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Extending the Task-Technology Fit Theory with a Skill Fit Construct: A Case Study of a Transaction Control Log and Accounting System

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ABSTRACT

Numerous studies have employed the Task-technology fit (TTF) theory to examine the impact of information systems used for training. While some of these studies reported positive outcomes, others presented mixed results on the impact of the systems improving users' performance in problem solving and learning. One possible explanation for these inconsistencies is likely caused by additional factors beyond the task and technology characteristics emphasized in TTF. This research is a preliminary study to enhance understanding of TTF and its impact on system usage and work performance. The study argues that task-technology alignment should also consider users' skills and the fit between the task and technology. Therefore, this research explores the effects of task characteristics, technology characteristics, and users' skills on system usage and work performance. Data from 210 participants of the Revenue Department of Thailand was analyzed using a two-way factorial multivariate analysis (Factorial MANOVA) to assess the impact of Task-technology-skill fit (TTSF) on system usage and work performance. Additionally, a simple regression analysis was conducted to examine the effect of system usage on work performance. The findings indicated that the fit among tasks, technology, and skills significantly impacts system usage and work performance. However, the system usage does not directly affect work performance. This study proposed a factorial design to depict the task-technology-skill fit, the first to introduce this integrated framework.

KEYWORDS

Task-technology fit; task-technology-skill fit; usage; work performance.

INTRODUCTION

Many research studies over the past decade have used Task-technology fit (TTF) theory to predict and explain software utilization and users' performance. The TTF theory posits that the fit between tasks and technologies positively affects technology use and performance. Research papers published between 2014 and 2024 from two databases (EBSCOhost and Scopus) were searched. The number of research papers incorporating TTF in their research title is 1,448 and 212 papers from EBSCOhost and Scopus, respectively. These two databases were selected because they provide broad coverage and comprehensive access to research publications from around the world.

Though numerous studies have applied TTF to explain research results, some studies, i.e., McGill and Klobas (2009) and Rustiana et al., (2021), have noted adverse effects on use and performance when incorporating different technologies into tasks (Mikalef & Torvatn, 2019a; Mikalef & Torvatn, 2019b). Recently, some researchers have refined and extended the TTF theory, including Howard & Hair (2023) and Howard & Rose (2019). They mentioned that four factors (conceptualizations of TTF, operationalizations of TTF, oversight of misfit, and overemphasis on direct effects) were the causes of the contradictory research results. They also described how the magnitude of features affects the outcome of performing a task. In addition, they also examined the effect of the magnitude of task-technology misfit on the constructs in the Technology Acceptance Model (TAM).

This study seeks to extend the TTF theory by addressing the knowledge gap in usage and performance, assessing Task Technology Skill Fit (TTSF) using a Transaction Control Log and Accounting System (TCL) as the test case. TCL was selected because this system provides nationwide taxpayer services in Thailand. The system covers both taxpayer service activities and internal functions within the Revenue Department of Thailand, including tax calculation, collection, taxpayer registration, tax assessment, tax refund, tax status updates, and various reporting tasks. Furthermore, the inefficient use of the TCL system can affect the output quality of other systems that require input data from it. This inefficient system use can impact senior management within the Revenue Department and the Ministry of Finance, making it challenging to use the data effectively for management and administration purposes. In addition, Tarafdar et al. (2010) revealed that increasing digital technology development within an organization may lead to negative perceptions and stress among users. When information technologies are introduced or expanded, users may need skills to use the systems efficiently.

