Task-Technology Fit Analysis: Measuring the Factors that influence Behavioural Intention to Use the Online Summary-with Automated Feedback in a MOOCs Platform

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Abstract: The purpose of this study was to evaluate the factors that influence behavioural intention (BI) to use the Online Summary-with Automated Feedback (OSAF) in a MOOCs platform. Task-Technology Fit (TTF) was the main framework used to analyse the match between task requirements and technology characteristics, predictng the utilisation of the technology. The relationships between TTF and BI was moderated by students' performance. This TTF provides an illustration of the extent to which the suitability of technology support for tasks will affect the performance and utilization of technology. There were 9 hypotheses examined in this study. The participants consisted of 151 students at a public university in East Java, Indonesia. In order to analyse the collected data, PLS-SEM (partial least squares - structural equation modeling) was employed, using SmartPLS 3.0. In this study, several points can be concluded, namely: 1) task characteristics and technology characteristics were not positively and significantly effected by TTF, while students' characteristics had a positive and significant effect on TTF; 2) TTF and utilization which are influenced by social influence, have a positive effect on performance impact. In this case the performance impact is constructed from 3 dimensions, namely: learning performance, personal integrity, self-confidence, except TTF were not postitive and were significantly affected by self-confidence. 3) TTF and performance impact positively influence behavioural intention, except in the dimension of performance impact, personal integrity was not postively and significantly effected by behavioural intention.

Keywords: Automated feedback, Formative assessment, Online summary, Task-Technology Fit (TTF), MOOCs

1. Introduction

MOOCs have provided innovative open learning environments since the term was first introduced in 2008 (Littlejohn and Milligan, 2015). MOOCs have been derived from distance education. The MOOCs platform providers collaborate with many top educational institutions and organizations to create courses and programs, giving students all over the world access to variety of subjects at low cost or even zero cost (Jung and Lee, 2018). Therefore, until now the number of users of the MOOCs platform continues to show very rapid development. This positive trend can be seen in Coursera which is one of the popular MOOCs platforms which currently has 92 billion students with an increase of 29% in the number of students year on year by 2021 (Coursera, 2021). So, it is only natural that there is an assumption that MOOCs will revolutionize learning in higher education.

In the past few years, there have been many studies regarding how MOOCs have the opportunity to be used to obtain a formal education (Goodman, Melkers and Pallais, 2016; Mohsen, 2016), and today , MOOCs have been increasingly positioned as a platform to integrate formal traditional courses with informal learning experiences included in the K-12 context (Cha and So, 2021). Since its popularity, many questions have arisen regarding the quality of education offered by MOOCs. Bayne and Ross (2014) said that there are three issues that arise in MOOCs pedagogy, namely: 1) the role of the teacher, 2) student participation and 3) assessment.

This paper will focus on assessment since it is an important component in a learning process. There are some assessment methods that can be selected to collect the students' learning perfomances and progress. This research focused on online summary writing. Online summary means students summarize the learning materials through online tool, in this research, the tool was embedded in MOOCs Platform. The online summary tool equipped with a summary checker tool that could give automated feedback which contained scores and informative comments in real-time). This MOOCs platform was originally design and developed by the authors (see Figure 1). One of the benefits of Using Summaries as Assessment is measuring the students' reading comprehension and by providing the automated feedback to students, this system enabled the students to self-evaluate and monitor their learning progress or performance (Sung, et al., 2016).

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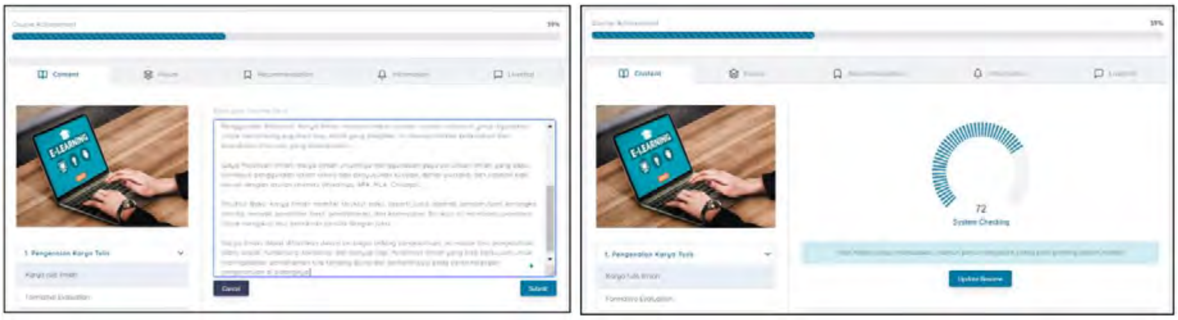

Figure 1: Interface of online summary-with automated feedback in MOOCs platform

The objectives of this research is to measure the relationship between Task-Technology Fit (TTF), student performance impact and behavioural intention (BI). Goodhue and Thompson (1995) proposed the concept of TTF; it is a theoretical framework that studies the relationship between a task's qualities and the attributes of the technology used to do it. In essence, it evaluates how well a technology meets users' demands to complete particular tasks. The purpose of TTF in this research is to understand the relationship between the characteristics of a task, in this case summary writing, and the features of a technology used to perform that task namely the summary writing with automated feedback.

