study to revisit the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which builds upon the original TAM framework. Their investigation was aimed at assessing the model's application and validity within various contemporary digital contexts, including the realm of e-recruitment. The findings from this research suggest that while UTAUT may be applicable and useful in certain industries due to its inclusive and adaptive design, it may not be universally suitable across all sectors. This disparity likely stems from industry-specific variables such as distinct user behaviors, technological engagement levels, and unique organizational cultures that the generalized model may not fully encapsulate (Yousafzai et al., 2007: Stoica et al., 2020).Thus, the study advocates for a tailored approach, where the model is modified to better align with the particular technological acceptance factors relevant to each industry. In the same vein, Alalwan et al. (2021) adapted the TAM model specifically for online food delivery services in Saudi Arabia, with findings indicating the need to modify certain elements pertaining to trust and perceived risk to enhance the model's relevance to e-recruitment platforms. These factors, critical in the context of online transactions and service delivery, could similarly affect the user's intention to use digital hiring platforms, suggesting the importance of tailoring the model to account for industry-specific trust and risk perceptions (Venkatesh & Bala, 2008; Karim et al., 2021).

In the realm of e-recruitment, the Technology Acceptance Model (TAM) has been utilized to understandthe determinants that influence both job seekers' and employers' intentions to use e-recruitment platforms. Despite its extensive use, the efficacy of TAM in predicting behaviors related to e- recruitment has been a topic of significant debate. Consequently, this study aims to develop and validatea survey questionnaire grounded in the TAM framework, which could serve to pinpoint the factors thatshape job seekers' intentions to engage with e-recruitment services.

Methodology

The study employed a cross-sectional research design, collecting data at a single point in time (Sekaran& Bougie, 2016). Data were gathered from the top ten IT companies in Kuala Lumpur, Malaysia, using simple random sampling to select respondents from these firms. The items measuring perceived usefulness, ease of use, trust, and intention to use e-recruitment were adapted from existing literature. Additionally, some items were developed using an elicitation survey, a method recommended by Shanthi et al. (2021) for creating a TAM-based survey instrument. This elicitation survey involved 26 participants, surpassing the recommended minimum of 25 (Francis et al., 2004). To ensure the validity and reliability of the TAM for the actual fieldwork, a pre-test was conducted. Content validity was assessed by three content experts with extensive experience in IT human resource departments. A statistical expert evaluated the criterion validity to ensure the scale's appropriateness. Face validity was established through back-to-back translation from English to Malay (Bahasa Malaysia) by a certified translator. Following the validation process, the TAM was pre-tested on a sample of 10 randomly selected respondents. Their responses were analyzed to assess the consistency of their answers and to gather feedback on any unclear terms, as well as the clarity of questions and the questionnaire design. Based on the feedback received, necessary revisions were made to address the identified issues. After incorporating suggestions from the panel of experts and pre-test participants, a pilot study wasconducted (Zikmund & Babin, 2010). The pilot study was conducted in Kuala Lumpur, the capital cityof Malaysia, chosen for its status as the nation's hub for IT job opportunities (Yau et al., 2016). This setting provides a diverse and rich context for exploring IT professionals' perspectives, making it an ideal location for the study. A total of 126 valid responses were obtained, exceeding the required minimum sample size of 100 (Awang, 2015; Bahkia et al., 2019). The pilot study data were subjected to exploratory factor analysis (EFA) to examine the underlying factor structure of the TAM. The insightsfrom the pilot study contributed to further refinement of the TAM questionnaire, ensuring its suitability and effectiveness. With the necessary revisions made, the TAM questionnaire was ready for use in theactual survey during the subsequent fieldwork.

The finalized TAM instrument featured 28 items, excluding demographic queries, and adopted a 10- point Likert scale, ranging from 1 (strongly disagree) to 10 (strongly agree), a recommendation by Awang (2015) to maintain data independence. In the actual survey, a total of 366 responses were collected, out of which 329 were considered valid for analysis, while 37 were excluded due to issues with normality. The data analysis was conducted using the Statistical Package for the Social Sciences (SPSS) for data screening and exploratory factor analysis (EFA), and Analysis of Moment Structures (AMOS) for confirmatory factor analysis

(CFA). The CFA process validated the measurement model's unidimensionality, validity, and reliability as suggested by Afthanorhan et al. (2019), Awang (2015), Awang et al. (2018), Mohamad et al. (2018) and Mahfouz et al. (2019).