LITERATURE REVIEW

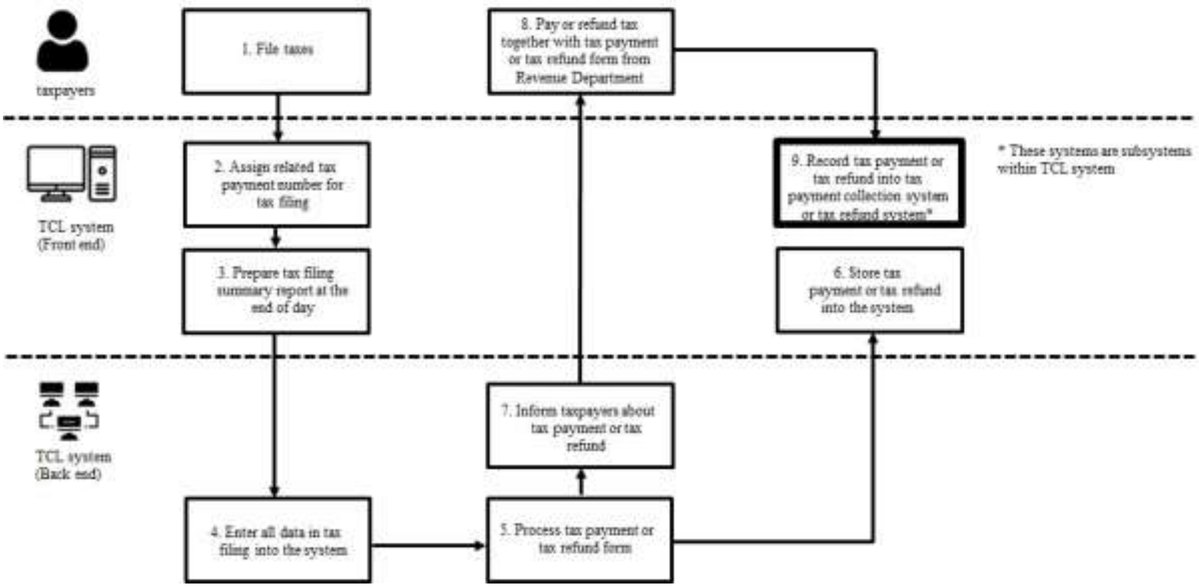
Characteristics of a Transaction Control Log and Accounting System

The Transaction Control Log and Accounting (TCL) system is a large-scale online real-time enterprise software system. It provides tax services nationwide to tax players via 850 branch offices of the Revenue Department of Thailand. In addition, it handles complex service transactions and data processing, serving over 25,000 current system users. The TCL system's main operation is divided into two main functions: the transaction control log and accounting. The transaction control log function involves various tasks, e.g., calculating tax payments and preparing tax payment forms, tax payment summary reports, and tax refund and assessment notification letters. In addition, this function automatically assigns reference numbers used for retrieving data, storing data, refunding notification numbers, and organizing batch numbers of documents. At the same time, the accounting function handles accounting-related tasks related to tax collection, including updating the status of outstanding tax debt. This subsystem involves various tasks, such as tax payments and refunds.

The TCL system has been developed with new functionalities and enhancements, including updates to over 200 work menus. It covers taxpayer service activities and internal functions within the Revenue Department. Figure 1 illustrates the system's operational workflow.

Figure 1.

TCL system operational workflow



This study examines the two main subsystems, tax payment collection and tax refunds, incorporated within the TCL system. The tax collection subsystem records tax payment data for all tax types, while the tax refund subsystem records tax refund receipts and cancellations. They possess distinct characteristics that will help investigate the impact of technology and users' skills, which will be discussed later. Users of TCL who use the tax payment collection subsystem should know how to calculate tax. However, the users of the tax refund subsystem only require a limited knowledge of tax calculation because they only retrieve the precalculated data of tax payments.

Task-Technology Fit Theory

The Task-Technology Fit (TTF) theory was developed by Goodhue and Thompson in 1995. This theory describes that the fit between task and technology characteristics enhances utilization, and performance (Zang et al., 2024). The task characteristics refer to users' activities in performing specific sets of instructions to input data into the system and then generate the output. Therefore, task characteristics are demonstrated through processes and work activities (Ulfa et al., 2024; Ye, 2021), while technology characteristics are features that support the requirements of a task.

