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Exploring the Determinants and Consequences of Task-Technology Fit: A Meta-Analytic Structural Equation Modeling Perspective

Thira Chavarnakul [1, 2], Yu-Chun Lin [3], Asif Khan [4, 5*], Shih-Chih Chen [3]

[1] *Department of Commerce, Chulalongkorn Business School, Chulalongkorn University, Bangkok, Thailand.*

[2] *Transportation Institute, Chulalongkorn University, Bangkok, Thailand.*

[3] *Department of Information Management, National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan*

[4] *Southern Taiwan University of Science and Technology, Tainan, Taiwan.*

[5] *ANScientistify INC., Tainan, Taiwan.*

Abstract

Objectives: Task-Technology Fit (TTF) is mainly used to determine the users' performance based on the tasks and technological attributes. This study integrated and evaluated TTF with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). This paper aims to compile and analyze the literature on task-technology fit (TTF) since 2000. *Method:* Through the meta-analytic structural equation modeling (MASEM) approach, understand the application of TTF in the last 20 years and explore future research directions. In addition, this paper employs subgroup analysis and sample sub-grouping to better understand the differences between these studies. The samples were divided into two categories: identity groups (employee, individual, and student) and voluntary groups (voluntary and non-voluntary). *Findings:* The relationship between the variables belonging to the original TTF model (including TASK, TEC, TTF, PI, and UT) was found to be relatively stable. After combining the variables of UTAUT2 (including PEOU, BI, and PE) and IC, all paths were also found to have a medium or high effect. The TTF-BI path was significant in the identity-based subgroup analysis, and the IC-TTF path was significant in the voluntary-based subgroup analysis. *Novelty:* Given that the traditional TTF literature is too subjective, this paper adopts MASEM as applied in management research. There are few similar studies so far. Therefore, this paper not only analyzes TTF objectively through MASEM but also provides some directions and suggestions for expanding the TTF model and hopes to give a stronger explanation for future research.

Keywords:

Task-Technology Fit;

Meta-Analytic Structural Equation Modeling;

Performance Expectancy;

Perceived Ease-of-Use;

Individual Characteristics.

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1- Introduction

Task-Technology Fit (TTF) was introduced in 1995 as a theoretical framework for information systems (IS) research. It is often used in many studies to explain the performance of information technology (IT) and to apply the theory in different fields such as wearable medical devices [1], the Internet of Things [2], and human resources [3]. In addition, some studies applied TTF to academics and the learning process. For example, McGill & Klobas [4] studied how TTF influences the performance impacts of learning management systems. D'Ambra et al. [5] applied TTF to structure and evaluate the adoption of e-books by academics. Numerous research studies have been conducted on applying TTF to mobile information systems. For instance, Gebauer et al. [6] presented a three-step conceptual model to set up a fit between managerial tasks, mobile IT, and the mobile use context. Kim et al. [7] applied TTF to investigate the impact of motivations (value, enjoyment, time-saving, and mobility) on consumer satisfaction in the mobile tourism shopping context. Lee et al. [8] modified TTF to explore the factors affecting the effective adoption of mobile commerce in the insurance industry.

* **CONTACT**: khan_asif04@yahoo.com

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Numerous studies apply TTF in combination with other theories. For example, the TTF was used to investigate technology fit in higher education and to combine the Technology Acceptance Model (TAM) to study the immediacy and compatibility of the system [9]. Moreover, Dishaw and Strong [10] introduced an integrated model that combines TAM and TTF. They tested the model using path analysis, and the results showed that the integrated model provides more explanatory power than either model alone. Alturki & Aldraiweesh [11] also developed a new paradigm by merging TAM with TTF and other external elements, including subjective norms and quality of information, to study the adoption of Google Meet by postgraduate students. Faqih & Jaradat [12] proposed and tested a model based on integrating Task-Technology Fit (TTF) and Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) theories to investigate the adoption of augmented reality technology in education. Their results reveal the positive effect of task technology fit, performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation on behavioral intention.