Results

Exploratory Factor Analysis

The exploratory factor analysis (EFA) was utilized to explain and clarify the dataset, identifying correlated variable clusters (Zikmund & Babin, 2010). The EFA, leveraging pilot study data, sought to disclose the latent constructs within the Technology Acceptance Model (TAM), namely perceived usefulness, perceived ease of use, perceived trust, and intention to use e-recruitment. The criteria for a successful EFA included achieving a Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy value greater than 0.50 and a Bartlett's test of sphericity indicating significance ($p < 0.001$). These rule of thumbs, advocated by experts such as Hair et al. (2014), Awang (2015), and Bahkia et al. (2019), are critical benchmarks for the validity of the factor analysis.

Table 1: Results of KMO and Bartlett's Test of Sphericity

Construct	KMO (>0.50)	Bartlett's Test of Sphericity (p<0.001)
Perceived ease of use	0.816	0.00
Perceived usefulness	0.792	0.00
Perceived trust	0.823	0.00
Intention to use e-recruitment	0.779	0.00

During the exploratory factor analysis (EFA), the principal component analysis method was used to extract factors and determine which should be retained or eliminated. To enhance the interpretability of the factor analysis, varimax rotation-a widely-used orthogonal rotation method-was applied (Hair et al., 2014). Factor loadings with absolute values below 0.5 were considered insignificant and removed from further analysis, while those exceeding 0.5 were deemed significant and retained for measurement (Hair et al., 2014). Table 2 shows the EFA results, including the number of items for each construct before and after the analysis. Essentially, all items surpassed the minimum threshold of 0.5, thus, the initial 28 items in the Technology Acceptance Model (TAM) retained as same. The EFA results also showed thatall items fell neatly into the stated constructs without any mixed values.

Table 2: Item Retention Result after EFA

No	Construct	Items before EFA	Number of Items Dropped	Number of Items Retained after EFA
1	Perceived ease of use (PE)	6	-	6
2	Perceived usefulness (PU)	8	-	8
3	Perceived trust (PT)	6	-	6
4	Intention to use e-recruitment (ER)	8	-	8

Confirmatory Factor Analysis (Pooled-CFA)

This study rigorously validated the measurement models of latent constructs by examining unidimensionality, validity, and reliability, drawing on methodologies from several experts (Afthanorhan et al., 2017; Aimran et al., 2017; Awang, 2015; Hair et al., 2014; Mohamad et al., 2018). Confirmatory factor analysis (CFA) served as the foundation for this essential process. The researcher assessed the measurement model of the latent constructs through three validity tests: convergent, construct, and discriminant. The convergent validity was established by computing the average variance extracted (AVE), while construct validity was determined by analyzing the fit indices of the measurement model. To ensure discriminant validity, the researcher displayed a Discriminant Validity Index Summary. Additionally, the researcher showed Composite Reliability (CR) for the reliability evaluation, which is considered a more robust measure than the traditional Cronbach's Alpha, especially in the context of Technology Acceptance Model (TAM) analysis (Awang, 2015; Aziz et al., 2016; Hair et al., 2014; Yusof et al., 2017).