Utilization refers to the use of technology or systems. Generally, users use the system when they believe it will improve their work (Parkes, 2013). Ulfa et al. (2024) also found the effect of TTF on utilization. Swanson and Bellanca (2019) suggest that TTF and organizational culture can either facilitate or hinder the adoption and use of technology. A poorly designed system (e.g., a system with low TTF) will not enhance work efficiency. These poor systems might be widely used due to social factors such as habit and readiness. Performance refers to the ability of individuals to improve the quality of their work to achieve goals and ultimately achieve satisfaction (Parkes, 2013). Many researchers, e.g., Dang et al. (2020), Erskine et al. (2019), and Rai & Selnes (2019), found the impact of TTF on users' utilization and performance. However, some other researchers, i.e., Lu & Yang (2014) and Swanson & Bellanca (2019), found that not only TTF but other factors, such as social factors, also affect users' utilization and performance. In addition, Parkes (2013) found that TTF impacts technology efficiency but does not impact users' job performance. To enhance job performance, users should also possess the necessary skills to make the job successful.

Skill as a Critical Enabler in Technology Use

While the Task-Technology Fit (TTF) theory effectively posits that alignment between task requirements and technology capabilities enhances utilization and performance (Zang et al., 2024), empirical evidence also suggests that TTF alone may not fully explain variations in work efficiency and individual performance (Dang et al., 2020; Parkes, 2013). This indicates a crucial gap in accounting for the individual user's capacity to effectively leverage the technology-task alignment. In addition, a tax expert with 23 years of experience in this area revealed that specific skills, tasks and technology fit also play an essential role in improving work efficiency. Skill is the personal ability required to complete a particular task successfully.

This study argues that user skill represents a fundamental individual difference that significantly moderates and influences how users interact with and derive benefits from information systems. Skill is defined as the personal ability and proficiency required to successfully complete a particular task using a given technology (Connett, 2023). Without the requisite skills, even a perfectly designed system for a specific task (high TTF) may not translate into optimal utilization or enhanced performance, as the user lacks the competence to fully exploit the system's features or apply its output effectively to the task. The conceptual integration of skill into the technology adoption and performance paradigm can be understood through two primary facets relevant to information system usage: technical (hard) skills and soft skills.

Technical skills are abilities to perform a specific task or activity efficiently. The abilities involve understanding and proficiency in the required task's methods, processes, procedures, or techniques (Connett, 2023). This study used TCL as the test case to assess the research model. TCL is one of the information technologies used in the Revenue Department and therefore, technical skills are necessary to perform tasks efficiently. This skill helps users to proficiently apply computers to display helpful information and gather, store, transmit, and communicate useful information between individuals. It is necessary to have information technology skills to use the TCL system to support the core tasks of an organization, such as efficient tax collection. Thus, this research includes this skill for TCL users.

Soft skills are a combination of interpersonal people skills, social skills, communication skills, character traits, attitudes, career attributes, and emotional intelligence quotient (EQ), among others (Robles, 2016). These skills include working well with others and helping the organization be more productive. The specific soft skills that contribute to productivity in using the TCL system are calculation and analytical skills.

Calculation skills involve reasoning and utilizing numerical concepts (Brooks & Pui, 2010). Fundamental calculation skills encompass understanding basic mathematical operations such as addition, subtraction, multiplication, and division. Apart from knowledge and understanding of the fundamental structure of each tax, e.g., tax rates, tax payment periods, and penalty rates, one of the essential skills is the ability to perform tax calculations. This skill is needed for receiving display listings, verifying accuracy, and assisting in tax calculations from the TCL system. This skill is also crucial for developing logical thinking and reasoning strategies in job performance.

Analytical skills refer to organizing and breaking down complex problems into more manageable components for better handling (Dwyer et al., 2014; Rasheva-Yordanova et al., 2018). This skill is related to job performance success (Levasseur, 2013) and solving complex problems (Rasheva-Yordanova et al., 2018). Therefore skills, both technical and soft, are crucial for using information technology to perform organizational tasks efficiently. These skills represent the human capital necessary to bridge the gap between technology and its impact on performance. The argument is that effective work performance arises not only from a good fit between the task and the technology, but also from an alignment between the user's skills and the demands posed by both the task and the technology. Consequently, the task-technology-skill fit (TTSF) framework was proposed to measure the alignment's impact on work efficiency.