This paper considers the role of TTF in a MOOCs platform, and addresses the question of how TTF influences the students' performances and behavioural intention (BI) to use the technology, since BI is an important factor in predicting the adoption of new technology, in this case educational tools like summary writing with an automated feedback tool. By identifying the factors that influence BI, some strategies can be developed to encourage the desired technology adoption for educators or policy makers. In order to achieve the objective of this research, several hypotheses were constructed. A statistical method was used to analyse complex relationships between multiple variables.

2. Theoretical Frameworks

2.1 Assessment in MOOCs

Assessment is an integral component of Massive Open Online Courses (MOOCs) because it ensures that students have acquired the required knowledge and skills (Xiao, Qiu and Cheng, 2019). Students are able to monitor their progress, while teachers are able to determine which topics require additional attention. Assessments also shape students' educational experiences. In addition, assessment can provide a sense of accomplishment for each module, thereby increasing the motivation of students to complete the course (Xiao, Qiu and Cheng, 2019). Regular assessments ultimately ensure that students have mastered the necessary skills and knowledge prior to moving on to the next module.

Massive Open Online Courses (MOOCs) employ a variety of assessment methods. The two primary types of assessment used in MOOCs are summative and formative assessment. The purpose of summative assessments is to evaluate a student's knowledge and skills at the end of the course. Typically, these assessments are used to determine a student's final grade and may consist of tests, quizzes, and/or projects. Summative assessments provide a snapshot of a student's learning and can assist teachers in identifying areas where additional instruction is required. In contrast, formative assessments are used throughout the course to provide students with feedback and direction (Janelli and Lipnevich, 2021). Typically, shorter and less complex than summative assessments, formative assessments may consist of short answer questions, multiple-choice questions, and/or brief writing assignments as well as open-ended feedback (Nanda, et al., 2021). Formative assessments enable instructors to better comprehend their students' learning needs and verify that they are on the right track, student engagement, for example. (Sun, Guo and Zhao, 2020).

2.2 Task-Technology Fit in MOOCs

Task-Technology Fit (TTF) is a theoretical framework used to comprehend how technology can be employed to accomplish a specific task. It is the process of determining the optimal combination of hardware and software to meet the requirements of a given task. The TTF model focuses on the task, the technology, and the user. The objective of the TTF model is to identify the most suitable technology for a given task, taking the user's knowledge and experience into account (Kim and Song, 2022). To achieve an optimal Task-Technology Fit, the skills and preferences of the user must be considered. The features and capabilities of the technology should also be considered to ensure they are suitable for the task. In addition, the environment in which the technology is used should be considered to ensure that the user is comfortable with it. Lastly, the cost of the technology must also be considered. Task-Technology Fit can be utilized to enhance the user experience, performance, and overall system efficiency including its own acceptance by users (Khan, et al., 2018). It can be used to determine the most suitable technology for a given task and to ensure that users are comfortable with it. In addition, it is essential to note that Task-Technology Fit is an iterative process, as users must frequently adapt to the technology as they gain experience with it (Ouyang, et al., 2017).

TTF is a key concept in the design of MOOCs (Massive Online Open Courses). TTF is a measurement of how well the design and technology of a course or system correspond to the tasks a user must complete. It is the extent to which the design and technology of a course or system support the user's ability to learn or perform tasks (Kim and Song, 2022). When designing a course or system, it is essential to consider the TTF, as the user will struggle to learn if the technology and design do not match the tasks. An effective TTF necessitates that the course or system design takes into account the user's tasks and adapts the technology to facilitate learning (Wu and Chen, 2017). TTF is also closely related to the MOOCs continuance intention of the students (Shanshan and Wenfei, 2022). It also aims for the sustainability of students learning at MOOCs and the existence of the MOOCs themselves in the long term (Alyoussef, 2021).

TTF includes the user, the tasks they must complete, the technology employed, and the course or system's design. The design of the technology must facilitate user performance on the tasks. This involves creating a design that allows the user to complete tasks quickly and easily, is intuitive, and has a low learning curve. The technology must also be dependable, because if it fails, the user will be unable to complete the task. Additionally, the course or system must have an effective layout (Kim, et al., 2021). This includes clear instructions on how to complete the tasks, effective user feedback, and support for maintenance and troubleshooting. Lastly, the user must possess the necessary skills to complete the tasks, including the ability to use the required technology. TTF is an essential concept for the development of MOOCs. It is a measurement of how well the design and technology of a course or system correspond to the tasks a user must perform (Ouyang, et al., 2017; Khan, et al., 2018). It necessitates that the technology facilitates user performance and that the course or system design is effective (Jung, et al., 2019). Additionally, the user must possess the required skills to complete the tasks.