Figure 1: Result from Pooled-CFA Procedure

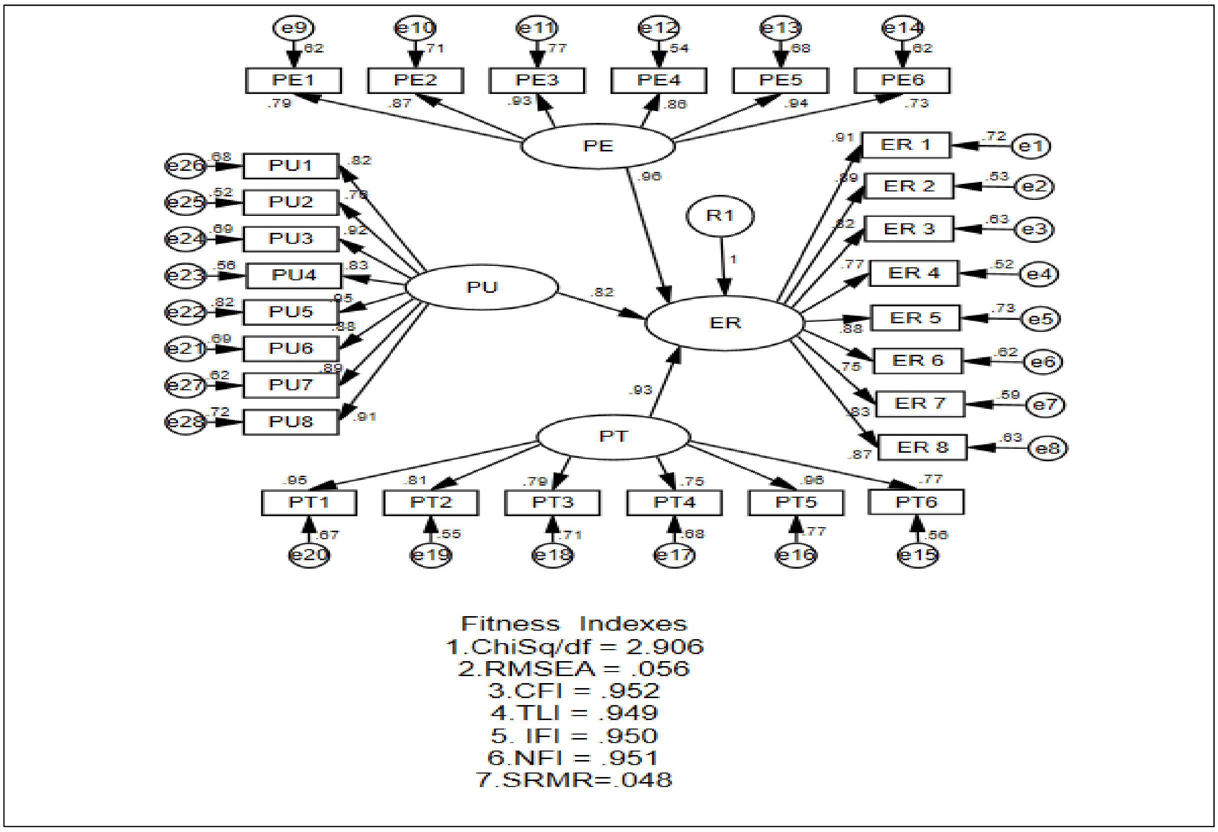

Figure 1 illustrates the simultaneous validation (Pooled- CFA) of all constructs within the model, achieved through pooled confirmatory factor analysis (Pooled-CFA). Awang (2015) and Awang et al. (2018) suggested that model identification is streamlined with the use of Pooled-CFA, as the method circumvents the issues typically associated with separate analyses. By ensuring each construct contains a minimum of three items (Awang, 2015), Pooled-CFA substantially increases the model's degrees of freedom, enhancing the robustness of the validation process. In this particular study, the researcher opted for Pooled-CFA due to its efficiency advantages, as it negates the need to conduct separate CFA for each measurement model, thereby streamlining the validation process and yielding more cohesive outcomes.

Unidimensionality

Unidimensionality occurs when a single construct sufficiently explains a group of variables (Hair et al., 2014). Awang (2015) suggests that this concept is confirmed when all items measuring a construct showsatisfactory factor loadings (> 0.50). Items in a confirmatory factor analysis (CFA) that display low factor loadings are recommended to be removed to enhance the model until acceptable fit indices are obtained, as recommended by research from Afthanorhan et al. (2017), Asnawi et al. (2019), Awang (2015) and Hair et al. (2014).

Based on Awang (2015) and Awang et al. (2018), the criteria for removing items from a scale were specified. For items that have been recently developed, they must have a factor loading of at least 0.5to be retained. For items that are already established, the threshold is slightly higher, with a minimumfactor loading of 0.6 required for the item to remain.