RESEARCH MODEL AND HYPOTHESES

The task-technology-skill fit (TTSF) is depicted by a 3x2x3 factorial design (see Table 1). This factorial design used to measure each TTSF is based on Karan et al. (1995) and Wongpinunwatana et al. (2000). The design also used suggestions from interviewing two expert revenue officers proficient in using the tax payment collection and the tax refund subsystems within the TCL system. It has three factors: task characteristics with three levels, technology characteristics with two levels, and skills with three levels.

This study employed an input-process-output (IPO) model to extract items used as three levels of task characteristics. Input is the method users use to enter data into the system. The process is the operations performed on the inputs. Output is the outcomes produced by the processes. The tax payment collection and the tax refund subsystems within the TCL system are the two levels of technology characteristics. These subsystems were selected because they possess some different characteristics. The tax payment collection subsystem is designed to compute the amount of the taxes owed by taxpayers for all types of taxes. The tax refund subsystem is used to record tax refund receipts and cancellations. This subsystem serves the purpose of enabling users to retrieve and refund any excess taxes that taxpayers are entitled to receive. Tax cancellations are the excess amount a taxpayer must return to the Revenue Department when a taxpayer receives a tax refund exceeding the eligible amount. Technology skills, calculation skills, and analytical skills are the three levels of skills required for this subsystem.

The analysis of interview data from the two tax experts indicated that the nature of the tax collection subsystem exhibited a higher level of TTSF than the tax refund subsystem. The computational skills were notably different between the two systems. Users must possess the following steps to effectively utilize this system when performing tasks with the tax payment collection and tax refund subsystems. Therefore, the three items based on the IPO model in the TTSF framework are as follows.

First, the users must input data into these subsystems through open-ended and drop-down entries. For open-ended entries, the users are required to input a brief explanation of tax information in an open-ended text box. Users then must select a menu from various options in a drop-down entry. Due to the TCL system having over 600 tax declaration forms and more than 200 work menus, the data input into this system is complicated. The complexity of input data is the level of difficulty and intricacy involved in inputting the parameters into the tax payment collection and tax refund subsystems. When the tax payment collection subsystem calculates the taxes owed, users must input data into the system using designated open-ended text boxes and drop-down entries corresponding to the type of tax involved. This ensures precision in determining taxpayers' tax liabilities. In addition, the users must select the appropriate form and menu to input related tax data; e.g., tax rates, tax payment periods, and penalty rates, into the subsystem to perform tax calculations. Likewise, the amount of tax refund and cancellations are calculated from the tax payment collection subsystem. This system ensures fairness and accuracy in tax payments and refunds.

Second, the users must follow well-established guidelines in processing tax payment collection and tax refunds. Well-established guidelines are a clear and complete set of procedures to perform tasks (Bahadur, 2014). These guidelines provide clear, unambiguous advice on using the tax payment collection and tax refund subsystems. The Revenue Department has established guidelines for using these subsystems, which enhance efficient use of the systems. Well-established guidelines enhance user understanding and ensure accuracy and effective operations. Therefore, well-established guidelines for the subsystem process improve overall efficiency.

Third, clear and sequential steps are required for users to get reports from the tax payment and tax refund subsystems. These clear processes to find outcomes are detailed steps to achieve a specific outcome (Bahadur, 2014). Apart from achieving the processing outcome, the users of the tax payment collection subsystem must verify the accuracy of tax payment calculations. Suppose the users are still determining the results. In that case, they must recheck the accuracy of all input data; e.g., tax rates, tax payment periods, and penalty rates, and process the tax payment again. The results usually come from the tax payment collection subsystem for tax refunds or cancellations. The users only have to get the results of the taxpayers under review.