2.3 Students' Performance in MOOCs

The performance of students in MOOCs can be affected by a variety of variables, including the type of course, the instructor, the medium of instruction, and the students' own disposition (Sari, Bonk and Zhu, 2020). The type of course is a significant factor in student performance. A course that is either too easy or too difficult can result in either boredom or confusion (Jung, et al., 2019). The instructor is also a significant factor in the performance of students in MOOCs. An effective instructor can cultivate a stimulating learning environment and provide students with feedback and direction throughout the course (Janelli and Lipnevich, 2021). A poor instructor, on the other hand, can create a hostile environment that makes learning more challenging and less enjoyable (Sari, Bonk and Zhu, 2020). Regarding student performance, the medium of instruction is also essential.

Multiple factors can influence a student's success in MOOCs. These include the student's dedication to the course, the time and effort they devote to it, their level of engagement with the material, and their capacity to work independently and motivate themselves (Janelli and Lipnevich, 2021; Shah, et al., 2022). In addition, having access to the necessary resources, such as textbooks, course materials, and dependable internet access, can help students to learn. To help students in achieving their optimal learning performance, MOOCs must be designed to encourage students' active participation in knowledge construction. This pertains to independent learning or more often known as self-regulated learning (Tang and Bao, 2022). Even though self-directed learning is rife with learning motivation, in the context of MOOCs, the instructor must be able to design learning processes, and assignments that encourage students to investigate the material in depth (Kim, et al., 2021).

2.4 Behavioural Intention to Use Technology

Theoretically, BI is a development of the theory of planned behaviour (TBP) (Ajzen, 1991), which analyses an individual's intention to do and not do something based on attitudes, understood norms and perceived behavioural control (Luarn and Lin, 2005). Attitudes relate to a person's perception of whether he likes or dislikes the impact of an action. Meanwhile, subjective norms are interpreted as a person's perception of the norms adopted by the surrounding community. The perceived behavioural control is related to whether or not there are supporting sources available to carry out a behaviour (Ajzen and Madden, 1986). Research on the determinants of a person's intention to use MOOCs has revealed complex findings involving complex variables that encourage students to continue learning online using MOOCs. Research conducted by Li and Zhao (2021) reports the importance of perceived usefulness and perceived ease of use of systems used in MOOCs, both of which are fundamental components o Technology Acceptance Model (TAM) theory. This criterion explains how students perceive the usefulness of MOOCs in achieving their learning goals, and how easy it is to navigate the learning resources available in MOOCs. Considering that the aim of MOOCs is to make it easier for users, with the support of learning resources that are easily accessible, interesting, and important to master to increase their understanding and improve their skills, this can encourage active motivation in continuing online learning practices through MOOCs (Wang, van Hemmen and Criado, 2022).

2.5 Utilization of MOOCs

Utilization in the context of MOOCs is defined as a learning decision to use MOOCs as a way to improve the understanding and skills they need due to internal encouragement in the form of BI which arises because their expectations are fulfilled as a result of the services provided by the MOOCs provider (Samim, 2018). Research on factors influencing the use of MOOCs has produced varied findings, but the perception of ease of use and usefulness of MOOCs is often the driving factor for someone to like and apply MOOCs as an alternative way of learning and improving their competence (Liyanagunawardena, Adams and Williams, 2013). Apart from perceived ease and usefulness factors, social elements are also reported to be important in influencing someone to utilize MOOCs. Poquet, et al. (2018) emphasizes the importance of aspects of social presence, collaborative learning, and peer interaction in building a supportive environment in using MOOCs sustainably. Social presence also fosters a supportive and interactive atmosphere, enhancing meaningful learning experiences. This is what causes students to feel comfortable implementing MOOCs in their daily lives.

The Task-Technology Fit (TTF) paradigm, which assesses the relationship between technology and the system being developed, provides a useful perspective to examine aspects driving the implementation of MOOCS. A study conducted by Wu and Chen (2017) used TTF to analyse the implementation of MOOCs, highlighting the importance of matching MOOC platform features with the learning objectives that learners want to achieve. This research reports that when users perceive significant alignment between the features and services provided by MOOCs and the requirements of the tasks they have to perform, this has a positive impact on their intention to adopt MOOCS as their choice. Thus, appropriate task design influences learners' perceptions of using MOOCs. Furthermore, the TTF framework can also be extended to consider contextual elements, such as users' learning experiences before using MOOCs with their technical proficiency. A study conducted by Kim and Song (2022) highlighted the importance of individual traits in shaping the alignment between tasks and technology and features in MOOCs. Individuals with different levels of proficiency in using technology may have different levels of adaptation in implementing MOOCs.

