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Teachers and Crowdsourcing Platform: Using UTAUT to Examine Behaviour Intention and Use Behaviour

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Abstract

The rapid development of technology requires teachers to use technology efficiently to deal with the increased workload. The use of crowdsourcing is seen to help lighten a teacher's task. This study tests the relationship between intention to use (BI) and actual use or involvement (UB) for a crowdsourcing platform called krumun.org. By adopting the UTAUT model, the main objective of this study is to determine the relationship between performance expectations (PE), effort expectations (EE), and facilitating condition (FC) with behaviour intention (BI) of krumun.org. The study also investigates the relationship between BI and the actual use of the platform; use behaviour (UB). The study uses a survey method, with a questionnaire as an instrument. The descriptive analysis using IBM SPSS 25 software and the inferential analysis using SmartPLS 4 were employed to analyse 384 responses. The study's findings show that PE, EE, and FC influenced the intention to use krumun.org, with an explanatory power of 72.3%. The BI, however, can only explain 4.0% of UB in Krumun.org. Overall, there is a positive relationship between the constructs of acceptance and the use of krumun.org. In conclusion, the crowd intends to use or accept krumun.org. However, this intention has a minor influence on the crowd's actual use of krumun.org.

Keywords: Crowdsourcing, Teachers, Utaut, Behaviour Intention, Use Behaviour.

Introduction

In 2015, crowdsourcing initiatives in Malaysia were considered at an early stage and were not optimally used by the Malaysian community (Arshad et al., 2014). Although the government encourages this concept through Malaysia's Digital policies, the efforts are more focused on commercial use (Zakariah et al., 2014). Furthermore, local platforms compete with many international crowdsourcing platforms (Hassan et al., 2017). Nevertheless, in the last five years (2016 - 2020), crowdsourcing applications have been getting more attention and are being introduced actively in Malaysia. It is because Malaysia has advantages in many aspects, such as a good Internet network infrastructure and a workforce with the ability to speak various languages (Hassan et al., 2017).

In promoting crowdsourcing in Malaysia, the Malaysia Digital Economy Corporation (MDEC) is monitoring and coordinating the implementation of the crowdsourcing initiative (Mansor et al., 2018). MDEC is an agency under the Malaysian Ministry of Communications

and Multimedia (MCMC) responsible for driving the country towards a Digital Economy by empowering Malaysians, businesses, and investments through the Internet and Information Technology (MDEC, 2020). These days, crowdsourcing platforms have become one of the business strategy tools to improve financial performance in the context of reducing operational costs (Mansor et al., 2018). Since crowdsourcing is an essential element that can help business and non-business organisations complete tasks, it can also be applied to assisting teachers in carrying out their daily tasks (Zualkernan et. al., 2012). The responsibilities and functions of teachers in Malaysia are increasing, which may affect the quality of the teaching and learning process in terms of innovation and effective teaching (Shafie et al., 2017; Othman & Sivasubramaniam, 2019). A balanced workload improves the quality of teaching but also the commitment of teachers to the school organisation (Ibrahim et al., 2019).

Crowdsourcing initiatives are seen as an enabler in supporting teachers to complete their daily tasks. Nevertheless, whether the crowdsourcing platform can ease teachers' tasks depends on several factors, including the teacher's acceptance of the platform. It is documented that if an individual has a high level of technology acceptance, they have no difficulties engaging with crowdsourcing platforms (Amir et al., 2019). Previous studies have also found that several factors influence a person to accept new technology, such as devices, software, applications, and communication networks. Among the theoretical models often employed to determine technology acceptance is the Unified Theory of Acceptance and Use Technology (UTAUT) Model (Venkatesh et al., 2003).

The UTAUT model, introduced by Venkatesh et al (2003), is a technology acceptance model that combines eight leading models that are often used in past studies to study information technology acceptance. Each construct in UTAUT gets its foundation from these earlier models. However, the level of influence of these models in UTAUT is different. The UTAUT model's use is extensive, and its application covers various fields. Since the UTAUT model has a construct that measures work performance, it is often applied by organisations that want to measure the extent to which employees accept the introduced technology. In developing the UTAUT model itself, Venkatesh et al (2003) tested the UTAUT model in four organisations. The test results confirm the relationship in the model. Although this model was tested for technology acceptance by employees in the private organisation, recent developments show that the UTAUT model is now being used to study the use of technology by the public setup. For example, the application of UTAUT to examine the teachers' acceptance of education technology (Kim & Lee, 2020; Shah et al*.,* 2020; Khechine et al., 2019; Raman & Rathakrishnan, 2018).