TAM and TTF are both considered to be significant information system frameworks, but both of these models have their limitations. For instance, the TAM model has the limitation to capture the task attributes of a new technology adoption. Furthermore, TTF also has a barrier to contemplating the user's attitudes regarding the technology, which is considered an important aspect of technology adoption and a core concept in TAM. Hence, in order to compensate for the shortcomings of both of these models, the ideal strategy is to connect them. This integration of TAM and TTF will provide in-depth insights that would not have been possible if any of these models were used alone [13]. Previous research has successfully linked TTF with TAM’s perceived ease of use (PEOU) and found a significant relationship between these two constructs [14]. Consequently, the current study aims to connect TTF with TAM’s PEOU to get deeper insights regarding the technology adoption concept.

Behavioral intention (BI) is a notion related to the user’s intention to participate in a specific activity or task. If users have a strong BI to use or adopt a task, they will be more motivated to be engaged in that activity. Previously, BI regarding the use of technology has been linked to TAM, which can explain the acceptance or rejection of an intention to use a technology. The TAM model deals with the users’ perception of the technology’s usefulness and PEOU, hence building the users’ BI toward adopting that technology. However, previous studies have found limitations regarding the TAM’s measurement of BI and hence have added various exogenous variables to the TAM to measure the BI of users. Some studies have employed social motivation [15], and others have employed TTF as an exogenous variable to measure BI. Hence, keeping in mind the previous research gaps, this study aims to use TTF to measure the impact of BI [16].

The TTF model explains the relationships between tasks, technological attributes, and performance [15]. The TTF model is based on a total of five technological constructs. These constructs include performance, utilization, technological features, tasks, and task-technology fit. TTF has been discovered to impact the utilization and PEOU of new technologies [15]. Additionally, it is discovered that in the TTF model, task and technological attributes are found to impact the task-technology fit, and task-technology fit is, in turn, found to impact utilization [17] significantly and performance [18]. Hence, based on the previous research, this study aims to discover the relationships of TTF with utilization and performance.

In addition, another concept that can be linked to TTF is performance expectancy (PE). PE can be described as the degree to which users perceive a technology will aid them in achieving their work objectives and goals. The Unified Theory of Acceptance and Use of Technology (UTAUT) considers PE to be the core factor in determining the BI of users to adopt or use a technology. Furthermore, previously adequate information regarding the support of PE in behavioral studies is available. The TTF model predicts the users’ adaptability to a technology based on its links with technological attributes and PE [19, 20]. Similarly, TTF is found to impact the PE and BI of users for technology adoption and utilization [21]. Hence, based on the previous research, this study aims to assess the relationship of TTF with PE.

On the other hand, meta-analytic structural equation modeling (MASEM) refers to the use of meta-analysis (MA) to find similar studies in the past, build correlation matrices, and then perform structural equation modeling (SEM), which can be used to test whether the model is good or bad [22]. Since MASEM is a combination of MA and SEM, it can overcome the difficulty of integrating research on different issues, so it is widely applied in research in many fields. However, the use of MASEM to analyze TTF research is relatively scarce. However, the topic of the application of TTF has become more and more extensive in recent years. In addition to common IS and IT, it is now used to discuss wearable medical care, human resources, digital education, etc. Therefore, this paper argues that TTF is suitable to be analyzed by MASEM. In order to better understand the research development of TTF in recent years and to explore in depth the research in different backgrounds, it is necessary to integrate TTF-related research results to provide more comprehensive academic support for future research. To conduct a study, researchers have to learn from the past to the present. Thus, in order to understand the past studies that applied TTF and explore future trends through MASEM, this paper adopts the six-stage analysis proposed by Cooper et al. [23], including problem formulation, literature search, data evaluation, data analysis, interpretation of results, and presentation of results. Through these stages of conducting meta-analysis, a more comprehensive and robust explanation of TTF can be achieved [24].