3. Research Model and Hypotheses

This study uses a model of the TTF. Goodhue and Thompson's Task-Technology-Fit (TTF) model has been used as a predictor of performance in a technology context (Goodhue and Thompson, 1995). The general premise of the TTF Model is that if an information system has a good fit with the tasks it supports, it will have a positive impact on the user's performance of the task. The concept of "fit" defined by Goodhue and Thompson (1995) is the extent to which a technological system provides necessary features and support required by a task. TTF also affects user behavioural intention (BI) to use technology. Goodhue and Thompson (1995) also state that TTF is a significant predictor of BI. Figure 2 illustrates the research model and hypothetical framework of this study.

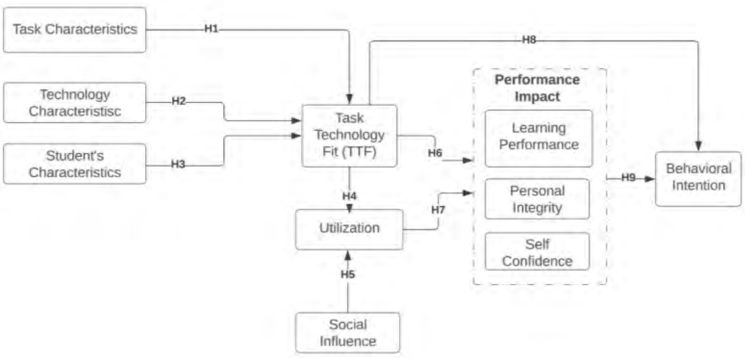

Figure 2: Research model and hypothetical frameworks

Overall, there were fifteen hypotheses tested in this study. In detail, the research hypotheses investigated can be seen in Table 1.

Table 1: Research Hypotheses

H-Code	Hypothetical statement
H1	Task characteristics has a positive and significant effect on Task-Technology Fit
H2	Technology characteristics has a positive and significant effect on Task-Technology Fit
H3	Student's characteristics has a positive effect and significant on Task-Technology Fit
H4	Task-technology has a positive and significant effect on utilization
H5	Social influence has a positive and significant effect on utilization
H6a	Task-Technology Fit has a positive and significant effect on learning performance
H6b	Task-Technology Fit has a positive and significant effect on personal integrity
H6c	Task-Technology Fit has a positive and significant effect on self-confidence
H7a	Utilization has a positive and significant effect on learning performance
H7b	Utilization has a positive and significant effect on personal integrity
H7c	Utilization has a positive and significant effect on self-confidence
H8	Task-Technology Fit has a positive and significant effect on behavioural intention
H9a	Learning performance has a positive and significant effect on behavioural intention
H9b	Personal integrity has a positive and significant effect on behavioural intention
H9c	Self-confidence has a positive and significant effect on behavioural intention

4. Research Methodology

This study uses a quantitative method. It is measurable and a questionnaire was used for the data collection. The proposed model and questionnaire were conceptualized, validated, and examined using the structural equation modelling (SEM) software, SmartPLS 3 (Chin, 1998).

4.1 Research Participants

The participants in this study were Educational Technology Department students from a public university in the city of Malang, in the province of East Java, Indonesia. The participants numbered 151 students with a composition of 49.4% female and 50.6% male.

4.2 Data Collection and Research Procedure

The data was gathered using a structured questionnaire survey in November 2022. The research participants were asked to register a course at a MOOCs platform. The following is the learning procedure:

- A student accesses the course in a MOOCs platform consisting of 3 chapters per course.
- MOOCs provide a formative evaluation in each chapter. After completing each chapter, a student should complete a formative evaluation. The type of formative evaluation is an open-ended question, namely summary writing.
- The system will automatically analyse and grade the student's summary and provide immediate feedback to the student in real-real time. Feedback would be different for each student, as it depends on the student's summary score.
- Each student can make multiple attempts to write the summary until getting a satisfying score.

4.3 Instruments

A questionnaire survey was used to assess the Task -Technology Fit (TTF) of the effectiveness of Online Summary-with Automated Feedback in Massive Open Online Courses (MOOCs) Learning Environment. The initial part of the survey consisted of information used in TTF to measure the conceptual construction of the model, namely: task characteristics (TCK), technology characteristics (TC), student characteristics (SC), Task-Technology Fit (TTF), utilization (U), social influence (SI), plus performance impact which consist of three categorizes, namely: learning performance (LP), personal integrity (PI), and self-confidence (SC). The conceptual construct used a 5-point Likert scale. Table 2 shows the variables and question items on the instruments used in this study.