This paper focuses on teacher perceptions by applying the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Crowdsourcing initiatives are viewed as enablers to help teachers complete their daily tasks. However, there is currently not much research to examine the effectiveness of using crowdsourcing platforms for teachers. To this end, it is important to learn about perceived usefulness from the teacher's perspective. By better understanding these perceptions, the results of this study can help policymakers and software designers make better investment decisions, and help teachers use this technology more effectively. In addition, it can help teachers to improve their daily duties as teachers and also for a better working life to achieve a high level of job satisfaction.

Literature Review

Crowdsourcing

In principle, Internet technology introduced in the early 1990s and Web 2.0 technology in the era after 2000 have made crowdsourcing initiatives more accessible and effective (Di Guardo & Castriotta, 2013; Howe, 2006; Shen et al., 2014). Web 2.0 technology has allowed information to be accessed by a larger crowd. The ability to interact with a potential crowd in real-time has enabled crowdsourcing to be realised (Shuen, 2018). Crowd activities can be controlled, monitored, and nurtured more quickly and easily (Lv & Luo, 2021). Besides the excellent capabilities, Web 2.0 does not require high skills with minimal cost. Web 2.0 technology requires no prior knowledge and is highly flexible, interactive, and user-centred. Because of that, new users can use it efficiently, be ready for their daily activities, and manage information online (Lv & Luo, 2021; McAfee, 2009).

As a result, sharing of information and knowledge through virtual discussions is growing (Gaál et al., 2015; Hasan et al., 2013; Sharratt & Usoro, 2003). It has also enabled people to "meet" and do online collaborative activities (Barry, 2014). The "meeting" and undertaking collaborative activities online have been seen as an opportunity to encourage activities with collective intelligence in doing a task or solving a problem. Various parties have exploited this new technology by increasing collective intelligence in the field they are engaged (Malone et al., 2009; Oh, Agrawal & Rao, 2013; Shen et al., 2014).

Collective intelligence is a form of group cognitive (thinking power) in which a group of people act to do small tasks to achieve a big goal (Beucheler et al., 2011). Collectively, cognitive abilities can be improved in performing tasks to predict the market, solve problems, and "jam ideas" (Howe, 2009, p. 135). It has opened an opportunity for those who need the public's help in completing a task to offer rewards to the public who want to perform the required tasks online (Malone et al., 2009). The activity of providing and completing tasks to people online with no strings attached while offering a commensurate reward was termed "Crowdsourcing" by Jeff Howe in 2006.

Crowdsourcing applications have four primary constructs: task, crowd, platform, and control (Saxton et al., 2013). The crowdsourcing process begins when a task is triggered by a task trigger from an organisation or even a private individual (Muhdi et al., 2011; Pollok et al., 2019). These assignments will be submitted to the online platform through a website built by the initiator or using a third-party platform. Then the crowd that sees the task sent will give a response in the form of ideas, new designs, or comments to complete the task. Finally, the trigger evaluates and selects the best solution. In many circumstances, the crowd will be given a reward in the form of money or non-monetary. This selection and reward are seen as one of the methods of controlling resource initiatives (Saxton et al., 2013).

At the initial stage of introduction to crowdsourcing activities, the tasks performed by the crowd are more about solving simple but trivial problems with cheap wages (Irani, 2015). There are also platforms developed for innovation or solving problems using external services (Busarovs, 2011) by offering rewards to the crowd who provide the best ideas. Crowdsourcing platforms can also be developed to provide freelance services such as consulting, photography, accounting, publishing, and selling digital products and services (Bharadwaj et al., 2013; Busarovs, 2011). However, crowdsourcing has become increasingly complex with application that includes various purposes implemented online and requires intelligence, social networks, and human collaboration. Crowdsourcing is "a form of innovation that provides an alternative way for us to innovate" by sourcing knowledge, creativity, and ideas to trigger innovation that can benefit businesses and society (Saxton et al., 2013).

Crowdsourcing in the Education Setting

Crowdsourcing is seen to be applicable in the educational community in Malaysia since the academic community has been exposed to Internet technology and has the skills and is ready to use this technology in carrying out their duties as a teacher (Amir et al., 2019; Ah-Choo 2008; Ismail et al., 2011; Teck-Cha et al., 2010). In 2013, the Malaysian Ministry of Education outlined six main aspirations for school students in the Malaysian Education Development Plan 2013-2015 (Preschool to Secondary Education). They are knowledge, thinking skills, leadership skills, bilingual skills, ethics, spirituality, and national identity. Consequently, nine main fields with eleven shifts have been carefully planned to produce three waves of education from 2013 to 2025 (Kementerian Pendidikan Malaysia, 2013).