In addition, this study explores TTF-related studies and discusses the effects between TTF and other variables. On the other hand, meta-analysis has been applied in various research fields. For example, TAM [9] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [1]. Based on the above reasons, this paper adopts the MASEM proposed by Viswesvaran & Ones [22] to study TTF and achieve the following research purposes: (1) to understand the application and future trend of the extended TTF model after 2000 and to further explain the model; (2) to explore the following relationships to demonstrate the rationality of the extended TTF model. First, explore the relationship between TTF and PEOU to connect TTF with TAM. Second, to examine the association of TTF with the BI of users. Third, to analyze the links of TTF with utilization and performance. Finally, to assess the association between TTF and PE. This research is structured in the following sections: Section two of the research provides a description of the theoretical background for the study. Section three is related to the description of the data collection procedures and tools of the study. Section four provides the results gathered from the data analyses. Section five contains discussions related to the comparison of results, theoretical implications, practical implications, and future research directions. Section six offers concluding remarks regarding the significance of the study. The flow chart to conduct this study is shown in Figure 1.

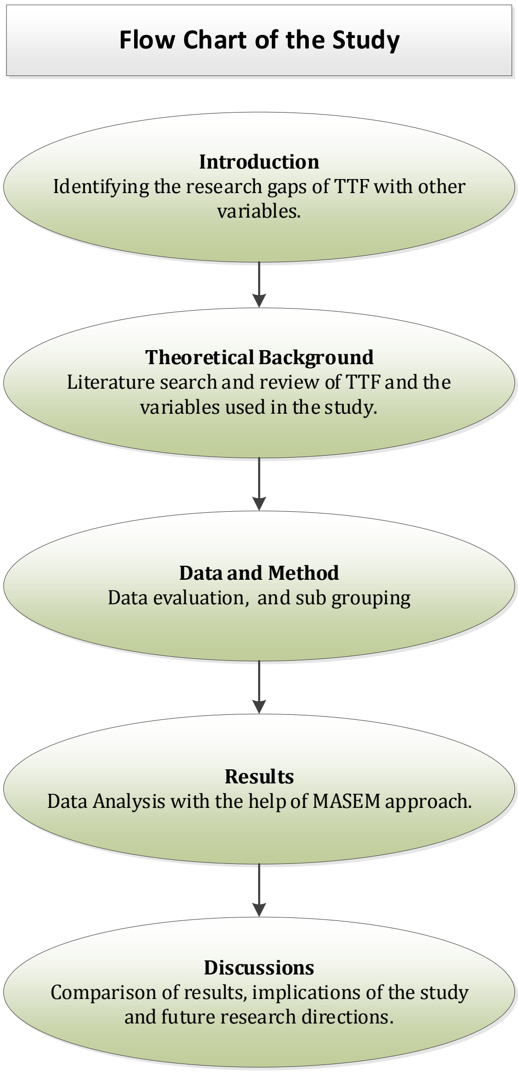

Figure 1. Flow chart of the study

2- Theoretical Background

2-1- Task-Technology Fit Model

The Task Technology Fit (TTF) model is an IS theory proposed by Goodhue & Thompson [25]. It is often applied to exploring IT, task fit, and IS performance studies. TTF is mainly used to determine the users' performance based on the task and technological attributes [15]. Both task characteristics and technological attributes are found to have impacts on TTF. Consequently, the TTF framework is found to be an emerging concept of interest [24]. TTF describes the fit between task and technology and emphasizes the importance of using suitable technology to accomplish a task [26]. Therefore, TTF is an important theory in the IS/IT field. This paper uses the TTF model to explore studies on the application of TTF after the year 2000. The TTF model has five key factors [25, 26], which are explained as follows: (1)

Task characteristics refer to information about a task involving specific activities and behaviors; (2) Technology characteristics refer to the attributes of the tools used by users to perform specific tasks; (3) Task-technology fit refers to the degree of fit between the task to be achieved and the technology used; (4) Performance impacts refer to efficiency, effectiveness, and work quality; (5) Utilization refers to the usage rate of IS/IT. Since many studies have applied the TTF model in the last 20 years, this paper uses the model as the basis of research.