Table 2: Research instruments

Variables		Items	References
Task	**TK1**	Through the use of the online summary-automated feedback feature, I can understand the content or materials	(Bridgeman and Carlson, 1983; Bigot and Rouet, 2007; Akbari Chermahini, Hickendorff and Hommel, 2012)
	TK2	The online summary-automated feedback feature can train me to make a summary	
	TK3	The online summary-automated feedback feature can encourage me to monitor my learning progress	
	TK4	The online summary-automated feedback feature can generally help me understand what parts of the content I don't understand	
	TK5	The online summary-automated feedback feature in general can help personalize learning because it suits my learning needs	
Technology	**TC1**	Simple online summary-automated feedback user interface with a clear layout	(Pantic and Rothkrantz, 2003; Ho, et al., 2018; Huang and Renandya, 2020)
	TC2	The navigation system on the online summary-automated feedback user interface is clear and easy to use	
	TC3	Visual presentation of material content is simple and attractive	
	TC4	Material content is creative and not monotonous	
	TC5	The existing user interface is interactive and fun to use	
	TC6	I am satisfied with the interface design on the MOOCS platform	
	TC7	The online summary-automated feedback feature provides real-time feedback	
	TC8	The feedback provided by the online summary-automated feedback system is accurate	
	TC9	I can understand the message (feedback message) given by the online summary-automated feedback feature	
Task-Technology Fit	**TTF1**	The use of online summary-automated feedback can improve reading comprehension skills	(Ouyang, et al., 2017; Wu and Chen, 2017; Khan, et al., 2018; Alyoussef, 2021; Kim and Song, 2022)
	TTF2	The use of online summary-automated feedback can train me to determine the main idea in reading (study material)	
	TTF3	Using online summary-automated feedback can help me focus on important words or phrases in the text (study material)	
	TTF4	The use of online summary-automated feedback can train me to rewrite ideas (paraphrases) in reading texts (learning materials).	
	TTF5	The use of online summary-automated feedback can give me an idea of which parts I understand and do not understand	
	TTF6	The use of online summary-automated feedback can show correct and inaccurate answers	
Student's characteristics	**SC1**	I prefer to get an assessment of my (exam) work in person rather than an assessment given sometime after the exam	(Thurmond, et al., 2002; Bernard , et al., 2004)
	SC2	I prefer studying online by accessing digital content rather than studying through textbooks	
	SC 3	I prefer online-based exams/assessments rather than paper-based (written exams)	
	SC4	In studying, I like to make my own schedule (to record targets that must be achieved) and try to achieve them	
	SC5	I like to study independently	
	SC6	I like the flexible learning style without being bound by time and space	
	SC7	I like solving learning problems on my own by searching for answers/solutions through searching on the internet	
	PI1	Online summary-automated feedback-based exams can improve integrity	

Variables		Items	References
Personal Integrity	**PI2**	The use of online summary-automated feedback can support fairness (honest and fair) learning, because the assessment is according to my ability	(Hartman, DesJardins and MacDonald, 2011; Hussein, 2017)
Self-Confidence	**SC1**	Online summary-automated feedback-based exams can increase confidence in learning	(Scott, 2017; Ross, et al., 2018; Jensen, Bearman and Boud, 2021)
	SC2	The online summary-automated feedback-based exam increased my learning independence	
	SC3	The online summary-automated feedback feature can increase my motivation to continue learning	
Social Influence	**SI1**	I was asked by my lecturer to use this feature	(Venkatesh, Thong and Xu, 2012)
	SI2	My friend recommended the use of this feature to me	
Utilization	**U1**	I often use this kind of system	(Goodhue and Thompson, 1995)
	U2	I often use the online summary-automated feedback feature repeatedly	
Learning Performance	**LP1**	The online summary-automated feedback-based test has a positive effect on my learning performances	(Pedrosa-de-Jesus, et al., 2018; Cavalcanti, et al., 2021)
	LP2	An online summary-automated feedback-based exam can improve my critical thinking skills	
	LP3	The use of online summary-automated feedback can increase my productivity in learning	
	LP4	The use of online summary-automated feedback can increase effectiveness and efficiency in learning	
Behavioural intention	**LP1**	I intend to frequently use a feature like this online summary-automated feedback	(Marikyan, et al., 2022)
	LP2	I will use the MOOCSs platform which is equipped with summary-automated feedback in the future	

4.4 Data Analysis

A total of 151 questionnaire forms were completed by research participants via Google Forms. The analysis used 151 completed questionnaire sets which were sufficient based on Hair, et al. (2021) that served as a rule of thumb for the sample size required in PLS-SEM (partial least squares - structural equation modelling).

5. Research Findings

PLS-SEM (partial least squares - structural equation modeling) model consists of two steps: the outer model assessment and the inner model assessment. In the evaluation of the outer model, the reliability and validity of reflective constructs and the validity of formative constructs were determined, meanwhile, the internal model evaluation comprised a variance explanation of endogenous constructs, measurement of effect sizes, and predictive significance (Table 3).