Table 3. Factor Loading of All Items

No	Construct/Item	Factor Loading
	Perceived Ease of Use (PE)	
1	The e- recruitment sites save me time to submit my resume compared to traditional method	.79
2	The e-recruitment sites provide all the information required to apply for a job	.87
3	The e-recruitment sites offer a variety of careers/jobs to apply for	.93
4	The e-recruitment sites provide information such as FAQs	.86
5	The e-recruitment sites provide feedback service	.94
6	The e-recruitment sites enable me to compare between different vacancies in my country and other countries	.73
	Perceived Trust (PT)	
1	The e-recruitment platform securely handles my personal information.	.95
2	The job postings on the e-recruitment platform are genuine and not scams.	.81
3	The e-recruitment platform will not misuse my data for unauthorized purposes	.79
4	My privacy is respected and upheld when using the e-recruitment platform.	.75
5	The e-recruitment platform takes sufficient steps to ensure the confidentiality of my application process.	.96
6	The information provided by employers on the e-recruitment platform is accurate and reliable.	.77
	Perceived Usefulness (PU)	
1	The e-recruitment platforms enhance my effectiveness in the job application process.	.82
2	The e-recruitment platforms enable me to apply for jobs more quickly.	.76
3	The e-recruitment systems provide more comprehensive job details compared to traditional methods.	.92
4	The e-recruitment platforms increase my chances of finding a suitable job.	.83
5	The e-recruitment platforms improve the efficiency of my job search.	.95
6	The e-recruitment platforms offer a wider range of job opportunities than traditional methods.	.88
7	The e-recruitment platforms offering feedback and notifications are useful for tracking my application status.	.89

8	The e-recruitment platforms streamline the job application process, making it more organized and manageable.	.91
	Intention To Use E-Recruitment (ER)	
1	The e-recruitment platforms regularly in my job search.	.91
2	To apply for a job through e-recruitment rather than traditional methods.	.89
3	Using e-recruitment platforms for future job applications.	.82
4	The e-recruitment becoming my primary method for job hunting in the next year.	.77
5	To choose e-recruitment platforms over other recruitment methods.	.88
6	The-recruitment platforms to friends or colleagues seeking employment	.75
7	The features and benefits of e-recruitment platforms.	.83
8	To myself with multiple e-recruitment platforms to enhance my job search.	.87

Table 3 shows that each item across all constructs exceeded the factor loading thresholds suggested by Awang (2015) and Awang et al. (2018), resulting in no items being removed from the survey.

Convergent Validity

Convergent validity is the degree to which a set of indicators is believed to accurately measure an underlying construct, as described by Hair et al. (2014), Kline (2011), and Awang (2015, 2018). Brown (2006) emphasized that convergent validity is indicated by the strong interrelations among items assumed to reflect the same latent variable. To confirm a construct's convergent validity, one calculates the average variance extracted (AVE), which should exceed the benchmark of 0.5, a standard set forth by Awang et al. (2018), Awang (2015), Fornell & Larcker (1981), and Hair et al. (2014).

Table 4 reveals that the average variance extracted (AVE) for all constructs exceeded the minimum threshold of 0.5, indicating strong convergent validity within the model. Specifically, perceived usefulness (PU) recorded the highest AVE at 0.760, while intention to use e-recruitment had the lowest, yet satisfactory, factor loading at 0.709. Additionally, perceived trust (PT) and perceived ease of use (PE) showed AVEs of 0.710 and 0.734 respectively. In essence, these results clearly demonstrate that the model successfully meets the criteria for convergent validity.

Table 4: Average Variance Extracted for All Constructs

Codes	Construct	AVE (Above 0.5)
1	Perceived Ease of Use (PE)	0.734
2	Perceived Trust (PT)	0.710
3	Perceived Usefulness (PU)	0.760
4	Intention To Use E-Recruitment (ER)	0.709

Construct Validity

Construct validity is confirmed when a model's fitness indicators meet the established criteria (Awang, 2015; Awang et al., 2018). To determine construct validity, it should consider three categories of model fit: absolute fit indices, incremental fit indices, and parsimonious fit indices, as noted by Awang et al. (2015, 2018), Kashif et al. (2015, 2016), and Yusof et al. (2018), Asnawi et al. (2019). The most commonly employed metrics for assessing model fit include the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the normed Chi-Square (χ^2/df) (Awang, 2015; Awang et al., 2018). Table 5 presents a summary of the categories of fitness indices and their acceptable levels as outlined in the scholarly literature.