A questionnaire was distributed to 20 users to validate the 3x2x3 factorial design. The questionnaire had 18 statements regarding aligning task characteristics, technology characteristics, and skills. Users were asked to indicate their agreement with each statement on a five-point scale ranging from 1-Strongly disagree to 5-Strongly agree. Table 1 shows the average alignment values from the responses of these 20 individuals. The results indicated that users require high technology skills regardless of the system or task (average scores generally above 4.20). Analytical skills are also highly desired, especially for inputting data (4.70 for payment, 4.45 for refund) and generating reports (4.35 for payment, 4.40 for refund). However, users indicated low analytical skills for processing tasks (1.85 for payment, 1.75 for refund). Users may not perceive a high analytical demand in the processing phase, perhaps due to the automated nature or strict guidelines. Furthermore, there is a noticeable difference in the need for calculation skills between the two subsystems. While the results show moderately desired calculation skills for input and reporting in the tax payment subsystem (4.65 and 4.40 respectively), it was notably low across all tasks for the tax refund subsystem (average around 1.80). This highlights the distinct computational demands of each subsystem. Therefore, this research proposed the classification of average scores that show the alignment among task characteristics, technology characteristics, and skills, as shown in Table 1.

Couper et al. (2011) revealed that the design of data entry fields affects user input. Using a template that matches user needs promotes accurate data entry. An open-ended text box allows users to input data in the desired format. A drop-down data entry reduces errors and saves time for short data entries, while slightly increasing time for longer entries. Drop-down entries might only be suitable for some data types, such as multiple-choice options or payment types (Söderlund, 2018). In addition, the complexity places demands on the cognitive load of problem solvers. The complex task requires more attention, memory, reasoning, and information processing, which can impact the effectiveness of task performance. Liu and Li (2011) indicated that the complexity of tasks influences behavior and work efficiency. Complex tasks define behavior and work efficiency despite various tools, such as computers and supporting tasks. Highly significant systems or those related to security often present user limitations or vulnerabilities that affect performance.

Table 1.

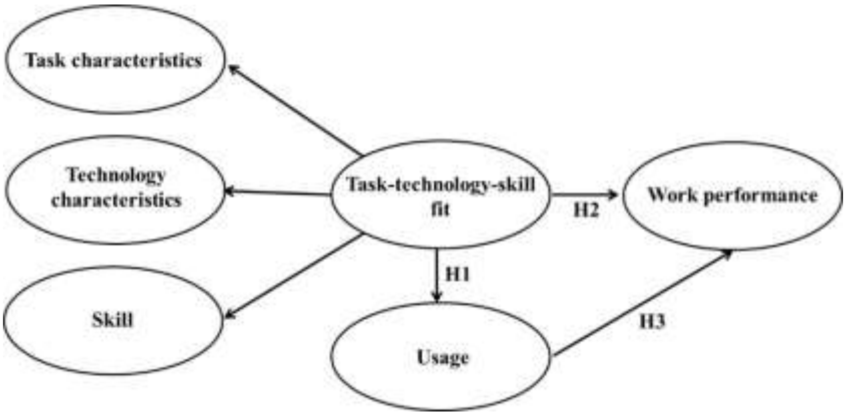
The average perceived alignment scores of Task-Technology-Skill Fit (TTSF) by subsystem and skill type (N=20)

Task characteristics (IPO model)	Tax payment collection system			Tax refund system		
	Technology skills	Calculation skills	Analytical skills	Technology skills	Calculation skills	Analytical skills
Complexity of input data	4.60	**4.65**	4.70	4.45	**1.75**	4.45
Well-established guidelines in processing tasks	4.75	1.80	1.85	4.25	1.85	1.75
Clarify step-by-step to get various reports	4.20	**4.40**	4.35	4.30	**1.85**	4.40

This research proposed the following conceptual model by extending the task-technology fit theory with skill. This model posits that the level of TTSF impacts usage and work performance (Figure 2). In this research, usage refers to utilizing the TCL system of revenue officers to execute their assigned tasks successfully according to job characteristics.

Figure 2.

Task-technology-skill-fit (TTSF) framework



Lepanto et al. (2011) found that TTF positively influences the usage of a radiology image management system. However, the level of usage differs significantly between radiologists who have lower workload but higher complexity compared with those with higher workload but lower complexity. This is consistent with the study by Lin (2012), which discovered that TTF has a positive impact on the usage of virtual learning systems. Many researches, e.g., Dang et al., 2020, Erskine et al., 2019, Rai, 2019, Ulfa et al., 2024, and Xia et al., 2024, also found the positive relationship between TTF and usage. Therefore, the following hypotheses is proposed:

H1: *Users with a high level of TTSF will use the system more than users with a low level of TTSF*. Howard and Rose (2019) found that TTF has a positive impact on work efficiency. Higher levels of TTF contribute to increased work performance. Additionally, Lin (2012), Mohammed et al. (2024), and Parkes (2013) found that TTF positively influences the efficiency of using information technology. Therefore, the following hypothesis is proposed:

H2: *Users with a high level of TTSF will experience higher work performance than users with a low level of TTSF*.