Table 3: Overall model assessment data

Variables	Items	Mean	Standard Deviation	Factor Loading	Cronbach Alpha	Composite Reliability	AVE
Task-Technology Fit	TTF1	4.139	0.750	0.795	0.866	0.901	0.604
	TTF2	4.032	0.767	0.852			
	TTF3	3.981	0.775	0.835			
	TTF4	4.139	0.725	0.757			
	TTF5	3.892	0.808	0.764			
	TTF6	3.810	0.956	0.639			
Task	TK1	4.108	0.690	0.819	0.863	0.901	0.647
	TK2	4.184	0.753	0.756			
	TK3	4.120	0.732	0.775			

Variables	Items	Mean	Standard Deviation	Factor Loading	Cronbach Alpha	Composite Reliability	AVE
	TK4	4.070	0.772	0.846			
	TK5	4.051	0.736	0.819			
Technology	TC1	4.228	0.770	0.710	0.903	0.919	0.559
	TC2	4.234	0.756	0.723			
	TC3	4.120	0.867	0.790			
	TC4	3.854	0.877	0.767			
	TC5	4.032	0.799	0.803			
	TC6	4.013	0.795	0.752			
	TC7	4.146	0.753	0.705			
	TC8	3.886	0.811	0.724			
	TC9	3.968	0.822	0.750			
Students' Characteristics	SC1	4.222	0.897	0.663	0.770	0.834	0.418
	SC2	3.981	0.889	0.652			
	SC3	4.152	0.828	0.634			
	SC4	4.120	0.830	0.623			
	SC5	3.797	0.877	0.574			
	SC6	4.411	0.843	0.659			
	SC7	4.165	0.786	0.714			
Personal Integrity	PI1	4.133	0.739	0.840	0.625	0.842	0.727
	PI2	4.070	0.764	0.865			
Self-Confidence	SC1	3.943	0.757	0.846	0.823	0.894	0.738
	SC2	4.139	0.725	0.862			
	SC3	3.994	0.742	0.869			
Utilization	U1	3.525	0.998	0.862	0.772	0.895	0.810
	U2	3.570	0.896	0.936			
Social Influence	SI1	4.430	0.774	0.474	0.126	0.669	0.527
	SI2	3.373	1.166	0.911			
Learning Performance	LP1	4.076	0.671	0.794	0.836	0.891	0.671
	LP2	4.000	0.779	0.784			
	LP3	3.943	0.74	0.856			
	LP4	4.063	0.744	0.840			
Behavioural intention	BI1	4.000	0.755	0.915	0.803	0.910	0.835
	BI2	4.177	0.725	0.913			

5.1 Overall Model Assessment

The purpose of measurement model evaluation is to evaluate the consistency and validity of constructs. Validity of the constructs was examined based on convergent and discriminant validity (Hair, et al., 2012).

According to Table 3, The lowest factor loading was 0.574 (student's characteristics). A loading value of 0.7 or higher was considered highly satisfactory (Götz, Liehr-Gobbers and Krafft, 2009). However, although a loading value of 0.5 is regarded as acceptable, the variables with a loading value of less than 0.5 should be dropped (Chin, 1998). On the contrary, Hulland (1999) argued that 0.4 should be acceptable. While Henseler, Ringle and Sinkovics (2009) suggested that variables with a factor loading between 0.4 and 0.7 should be reviewed before elimination.

To measure the reliability of the instrument, the internal consistency reliability method was used using the reliability coefficient Cronbach alpha (CA), which was intended to test the consistency of the constructs' items. In this study, the CA coefficient of all constructs was greater than 0.6, where it was acceptable for exploratory research (Hair, et al., 2006), except for the social influence construct which had a CA coefficient of 0.126. It had a lowest CA coefficient but had 0.527 for Average Variance Extracted (AVE). AVE is commonly used to assess convergent validity which is designed for measuring the validity of each indicator in the construct variables. Nunnally (1967) assumes that CA coefficients as low as 0.50 are appropriate for exploratory research. In addition, the social influence construct had a composite reality (CR) value of 0.669, therefore, the construct was reliable. According to Peterson and Kim (2013),an alternative to CA is composite reliability, which is usually calculated in conjunction with structural equation modelling. This research findings show all constructs had a CR value greater than 0.6, therefore, we can conclude that all the construct items were reliable.

5.2 Structural Model Testing

A bootstrapping technique is used to evaluate the structural model PLS-SEM. According to Chin (1998), the bootstrapping technique is one of the nonparametric approaches used for estimating the precision of PLS estimates. From this process, the path coefficient and significance value (t-statistics) were obtained (see Table 4).

The test criteria with the significance level of 5% was determined as follows: If |T statistics| > Tα, p-value < α (α is signifcance level) , |T statistics| greater than 1.96 and p-value < 0.05 then the hypothesis is accepted. If |T statistics| less than or equal to 1.96 and p-value >0.05 the hypothesis is rejected.