It is suggested that one of the ways to help teachers complete assignments more efficiently is by using ICT through the sharing of material resources among the education community. Such initiatives are known as crowdsourcing for education (CfE). In general, CfE is an online activity organised by an educational organisation or educator that requests the contribution of teaching materials in digital form from the crowd (crowd) of educators for teaching or learning (Jiang et al., 2018). Among the well-known crowdsourcing platforms for education are Massive Open Online Courses (MOOCs), Wikipedia assignments, and Betterlesson (Prester et al., 2019; Rubin & Brown, 2019; Zdravkova, 2020). Such a platform focuses on the interaction between teachers and students and knowledge sharing among the crowd. To further boost the activities of the online education community in Malaysia, this study provides a crowdsourcing platform for teachers to complete tasks by consensus to build assessment instruments in the form of sets of test and exam questions, known as krumun.org.

Krumun.org is a crowdsourcing platform explicitly developed for Malaysian teachers to participate in crowdsourcing activities (Khalid et al., 2021). This platform was initiated to encourage teachers to share and use assessment materials between them. The platform is built using PHP and JavaScript language and MySQL for database management. Krumun.org is a platform controlled by an administrator who will monitor all the activities on krumun.org. During a trial launch, the platform was introduced to a focus group of 155 teachers. A Facebook face is created to enhance the promotion and gather participants to the platform.

Acceptance and use of crowdsourcing

Venkatesh et al (2003) have combined eight previous models to develop the UTAUT model. The eight models and theories of user acceptance involved are the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis et al., 1989; Davis, 1985), The Hierarchical Motivational Model (HMM) (Vallerand, 1997), Planned Behavior Theory (TPB) (Ajzen, 2020), a combined model of TAM with TPB theory (C-TAM-TPB) (Taylor & Todd, 1995), Model PC Utilisation (MPCU) (Thompson et al., 1991), Innovation Diffusion Theory (IDT) (Moore & Benbasat, 1991) and Social Cognitive Theory (SCT) (Bandura, 1986). In their study, Venkatesh et al. (2003) evaluated these previous models and adapted them to the development of the UTAUT model. Each construct in UTAUT gets its foundation from these earlier models. However, the level of influence of these models in UTAUT is different.

The primary purpose of UTAUT is to examine the individual acceptance of technology that was motivated by several factors, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Condition (FC) (Figure 1). At the same time, there are also four more variables but as moderation to the basic construct, namely gender, age, experience and volunteering. This UTAUT model has been applied in various

fields and situations to explain individuals' acceptance and use of new technology (Williams et al., 2015). Due to its suitability in evaluating technology acceptance, the UTAUT Model was adopted in this study to examine krumun.org acceptance by teachers as the crowd.

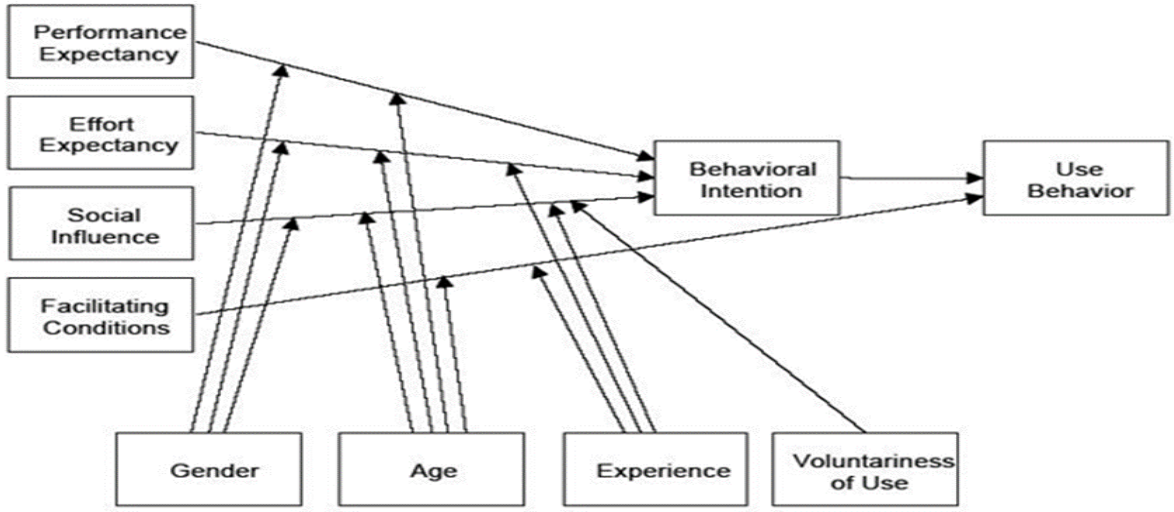

Figure 1: "User Acceptance of Information Technology: Toward a Unified View," MIS Quarterly, 27, 425-478 (Venkatesh et al., 2003).