2-2- Individual Characteristics

As mentioned earlier, task and technology characteristics are the key factors in the TTF model. They are employed to evaluate how IT affects user performance [15, 27]. Then, they further influence TTF [28]. Additionally, scholars have pointed out that individuals and technologies interact with or adapt to each other [29]. Therefore, Pal & Patra [30] argue that individual characteristics influence TTF more significantly than task characteristics. They define individual characteristics as prior experience with IT and propose that an experienced user perceives TTF better when evaluating it. Pal & Patra [30] studied online learning and found that personal characteristics significantly positively affect TTF. This paper draws on these studies to infer that individual characteristics are related to TTF and incorporates this factor into the research model.

2-3- Perceived Ease-of-Use

The technology acceptance model (TAM) has been extensively used to explore users' responses to technology adoption [14]. TAM is considered to be the most popular concept in information systems, and it has been employed in various research studies [14, 31–34]. Perceived ease of use (PEOU) is one of the essential factors of TAM. It refers to how easy it is for a person to use a particular IS [35]. Many studies have found PEOU to be an important factor influencing the behavior of users of new technologies [36–39]. The results of previous studies have shown a significant positive effect of PEOU on users' IT adoption. This paper infers that PEOU is a crucial factor for IS/IT research and is related to TTF.

2-4- Behavioral Intention

In the theory of reasoned action (TRA) [20], behavioral intention (BI) refers to a person's intention to perform an action. BI is related to the user’s desire to use a technology or any other constructs related to the evaluation of technology usage [21]. Davis et al. [35] developed TAM based on TRA to extend BI to the user's intention to decide to use IS. IS/IT studies have been paying attention to BI and even adding BI to the TTF model to be discussed together [26, 27, 40, 41]. These studies demonstrate that the factors of the TTF model are related to BI. Based on all the above research findings, this paper proposes that the two are related, so BI is included in this research model.

2-5- Performance Expectancy

Performance Expectancy (PE) is derived from the unified theory of acceptance and use of technology (UTAUT) model developed by Venkatesh et al. [42]. The UTAUT model and TAM are adopted to predict people's behavioral intentions for using IS/IT. Later, Venkatesh et al. [43] extended the UTAUT model and created UTAUT2. The predictive power of UTAUT2 is higher than that of UTAUT [44]. PE refers to the degree to which the individual perceives that using IS/IT is helpful to work [42]. It depends on indicators such as perceived usefulness, extrinsic motivation, job fit, and outcome expectations [45]. The UTAUT model has always attracted the attention of scholars [46–50]. Zhou et al. [41] combined the TTF model and UTAUT model to explore the usage intention of mobile banks and found that PE and TTF have a significant impact on usage intention. Therefore, this paper concludes that PE and TTF are related.

3- Data and Method

3-1- Sample

The research sample is the TTF-related literature, searched by publishers' databases and Google Scholar. The publishers are ScienceDirect, Emerald Group Publishing, Taylor & Francis Online, SAGE Publications, John Wiley & Sons, Inderscience Publishers, and Springer. Mainly the literature after 2000 and non-medical. Because most of the studies before 2000 were incomplete and difficult to collect, most of the medical studies applied TTF to explore treatments, which did not meet the requirements of this paper. Next, use "Task Technology Fit Model," "TTF," or "Task Technology" as keywords to search the publishers' databases. The total sample number is 17,054 articles; 135 articles were searched based on keywords; and 41 articles were finally obtained after two screenings. In addition, to explain the differences between the studies, they were grouped according to the identity of the respondents (employee, individual, student) and the voluntary (voluntary and non-voluntary) nature of these studies. If the study did not specify the respondent's identity, it was grouped as an individual. Among the identity groups, 11 articles belong to the employee group, 16 to the individual group, and 14 to the student group. For the voluntary groups, this paper refers to Fishbein & Ajzen [51], who mentioned whether the use is voluntary or not. 20 articles belong to voluntary groups, and 21 belong to involuntary groups. The sample collection and classification process are shown in Figure 2.