Table 4: Structural model testing

Hypothesis	Path	T Statistics	P-Values	Decision
H1	Task characteristics → Task-Technology Fit	1.554	0.121	Rejected
H2	Technology characteristics → Task-Technology Fit	0.760	0.448	Rejected
H3	Student's characteristics → Task- Technology Fit	4.163	0	Accepted
H4	Task-Technology → Utilization	3.057	0.002	Accepted
H5	Social influence → Utilization	1.361	0.174	Rejected
H6a	Task-Technology Fit → Learning performance	3.132	0.002	Accepted
H6b	Task-Technology Fit → personal integrity	2.838	0.005	Accepted
H6c	Task-Technology Fit → Self-confidence	0.907	0.365	Rejected
H7a	Utilization → Learning performance	11.116	0	Accepted
H7b	Utilization → Personal integrity	9.871	0	Accepted
H7c	Utilization → Self-confidence	8.462	0	Accepted
H8	Task-Technology Fit → Behavioural intention	5.018	0	Accepted
H9a	Learning performance → Behavioural intention	3.292	0.001	Accepted
H9b	Personal Integrity → Behavioural intention	0.632	0.528	Rejected
H9c	Self-confidence → Behavioural intention	2.288	0.023	Accepted

6. Discussion

Task-Technology Fit (TTF) put forward by Goodhue and Thompson (1995) is a theory that describes the relationship between three components, namely technology functionality, task requirements, and individual abilities when using an information system application. Goodhue and Thompson (1995) state that the objective of the TTF measurement is to examine the assumption that the utilization of particular technology results in increased performance only on the condition that technology functionality corresponds to users' task requirements. Spies, Grobbelaar and Botha (2020) define Task-Technology Fit as a theory devoted to quantifying the effectiveness of technology in a system by examining the relationship between the technology and the tasks the technology aims to support. The original model of TTF proposed by Goodhue and Thompson (1995) consists of five construct variables, namely: task characteristics, technology characteristics, TTF, utilization, and performance. In this research, in addition to the five constructs, these had been extended into ten construct variables, namely: task characteristics, technology characteristics, students' characteristics, TTF, social influence, utilization, learning performances, personal integrity, self-confidence, and behavioural intention.

6.1 Task-Technology Fit

In this study, the dimensions measured on TTF as shown in Table 2 focus on system functionality in learning. As can be seen from Table 4, the hypotheses H1 and H2 were rejected, while H3 was accepted. These findings shows that both task and technology characteristics did not positively effect TTF. Technology is a tool that helps someone complete their work (Spies, Grobbelaar and Botha, 2020). Each technology used has different characteristics in helping to complete the task. From this study, we can conclude that the characteristics of online summary-with automated feedback was not able to help the students to complete the task. There are some improvements in the tool that should be made in order to help the students to complete the task.

Meanwhile, students' characteristics had a positive effect on TTF. The students' characteristics represent the students' individual preferences regarding the online learning. According to Goodhue and Thompson (1995) this constructs variable relates to an individual's internal resources. Student characteristics in this study are more focused on students' learning preferences. Based on the results of this study, it is proven that these student characteristics have a positive and significant effect on TTF, similar to research conducted by Gu and Wang (2015) which uses self-efficacy as a representation of students' characteristics and positively influences TTF on e-Learning.

6.2 External Variables

In the evaluation of the TTF model in this study, the utilization variable is included in the model analysis. The dimensions measured are the level of utilization information system technology (see Table 2), and the variables that affect utilization are also measured, namely the social influence variable. In addition, the relationship between the utilization dimension and performance impact was also explored, and as a result the hypotheses of H4 was accepted and H5 was rejected (see Table 4). This research concluded that TTF has a positive and significant effect on utilization information system technology.

The research conducted by Thompson, Higgins and Howell (1991) confirmed that fit between job, and pc capabilities, and their long-term consequence has a strong relationship to utilization, where what it defines as information systems is related to the act of using the information system in this case the measurement of the frequency of use of the information system and the diversity of the use. Similar findings were also obtained in a study conducted by Anaam, Haw and Palanichamy (2022) which concluded that utilization is a major predictor of individual performance. In addition, McGill and Hobbs (2006) also emphasized that task-technology fit has a positive effect on utilization.

In information system (IS) research, social influence represents interpersonal consideration of the use of technology (Kaneshiro, et al., 2010). Meanwhile, according to Kelman (1958), social influence is a change in the thoughts, feelings, attitudes or behaviour of a person who is influenced by the results of interaction with another individual or a group. Previously, Seddon, Billett and Clemans (2004) had identified that social norms influenced utilization where social norms referred to user's beliefs as to the influence of other individuals to perform that behaviour. Social norms can influence individual behaviour as well as technology adoption but it does not mean it always has the same impact as in the research findings of Beldad and Hegner (2018) that confirmed that social norms do not have significant effects on the repeat usage intention on a fitness app.

6.3 Performance Impact

Performance impact refers to user outcomes which are the effects or impacts resulting from the use of information system technology. Goodhue and Thompson (1995) proposed the technology to performance chain model which describes the effectiveness of an information system technology. So, in this study the measurement of the relationship between task-technology fit was carried out by constructing the H6 hypothesis (H6a, H6b, and H6c) as shown in Table 1. Performance impact in this study focuses on learning performance, student integrity, and self-confidence.