Table 5 indicates that the Technology Acceptance Model (TAM) met all three required fitness index categories: firstly, the RMSEA value was below the 0.08 threshold at 0.078, affirming the model's absolute fit; secondly, the model demonstrated an adequate incremental fit, with a CFI value of 0.911, exceeding the cut-off of 0.90; thirdly, for parsimonious fit, the Chi-square to degrees of freedom ratio stood at 2.871, comfortably under the maximum recommended value of 3.0 as per Bentler (1990). Consequently, the study successfully established the construct validity of the TAM.

Table 5: Fitness Indices

Name of category	Name of index	Level of acceptance	Result	Status
Absolute Fit Index	RMSEA	RMSEA < 0.08 (Hu & Bentler, 1999)	0.056	Achieved
	SRMR	SRMR < 0.05 (Hu & Bentler, 1999)	0.048	Achieved
Incremental Fit Index	CFI	CFI > 0.90	0.952	Achieved
	TLI	TLI > 0.90	0.949	
	IFI	IFI > 0.90	0.950	
	NFI	NFI > 0.90 (Awang, 2012)	0.951	
Parsimonious Fit Index	Chi-Square/df	Chi-Square/df < 3.0 (Hu & Bentler, 1990)	2.906	Achieved

Discriminant Validity

Discriminant validity indicates that a construct's measurement model lacks redundant items; each item should not mirror another. Redundancy occurs when any two constructs in the model exhibit a high correlation. To assess discriminant validity, the correlation between exogenous constructs should not surpass 0.85 (Awang 2012). A correlation exceeding 0.85 between two exogenous constructs suggests redundancy and a significant multicollinearity issue (Awang et al., 2018; Awang, 2015; Hair et al., 2014).

Table 6: Discriminant Validity Index Summary

Construct/ Codes	PE	PT	PU	ER
Perceived Ease of Use (PE)	***0.734***			
Perceived Trust (PT)	0.320	***0.710***		
Perceived Usefulness (PU)	0.596	0.445	***0.760***	
Intention To Use E-Recruitment (ER)	0.103	0.066	0.361	***0.709***

The discriminant validity for each construct in the model is demonstrated by the fact that the square root of the average variance extracted (AVE) exceeds the correlation values with other constructs, as shown in Table 6. The diagonal values, which are highlighted in bold, are greater than any other values in their respective rows and columns, which further confirms discriminant validity. Therefore, the values listed in Table 6 indicate that all constructs in the Technology Acceptance Model (TAM) have achieved the required threshold for discriminant validity.

Composite Reliability (CR)

Generally, composite reliability (CR) assesses the reliability and internal consistency of a latent construct (Hair et al., 2014; Awang, 2015; Awang et al., 2018). A construct's composite reliability should be at least 0.6. The analysis showed that all constructs in the Technology Acceptance Model (TAM) had a composite reliability exceeding the 0.6 threshold, as detailed in Table 7. The construct with the highest composite reliability was behavioral intention to use (0.92), while perceived ease of use had the lowest (0.87). Therefore, the TAM achieved composite reliability.

Table 7: Composite Reliability

Codes	Construct	CR (Above 0.6)
PE	Perceived Ease of Use	0.921
PT	Perceived Trust	0.936
PU	Perceived Usefulness	0.962
ER	Intention To Use E-Recruitment	0.951

Normality Assessment

The normality distribution of the items measuring the constructs in the Technology Acceptance Model (TAM) was assessed. It is crucial for the skewness values of these items to conform to normality (Hair et al., 2014; Awang, 2015; Asnawi et al., 2019; Afthanorhan et al., 2019). Typically, skewness values are considered acceptable when they fall within the range of -2 to 2 (Hair et al., 2022).