The UTAUT model's use is extensive, and its application covers various fields. Since the UTAUT model has a construct that measures work performance, it is often applied by organisations that measure the extent to which employees accept the introduced technology. For example, for the development of the UTAUT model itself, Venkatesh et al. (2003) tested this UTAUT model in four organisations. The results confirm the relationship in the model. Another example by Ghosh (2019); Soh et al (2020) used the UTAUT model to study consumer behaviour toward online purchases. Ghosh's (2019) study was conducted in Calcutta to identify the factors influencing online purchases such as Amazon.com, flipkart.com, Snapdeal.com, and the like. While Soh et al (2020) also studied online purchases in Malaysia, focusing on people aged 50 years and above. Both of these studies changed the original UTAUT construct, where Ghosh (2019) only maintained the SI and FC constructs, while Soh et al. (2020) replaced the constructs of behavioural intention and actual behaviour with the constructs of perception, willingness, and acceptance of online purchases. The results of the studies showed that the constructs of UTAUT are appropriate, and the relationships were significant.

Recent developments show that the UTAUT model is currently used to examine the acceptance and use of mobile applications. Almaiah et al (2020) used the UTAUT model to study the acceptance of government mobile services in Saudi Arabia. Marinković et al (2020) focused on mobile trading services in Serbia, and Purwanto and Loisa (2020) studied the adoption of mobile banking in Indonesia. In terms of construct selection, the study by Almaiah et al (2020) maintained four factors, namely PE, EE, SI, and FC. Meanwhile, the study by Marinković et al (2020) only maintains three factors: PE, EE, and SI. Purwanto and Loisa's study (2020) maintains all the factors, namely PE, EE, FC, SI, BI, and UB, except the moderation factors. Two of these studies found that all UTAUT constructs influence the acceptance of the studied technology. Purwanto and Loisa's study (2020) found that PE and SI factors did not affect behavioural intentions.

Based on previous studies, the constructs in the UTAUT model may differ according to the study's objectives. Likewise with this study where, out of four factors, only three acceptance factors were studied concerning the intention to use, namely PE, EE, and FC. The social influence factor (SI) was dropped from the study framework. This is because the factor measures the extent to which other individuals influence the use of a specific technology. Such measurements can only be done if the technology has been widely introduced. The SI factor is considered irrelevant to this study because the krumun.org platform has just been built, and the introduction has not been done widely. In this study, the developed crowdsourcing platform aims to form a virtual crowd of teachers so they may complete tasks to create a set of quality tests and examination papers by applying collective thinking philosophy.

Methodology

The research framework

This study adapted the UTAUT model by using three primary constructs, namely PE, EE, and FC, to see the extent to which users intend to use the developed crowdsourcing platform. The justification for the Social Influence (SI) construct being dropped off from this study is that this platform is newly built and at an introductory stage. Therefore, social influence in this context cannot affect user acceptance of this platform. This study research framework is illustrated below (Figure 2)