Researchers, e.g., Al-Maatouk et al. (2020) and Al-Rahmi et al. (2023), found a positive relationship between usage and academic performance. These results align with the study by Ulfa et al. (2024), which found that TTF and usage positively impact learning performance. Users anticipate that improving work processes will positively affect their work efficiency. Therefore, the following hypotheses is formulated:

H3: *Usage positively affects work performance*.

METHODOLOGY

This study gathered survey data from 210 Revenue Department of Thailand officers. Participants had to use for more than one year either the tax payment collection subsystem or the tax refund subsystem incorporated in the TCL system. Participants were divided into two groups, with 105 people in each group. Group 1 were the participants with tax payment collection subsystem experience (high level of TTSF), while Group 2 were the participants with tax refund subsystem experience (low level of TTSF). The data was collected through electronic questionnaires via the Line application by sharing them within Line groups of personnel from various regional branches of the Revenue Department. Additionally, the questionnaires were disseminated through internal email communication within the Revenue Department. All responses were collected anonymously.

The survey is divided into two sections. Section one contained six statements to measure participants' usage and work performance. A five-point scale from 1-Strongly disagree to 5-Strongly agree was used for these questions. Section two was used to obtain participants' demographic data. Items in the survey for usage and work performance were adapted from Al-Maatouk (2020), Al-Rahmi (2023), Ulfa et al. (2024), and Ye (2021) to ensure content validity. Three items were included to measure usage: "I use the system frequently," " I spend the entire day using the system," and "I utilize all the system functions relevant to my work." Three items were also included to measure work performance: "The system improves my work efficiency," "I often waste time fixing data errors," and "I frequently need to correct completed work." Prior to distributing the survey, the questionnaire was reviewed and pilot-tested with experts in this area to ensure clarity and relevance of all items. The reliability of the usage and work performance factors was evaluated using Cronbach’s alpha, with values of 0.877 and 0.805, respectively. The alpha values of 0.70 and above are considered acceptable (Adamson & Prion, 2013).

Two hundred and ten participant results were analyzed. The participants included 87% females and 13% males. There were 11% of participants aged 21-30 years old, 30% of participants aged 31-40 years old, 30% of participants aged 41-50 years old, and 29% of participants aged over 51. In addition, 40% of participants' work experience was 1-10 years, 47% of participants' work experience was 11-30 years, and 13% of participants' work experience was more than 30 years.

RESULTS

This research employed a two-way factorial multivariate analysis (Factorial MANOVA) to analyze the impact of TTSF level (high vs. low) on the participants' usage and work performance. This allowed testing whether there were significant differences in the two variables between the high-TTSF and low-TTSF groups. In addition, simple regression analysis was used to analyze the usage prediction on work performance. A p-value of 0.05 was used as the significance level in the statistical tests. Evaluating assumptions of linearity, normality, multicollinearity or singularity, and homogeneity of variance-covariance matrices revealed no threat to multivariate analysis.

Analysis of the effect of TTSF on usage

Hypothesis 1 suggests that users with a high level of TTSF will use the system more than users with a low level of TTSF. The results of a Factorial MANOVA in Table 2 indicate significance for the effect of TTSF on all usage items, with a p-value of 0.0001.

Table 2.