Table 8: Normality Assessment Results

No	Construct/Item	Skewness
	Perceived Ease of Use (PE)	
1	The e- recruitment sites save me time to submit my resume compared to traditional method	-0.324
2	The e-recruitment sites provide all the information required to apply for a job	-0.449
3	The e-recruitment sites offer a variety of careers/jobs to apply for	-0.236
4	The e-recruitment sites provide information such as FAQs	0.661
5	The e-recruitment sites provide feedback service	-0.789
6	The e-recruitment sites enable me to compare between different vacancies in my country and other countries	-0.854
	Perceived Trust (PT)	
1	The e-recruitment platform securely handles my personal information.	-0.617
2	The job postings on the e-recruitment platform are genuine and not scams.	-0.835
3	The e-recruitment platform will not misuse my data for unauthorized purposes	-0.913
4	My privacy is respected and upheld when using the e-recruitment platform.	-0.798
5	The e-recruitment platform takes sufficient steps to ensure the confidentiality of my application process.	-0.646
6	The information provided by employers on the e-recruitment platform is accurate and reliable.	-0.539
	Perceived Usefulness (PU)	
1	The e-recruitment platforms enhance my effectiveness in the job application process.	-0.446
2	The e-recruitment platforms enable me to apply for jobs more quickly.	-1.202
3	The e-recruitment systems provide more comprehensive job details compared to traditional methods.	
4	The e-recruitment platforms increase my chances of finding a suitable job.	-0.917
5	The e-recruitment platforms improve the efficiency of my job search.	-0.828
6	The e-recruitment platforms offer a wider range of job opportunities than traditional methods.	-1.009

7	The e-recruitment platforms offering feedback and notifications are useful for tracking my application status.	-0.695
8	The e-recruitment platforms streamline the job application process, making it more organized and manageable.	-0.721
	Intention To Use E-Recruitment (ER)	
1	The e-recruitment platforms regularly in my job search.	-1.169
2	To apply for a job through e-recruitment rather than traditional methods.	-0.906
3	Using e-recruitment platforms for future job applications.	-0.822
4	The e-recruitment becoming my primary method for job hunting in the next year.	-0.671
5	To choose e-recruitment platforms over other recruitment methods.	-0.558
6	The-recruitment platforms to friends or colleagues seeking employment	-1.119
7	The features and benefits of e-recruitment platforms.	-0.763
8	To myself with multiple e-recruitment platforms to enhance my job search.	-0.915

All components in the model displayed skewness values between -2 and 2 (Hair et al., 2022), signifying that the data distribution closely aligned with a normal distribution. Consequently, the data within the Technology Acceptance Model (TAM) satisfied the criteria for a normal distribution.

Conclusion

This study aimed to develop and validate a survey to assess IT job seekers' intent to utilize e-recruitment during their job search. Results from exploratory and confirmatory factor analyses indicate that the survey, based on the Technology Acceptance Model (TAM), effectively measures factors influencing job seekers' e-recruitment intentions. The exploratory analysis confirmed the appropriateness of the items, requiring no major adjustments, while the confirmatory analysis validated the instrument's convergent, construct, and discriminant validity. Additional tests for unidimensionality and normality upheld the items' validity in the TAM survey. The consistent results from both analyses confirm the survey's reliability for examining IT job seekers' intentions toward e-recruitment in Kuala Lumpur, an IT-emerging city in Malaysia. These outcomes robustly endorse the TAM's relevance and adaptability in an Eastern context, suggesting the model's constructs are applicable across cultural boundaries. The successful validation of the TAM instrument in this Eastern setting implies that the factors driving e-recruitment usage in Kuala Lumpur, Malaysia share commonalities with those in Western regions. Therefore, the TAM stands as a universally applicable model, offering valuable insights into e-recruitment adoption across diverse cultural landscapes, including the Eastern milieu of Malaysia.

Limitation of Study

The study recommends applying the Technology Acceptance Model (TAM) across various research settings, particularly in light of the Malaysian government's push towards full digitalization. The TAM instrument is highly relevant in cultures with a collectivist orientation, like Malaysia, where individuals are often influenced by authority figures such as government bodies, local authorities, partners, or friends in their decision-making processes (Abdullah et al., 2009; Faridah et al., 2020: Nor, 2005; Hussein et al., 2013: Wok et al., 2016). For future research, it is advisable to investigate additional factors that may affect learners' intentions to use technology for adopting e-recruitment. These could include elements like self-efficacy, working environment conditions, the quality and accessibility of program feedback, equipment considerations, and aspects specific to the application itself. Further, enhancing the TAM instrument by integrating data on moderating variables such as material format, gender, and ethnicity would provide a more robust framework. At the same time, the inclusion of attitude and motivation factors in the instrument could offer a more comprehensive understanding of the influences on IT job seekers' intentions to adopt new technologies, like e-recruitment.

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