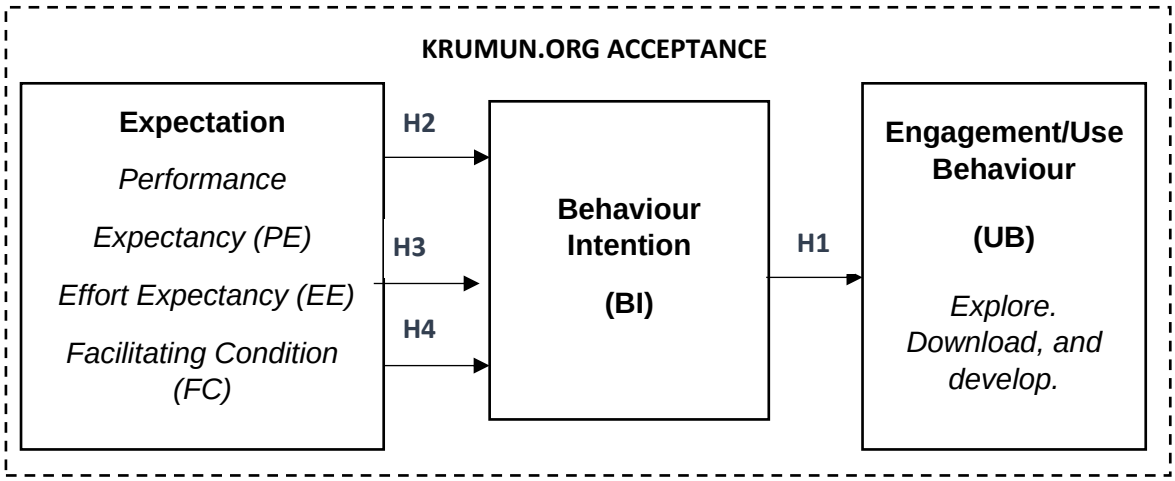

Figure 2: Research framework for the study

In general, four relationships are tested, namely (i) H1: BI – UB; (ii) H2: PE – BI; (iii) H3: EE – BI; and (iv) H4: FC – BI. Relationship (i) examines the extent to which a person intends to use the technology (BI) to the actual use of the technology (UB). However, in this study, this UB is called engagement. As for the relationship (ii) - (iv), it involves three constructs, namely PE, EE, and FC, which symbolise the elements that motivate a person to accept and intend to use the new technology (BI) introduced. BI is an endogenous variable influenced by three exogenous variables: PE, EE, and FC. This study measures the extent to which crowds accept the crowdsourcing platform, krumun.org (PE, EE, and FC), as well as the intention to use the platform (BI) and the actual use of the platform (Engagement/Use Behaviour – UB).

The focus is on the effect of the constructs on the intention to use (behaviour intention-BI) and the platform's actual use or engagement (UB), such as exploring activities, downloading, and building questions. These effects are tested with four hypotheses (as in

Figure 2). Next, each activity is weighed, where exploration is given the least and question building is given the most. These activities symbolise the level of involvement of a crowd, where exploring only requires the crowd to log in and explore the platform, whereas constructing questions requires the cognitive contribution and time of a crowd. So the more significant the crowd's contribution, the higher the level of involvement of a crowd in this crowdsourcing platform. The following is the research hypothesis:

- H_1: There is a positive relationship between Intention to Use (BI) and Crowd Engagement (UB).
- H_2: There is a positive relationship between Performance Expectations (PE) and Usage Intentions (BI).
- H_3: There is a positive relationship between Effort Expectancy (EE) and Crowd Intention to Use (BI).
- H_4: There is a positive relationship between Facility Support (FC) and Usage Intention (BI) (BI).

The Instrument

The study uses a questionnaire that contains two parts that examine the krumun.org acceptance. Part A involves the respondent's background, while part B relates to the UTAUT (Unified Theory of Acceptance and Use of Technology) constructs. The respondent's background includes gender, age, teaching field of study, and level of teaching (primary vs secondary school). Apart from the background, respondents were also asked to fill in their respective email addresses to identify the activities of the respondents while using the crowdsourcing platform.

The krumun.org acceptance questionnaire has several constructs and sub, namely (i) Performance Expectancy (PE); (ii) Effort Expectancy (EE); (iii) Facilitating condition (FC) and (iv). Behaviour Intention (BI). There is another construct studied to see the element of crowd engagement or actual use (Use Behavior - UB). The data for this construct is obtained through crowd log activity that is observed based on the activity performed in krumun.org. The information is collected through special programming in a form that can be achieved in .csv format and can be read using Microsoft Excel and formatted and read by software such as SPSS and PLS-SEM). It enables data from platform activities to be used for statistical analysis of the study.

Population and Sampling

The total population for this study comprises teachers who registered as a crowd on the krumun.org platform, which is a total of 403 people. Hair Jr, Hult, Ringle, C., and Sarstedt. (2017, p. 25) recommended determining the study sample for analysis using PLS-SEM can be guided by the rule of thumb suggested by Cohen (1992), who uses statistical analysis for multiple regression models. On condition that the measurement model has an acceptable outer loading value (greater than 0.7 with statistical power; (statistical power) is 80%). The Statistics Kingdom website (Kingdom, 2022) provides statistical calculation facilities that use mathematical formulas, as suggested by (Cohen, 1992). The results of calculations using the facilities provided by the Statistical Kingdom, and based on the study's conceptual framework, five UTAUT constructs and five ECM constructs; a suggested sample size of 117 people.