Effect of TTSF on three items of usage (N=210)

Source		DF	Type III SS	Mean Square	F	Sig.
Intercept	Use system frequently	1	3562.976	3562.976	4667.430	0.0001
	Spend whole day on system	1	3093.505	3093.505	3343.006	0.0001
	Use all relevant system functions	1	3272.576	3272.576	4074.861	0.0001
Type	Use system frequently	1	31.243	31.243	40.928	0.0001*
	Spend whole day on system	1	22.019	22.019	23.795	0.0001*
	Use all relevant system functions	1	13.376	13.376	16.655	0.0001*
Error	Use system frequently	208	158.781	0.763		
	Spend whole day on system	208	192.476	0.925		
	Use all relevant system functions	208	167.048	0.803		

* $p < 0.0001$

Analysis of the individual three items of usage factors indicated that the participants with high levels of TTSF have higher scores on (1) using the system frequently (mean score = 4.50, standard deviation = 0.652), (2) spending the whole day on the system (mean score = 4.16, standard deviation = 0.833), and (3) use all relevant system functions (mean score = 4.20, standard deviation = 0.752) than participants with low level of TTSF. The score of three items of participants with low levels of TTSF was (1) using the system frequently (mean score = 3.73, standard deviation = 1.049), (2) spending the whole day on the system (mean score = 3.51, standard deviation = 1.075), and (3) use all relevant system functions (mean score = 3.70, standard deviation = 1.020). Therefore, support was obtained for Hypothesis 1.

Analysis of the Effect of TTSF on Work Performance

Hypothesis 2 suggests that users with a high level of TTSF will experience higher work performance than users with a low level of TTSF. The statistical results in Table 3 indicate significance for "only time wasted fixing data errors" and "often correct completed work" variables with a p-value of 0.0001. However, the result is insignificant for the "system boosts efficiency" variable.

Analysis of the individual two items of work performance indicated that the participants with a high level of TTSF have lower scores on (1) the "time wasted fixing data errors" variable (mean score = 2.69, standard deviation = 0.812), and (2) "often correct completed work" variable (mean score = 2.66, standard deviation = 1.045). The scores of these two items of participants with low levels of TTSF were (1) the "time wasted fixing data errors" variable (mean score = 3.90, standard deviation = 0.861), and (2) "often correct completed work" variable (mean score = 3.50, standard deviation = 1.136). However, the "system boosts efficiency" variable in this study was not significant. Therefore, the results partially support Hypothesis 2.

Table 3.

Effect of TTSF on work performance (N=210)

Source		**DF**	**Type III SS**	**Mean Square**	**F**	**Sig.**
Intercept	System boosts efficiency	1	3721.219	3721.219	5870.516	0.0001
	Time wasted fixing data errors	1	2280.305	2280.305	3255.874	0.0001
	Often correct completed work	1	1993.376	1993.376	1672.506	0.0001
Type	System boosts efficiency	1	0.933	0.933	1.472	0.2260
	Time wasted fixing data errors	1	78.019	78.019	111.397	0.0001*
	Often correct completed work	1	37.719	37.719	31.647	0.0001*
Error	System boosts efficiency	208	131.848	0.634		
	Time wasted fixing data errors	208	145.676	0.700		
	Often correct completed work	208	247.905	1.192		

* $p < 0.0001$

Analysis of the Effect of Usage on Work Performance

To investigate whether usage is positively correlated with work performance (H3), the mean scores of usages and work performance factors were analyzed by simple regression. The statistic does not support H3 with $F(1, 208) = 3.288$, $p = 0.071$ (see table 4). Thus, usage does not affect work performance. This result is inconsistent with previous studies.

Table 4.

Effect of usage on work performance (N=210)

Model	Sum of Squares	df	Mean Square	F	Sig
Regression	2.286	1	2.286	3.288	0.71[a]
Residual	144.595	208	0.695		
Total	146.881	209			

[a] Dependent variable = work performance, Predictors = usage

DISCUSSION AND IMPLICATIONS

The findings of this study are as follows. First, users with a high level of Task-technology-skill fit (TTSF) use the system more than users with a low level of TTSF. This result is consistent with Dang et al. (2020), Erskine et al. (2019), Lepanto et al. (2011), Lin (2012), Rai and Selnes (2019), and Ulfa et al. (2024). Furthermore, the findings of this study are that users with a high level of TTSF use the system frequently, spend the whole day on the system, and use all relevant system functions.