Based on Table 4, it shows that in general, TTF has a positive and significant relationship to learning performance, therefore the hypothesis H6a was acceptable. Several studies have shown a significant relationship between TTF and student performance in online learning environments (Butt, et al., 2021). Previously, Shim and Jo (2020) also conducted an analysis of information quality, system quality and service quality which led to user satisfaction and perceived benefits in a health information system and concluded that TTF has a significant relationship with performance impact.

Personal integrity is a commitment held by students related to ethical decisions, such as being honest in the context of academic settings. Fishman (2014) defines academic integrity as a student's commitment to the fundamental values of honesty, trust, fairness, respect, responsibility, and courage. Academic integrity is an important issue in education, and one example of contravening academic integrity is dishonest behaviour unfairly violating educational rules (Farahat, 2022; Surahman and Wang, 2022). This form of dishonest behaviour is cheating during assessment, especially in online learning. Farahat (2022) said that one of the factors that contributed to academic integrity was academic performance. In this study, the use of the online summary feature with automated feedback can support students to improve their academic integrity so that in this study it is used as one of the variables in performance impact. This research shows that TTF positively and significantly affects personal integrity (H6b), therefore H6b was accepted.

Self-efficacy refers to a person's confidence in his ability to complete a certain task (Bandura, 1978). Self-confidence in this study refers to self-efficacy (SC1), self-regulation (SC2), and self-motivation (SC3) (see Table 1). Landrum (2020) summarizes that self-efficacy to complete an online course is a positive and significant predictor of satisfaction in online learning. In addition, Landrum (2020) also concludes that when self-regulation is coupled with self-motivation, it can make students more independent and confident in acting, and self-regulation behaviours can be implemented in online learning. Based on Table 4, it can be seen that the hypothesis of task-technology fit positively and significantly effecting self-confidence (H6c) was rejected.

Another predictor that influences performance is utilization as shown in Table 4, the hypotheses of H7a, H7b, and H7c were accepted. The results of this study are slightly different from the research conducted by Goodhue and Thompson (1995) which confirmed that utilization does not have power strong enough to predict performance.

6.4 Behavioural Intention

Several studies have combined the technology acceptance model and TTF in exploring the factors that can explain the use of information system technology and its relation to user performance. The technology acceptance model focuses on attitudes toward utilization of a particular information system technology which users develop based on perceived usefulness and ease of use of the information system technology (Davis, Bagozzi and Warshaw, 1989) while TTF focuses on the measurement of the functionality of the information system that supports the task at hand (Goodhue and Thompson, 1995). In this study, behavioural intention is influenced by predictors of task-technology fit and performance impact with the hypothesis as shown in Table 4, namely H8 and H9 (H9a, H9b, H9c). These research findings are in line with research conducted by Dishaw and Strong (1999) who used the TTF predictor in influencing behavioural intention. In extended technology acceptance model research, such as the work of Chao (2019), one of the predictors of behavioural intention is performance expectancy, and the results of the research show that performance expectancy has a positive and significant effect on behavioural intention.

Based on the results of this study (see Table 4) the hypothesis of H8, H9a and H9c were accepted while the hypothesis of H9b was rejected. Personal integrity may not be a direct determinant in technology adoption because it has a complex relationship and affected by several factors, such as ethical consideration, technology trust et cetera.

7. Conclusion

This research has revealed the factors that influence behavioural intention to use " the Online summaries-with automated feedback in a massive open online courses (MOOCs) platform" using task-technology fit (TTF) analysis, and students' performance or performance impact as moderator variables. Performance impact had 3 dimensions namely:, learning performance, personal integrity, and self-confidence. In this study, several points can be concluded as follows: even though the task and technology characteristics did not fit, TTF factors still proved the positive and significant effect on student performance in this case performance impact, TTF did not prove the positive and significant effect on self- confidence. However, the TTF factors and performance impact had shown the positive and significant effect on behavioural intention to use the online summaries-with automated feedback in a massive open online courses (MOOCs) platform.

Addressing the factors that influence behavioural intention to use online summary with automated feedback would be as important as understanding the potential adopters. Furthermore, these findings gave information about factors that can influence the relationship between TTF and behavioural intention to use online summary with automated feedback. As a result, we may understand more about factors that influences the successful implementation of online summary with automated feedback to continue to increase user retention and indeed recruit future users. One of the limitations of this research is the task and technology characteristics were not achieving a strong fit. However, in order to adjust and achieve this, the continuous improvement of technology should be ongoing especially in summarizing checker tool, the algorithm should be improved in order to give a better feedback to the students.

Declarations

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All authors declare that they have no conflict of interest.

All procedures performed in studies involving human participants were in accordance with the ethical standards of Universitas Negeri Malang.

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