The Data Collection

Data collection for this study was done in two ways: face-to-face and online. The distribution of questionnaires through face-to-face questionnaires involved teachers who are continuing

their studies at the post-graduate level at a public university. Before the questionnaire was distributed, a demonstration was conducted to introduce the krumun.org platform. Once the demonstration was done, respondents were asked to fill out a questionnaire on krumun.org about acceptance factors. Next, respondents are encouraged to register on the platform and contact the platform administrator if they experience problems registering and building assessment instruments while using the krumun.org platform.

The second approach is online. Tutorial videos provided on the krumun.org platform are disseminated by offering links to videos uploaded on Youtube.com through social media such as facebook.com and instant messaging applications such as WhatsApp. The video link was then extended to the WhatsApp group of school teachers voluntarily by the teachers who received the link. In addition, links to questionnaires for acceptance factors were distributed along with video links. Respondents were instructed to watch an introductory video. Several sides of the webinar using the Google Meet platform were also held as tutorial sessions and discussions with the crowd interested in using the krumun.org platform.

The Analysis

This study uses IBM SPSS 25 software for descriptive analysis and SmartPLS 4.0 for inference analysis to build research models. Before the constructed structural model is accepted, reliability and validity analysis is performed, such as loading factor analysis, variance inflation factors (VIF), Cronbach alpha, *rho*_A and composite reliability (CR), convergent validity (CV), and discriminant validity (DV). Several threshold values have been set in the study to evaluate reliability and validity. Hair et al. (2017) suggest that the minimum factor loading value set is 0.708. It means that each item must have a value that exceeds 0.708; if the value obtained is lower, the item will be dropped. While for the Average Variance Extracted (AVE) indicator, the minimum value is set at 0.5, according to (Benitez et al., 2020; Hair et al., 2019). The threshold value for Cronbach alpha, *rho*_A, and composite reliability (CR) was set at 0.700. The additional threshold to the CR value is not to exceed 0.95.

Next, there are several variations of the minimum value of VIF, which are three, five, and ten. This study uses the recommendation by (Hair Jr et al., 2017) where VIF ≤ 5. VIF is an indicator of multicollinearity, which refers to an item with the same meaning as another item. If the minimum limit of the item exceeds the limit, the item will be dropped.

For validity, construct validation looks at discriminant validity (DV) based on the Fornell & Larcker Criterion, which is the square root of the AVE (square root of the AVE) for each construct and must be compared with the correlation between the constructs. The square root value of AVE needs to be higher than its correlation value with other constructs to reach a satisfactory level for DV (Fornell & Larcker, 1981; Hair et al., 2017; Hair Jr. et al., 2017). In addition to Fornell and Larcker (1981), the study also refers to the Heterotrait-Monotrait Criterion (HTMT). According to (Hair Jr. et al., 2017), if the HTMT value is less than 0.90, discriminant validity can be confirmed (established) between the two reflective constructs.

Findings

Of the 403 responses from the crowd, nine did not fill in part A, and ten (10) responses did not answer part B. Therefore, out of 403, 384 responses were analysed. Female respondents represent a more significant number of almost 75.0% compared to male respondents (25.0%). The breakdown of respondents according to the teaching level is as many as 29.6% primary school teachers and 70.4% secondary school teachers. Of the observations made, 32.5% were language and art teachers, 45.0% were social sciences and humanities teachers, and 22.5%

were science and engineering teachers. As for age, the mean age is 34, while the median is 29 and the mode is 25.

Table 1 shows each item's value of the factor loading and Variance Inflation Factor (VIF). The minimum value of the loading factor set is 0.708. Overall, all factor loading values for each item are above 0.708, so all items are retained. If seen in detail, all PE and BI indicators have a factor above 0.8. It symbolises the high internal consistency of these constructs. Next, referring to Table 1, the VIF value for the items in this study is less than three. Therefore, it can be concluded that the items of the factor-krumun's acceptance factor do not have multicollinearity issues.