Second, this study only partially supports the correlation between the level of TTSF and work performance. Users with high TTSF levels spend less time fixing data errors and correcting completed work. Both users (high and low levels of TTSF) did not indicate that the system boosts their work efficiency. Therefore, the effect of TTSF on work performance is partially consistent with Howard and Rose (2019), Lin (2012), and Parkes (2013).

Finally, usage does not affect work performance. This result is inconsistent with previous studies; e.g., Al-Maatouk et al., 2020, Al-Rahmi et al., 2023, and Ulfa et al., 2024, who found that usage affected work performance.

The reason for partial support and inconsistent results is that the Transaction Control Log and Accounting (TCL) system is used involuntarily, and users cannot choose alternative systems. Therefore, the impact on performance may be more dependent on user satisfaction. Additionally, the sample data is primarily middle-aged, with 59% of participants being 41 years or older, which may indicate less familiarity with information technology. As organizations continue to develop their systems, users might experience stress from being unable to meet the organization's technology demands. This stress could affect their usage and overall work performance. In addition, Tarafdar et al. (2010) state that technostress can impair system effectiveness and diminish work outcomes.

Implications

This research contributes to practitioners in four areas. First, this study extended the Task-technology fit (TTF) theory by adding skill constraints. This study filled the inconsistent results and the expanded TTF theory by adding skill fit to the alignment among task and technology characteristics. Task characteristics include the complexity of input data, well-established guidelines for processing tasks, and clear step-by-step instructions for generating various reports. Technology characteristics encompass the tax payment collection subsystem and the tax refund subsystem. Additionally, this study investigated user skills, including technology, calculation, and analytical skills.

Second, the study also proposed a factorial design to measure each Task-technology-skill fit (TTSF). This measure indicates the alignment between the tasks, technology, and users' skills. The system developers can adopt the proposed measurement of each TTSF from this study, which takes into account user skills to enhance system efficiency and usage.

Third, the study's findings suggest that organizations developing or implementing a system should consider the alignment between characteristics of tasks, technology, and the necessary skills for the job. This TTSF will improve individual usage and performance. The research findings were also in line with previous TTF studies. The research measured system usage in three aspects: frequency of use, time spent on the system throughout the day, and utilization of all relevant system functions. Work performance was evaluated based on system efficiency, time wasted fixing data errors, and correcting completed work.

Fourth, as system usage does not impact work performance, developers should continue paying attention to its effect on the performance constructs of TTSF. However, utilization in this study did not impact learning performance. Therefore, other factors, such as users' satisfaction, may impact work performance other than usage.

CONCLUSION AND LIMITATIONS

This paper examined the effect of Task-technology fit (TTF) theory by extending this theory with a skill fit construct. The related literature was reviewed, and the alignment framework among task characteristics, technology characteristics, and skills was proposed. Three hypotheses examined this framework. Two hypotheses were accepted, and one hypothesis was rejected. In the context of the tax payment collection subsystem and the tax refund subsystem for the Revenue Department of Thailand officials, the results of this study indicated that (1) users with a high level of Task-technology-skill fit (TTSF) will use the system more than users with a low level of TTSF, and (2) users with a high level of TTSF will experience higher work performance than users with a low level of TTSF. However, system usage does not impact work performance. A possible reason for this may be the impact of other factors, such as user satisfaction.

Limitations

This research has some limitations that hinder the ability to generalize the results. The study examined explicitly the TCL system from the Revenue Department, focusing only on tax payment and refund systems, which means it may only encompass some types of systems.

The findings of this research provide a solid foundation for future studies. Although the TTSF framework does not directly influence system efficiency—one of the measures of work performance in this study—it does indicate an impact on two aspects of work performance: time wasted fixing data errors and correcting completed work. Future research should extend the understanding of work performance. In addition, the research should incorporate other theories, such as flow theory, to understand factors that lead to enhanced performance and satisfaction. Finally, future research might extend this model by incorporating the quality of information provided by the system, perceived usefulness, suitability of the work environment, and satisfaction (Ayyoub et al., 2023; Hafeez et al., 2019; Wijayanti et al., 2024; Ye, 2021).

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