Table 1
Factor Loading and Variance Inflation Factor (VIF)

	BI	EE	FC	PE	UB	VIF
BI1	0.854					2.778
BI2	0.821					2.106
BI3	0.873					2.962
BI4	0.868					2.85
BI5	0.841					2.389
EE1		0.74				1.931
EE2		0.736				1.901
EE3		0.852				2.637
EE4		0.83				2.54
EE5		0.841				2.46
EE6		0.836				2.562
FC1			0.778			1.74
FC2			0.832			1.948
FC3			0.812			1.841
FC4			0.777			1.596
PE1				0.838		1.795
PE2				0.904		2.367
PE3				0.842		1.833
Create					0.791	1.775
Download					0.921	2.385
Explore					0.850	1.777

The next step is to evaluate the reliability of the construct displayed in Table 2. For Cronbach Alpha (α), *rho*_A (ρA) and Composite Reliability (CR), the minimum value is 0.70. According to Table 2, all three values for acceptance factors are above 0.70. However, for CR, the ideal value is 0.7 < CR <0.9. A value that exceeds 0.90 is accepted as long as it does not exceed 0.95. For the EE and BI factors, a CR value exceeds 0.90 but is still below 0.95. So, for these two factors, the CR value is acceptable, while the other three factors, namely PE, FC, and UB, are ideal. Apart from that, construct reliability also uses the Average Variance Extracted (AVE) indicator as an indicator. The minimum value for AVE is 0.5. The table shows that the AVE for each construct is above 0.50. For that, for the reliability of the construct, the acceptance factors analysed have reliability.

Table 2
Cronbach Alpha (α), rho_A (ρ_A) dan Composite Reliability (CR)) of constructs

	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted (AVE)
BI	0.905	0.906	0.93	0.725
EE	0.892	0.897	0.918	0.652
FC	0.812	0.816	0.877	0.64
PE	0.826	0.829	0.896	0.743
UB	0.818	0.860	0.891	0.732

Meanwhile, for validity, this model also goes through discriminant validity analysis. Meanwhile, construct validation looks at discriminant validity (DV) according to the Fornell & Larcker Criterion. The value of the square root of AVE is higher than the correlation value between the constructs, thus illustrating the appropriateness of the DV level. At the same time, DV was also assessed using the Heterotrait-Monotrait (HTMT) criteria. The study analysis found that the HTMT value for the constructs of the acceptance model is less than 0.90. It means that the constructs in the UTAUT model were successfully proven valid.

Next is a bootstrap analysis of the acceptance model to confirm that the relationship between the factors is significant at the $p<0.05$ level. Referring to Table 3, all relationships between all factors have a *t-statistic* > 1.96. The relationship between Performance Expectancy and Intention to Use has a *t-statistic* = 4.561; Effort Expectancy and Intention to Use is 6.306; Facilitating Condition and Intention to Use have a *t-statistic* of 9.36. Meanwhile, the relationship between Intention to Use and Engagement is 5.568. All of these relationships have a significant level with a value of $p<0.01$.

Table 3
Bootstrap Analysis

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> UB	0.199	0.203	0.036	5.568	0.00
EE -> BI	0.349	0.351	0.055	6.306	0.00
FC -> BI	0.353	0.353	0.038	9.360	0.00
PE -> BI	0.248	0.248	0.054	4.561	0.00

Next is the measurement and structural model for the acceptance and use of the krumun.org platform. Figure 3 illustrates this acceptance model along with the value of the path coefficient and r^2. The first hypothesis is to identify the relationship between intention to use (BI) and involvement (UB). The path coefficient value for this relationship is 0.199, and $r^2 = 0.040$. It illustrates that usage intention can only explain 4.0% of the engagement factor.

Meanwhile, H_2 - H_3 is the influence of PE, EE, and FC on BI. The path coefficient for the FC - BI relationship is the largest, 0.353, followed by EE - BI = 0.349 and PE - BI = 0.248. The r^2 value for this relationship is 0.723. It means that FC, EE, and PE can explain 72.3% of intention

to use krumun.org. In other words, FC, EE, and PE factors influence 72.3% of intention to use, with FC having the most influence, followed by EE and PE.

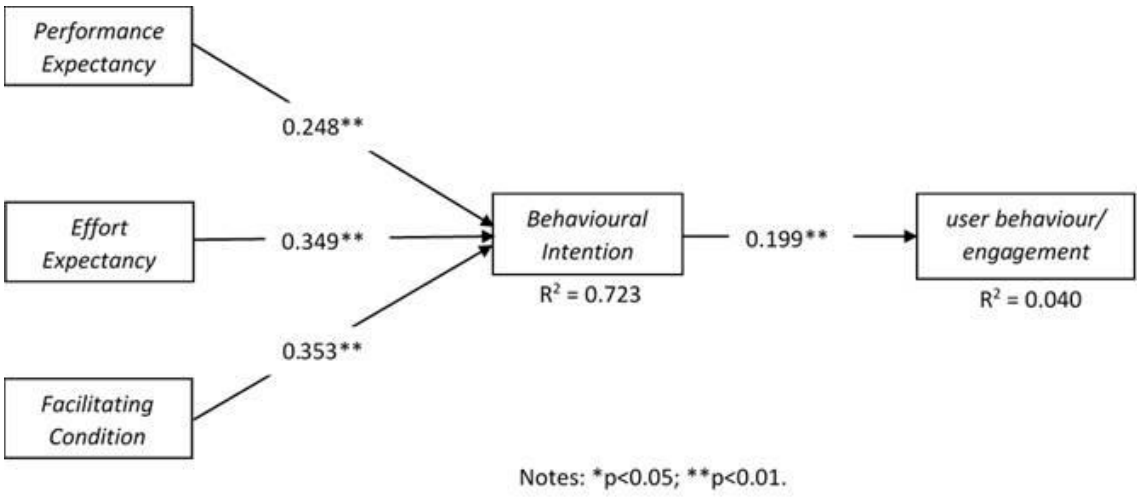

Figure 3: Model testing results

Discussions and Conclusions

The structural model of this study is developed through PLS-SEM analysis using SmartPLS 4 software based on the UTAUT model as introduced by (Venkatesh et al., 2003). The findings for krumun.org's acceptance are based on an analysis of 384 responses from respondents. This study's main objective is to determine whether the crowd's intention to use affects the actual use of krumun.org. The analysis results also show a positive and significant relationship between the three factors (PE, EE, and FC) and BI. It means that these three factors can explain the respondents' intention to use the krumun.org platform. The explanatory power shown by the r^2 value states that PE, EE, and FC strongly influence the intention to use krumun.org. However, intention to use can only explain 4.0% of crowd engagement in krumun.org. It indicates that other factors not examined in this study influence the crowd's actual use of this platform.

Compared to the results of previous studies that used the UTAUT model to identify the acceptance of technology by teachers, most obtained the same results. An example of a study that found that PE, EE, and FC influence the acceptance and use of technology is Shah et al (2020) in Pakistan et al (2020); Kim and Lee (2020) in the Philippines. While in Malaysia, a study by Raman and Rathakrishnan (2018) found that all factors have a positive relationship except EE for acceptance by teachers for the Frog VLE system, which is virtual learning. However, it should be emphasised that the Frog VLE system is different from krumun.org, where krumun.org is newly introduced and strictly voluntary. Although there are slight differences, the results of this study are consistent with previous studies that used the UTAUT model to see teachers' acceptance of the introduced technology.

Whereas, for studies that aim to make predictions (prediction) for the tested relationships, the r^2 value is one of the markers for accuracy in predicting the sample. A high value of r^2 or explanatory power usually means that the prediction is reliable because it has a small error (Moksony, 1999). However, there are several variations to this translation of explanatory power or r^2. Among those often used as references are (Falk and Miller, 1992; Chin, 1998; Bontis and Serenko, 2009; Henseler et. al., 2009; Hair, et al., 2011). The r^2 value is often divided into three strength levels: large (substantial), medium, and small. However, the

determination of the range of strength of the r^2 value sometimes differs among previous researchers.

For example, Henseler et al (2009); Hair et al (2011) stated that the value of the threshold range (threshold) of prediction represented by r^2 is 0.75, 0.5, and 0.25 depicting large, medium, and small. However, this is quite different from the threshold range of Chin (1998), who put r^2 values of 0.67, 0.33, and 0.19 to determine the strength of large, medium, and small for the prediction. Meanwhile, some researchers only determine an r^2 value as the minimum threshold value for the model's acceptability, such as Falk and Miller (1992) suggest an r^2 value equal to 0.1 or greater. Bontis and Serenko (2009) suggest an r^2 value of 0.20 and up above for management decision-making. Others feel the value of r^2 is given too much attention and think that reporting should focus on the effect of r^2 on the relationship between the constructs involved regardless of the high or low value (Cramer, 1987; Moksony, 1999).

For the findings of this study, two r^2 values result, namely intention to use (BI) and involvement (UB). These two have very different values. If using the threshold range by Henseler et al (2009); Hair et al (2011), the r^2 value of BI is close to a large power compared to UB being far below a small power. The acceptance factors tested, namely PE, EE, and FC, successfully explain most usage intention factors. However, the explanatory power for UB is too small and inappropriate to use. Therefore, the engagement factor in krumun.org needs to be identified in future studies. In conclusion, the crowd intends to use or accept krumun.org, but this desire factor does not influence the crowd to use krumun.org.

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