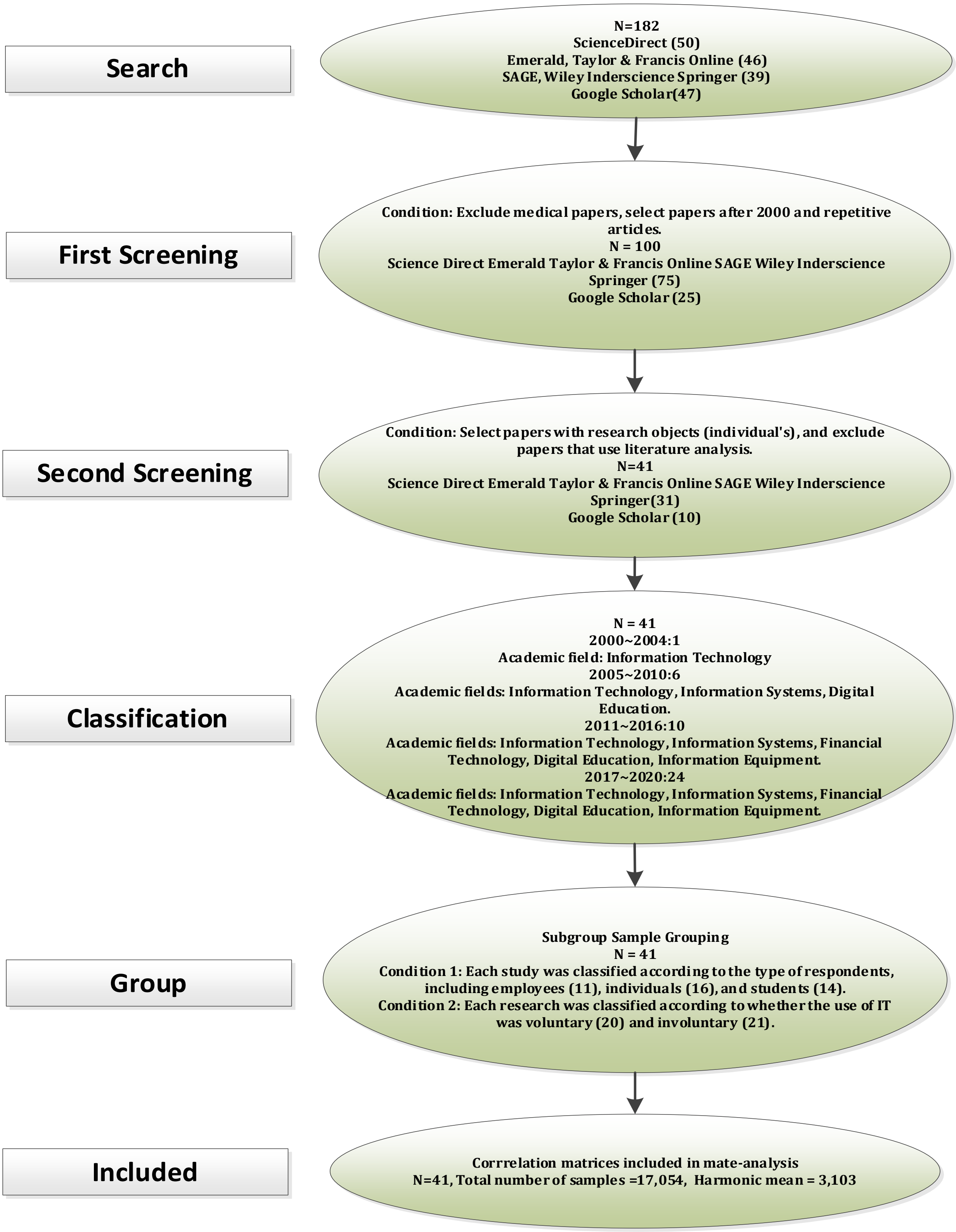

Figure 2. Data Collection Process

3-2- Meta-Analysis

Meta-analysis is a statistical method that integrates many research results. It is often applied in the social sciences, education, and medicine [52]. It can integrate the results of various studies, including opinion surveys, experimental studies, and regression analyses, and explore cause and effect. Traditional document analysis and literature reviews can also integrate past research results, but the results obtained by researchers using these methods are more subjective. Moreover, when studies are relatively large, traditional methods are difficult to use for integration and analysis. In addition, the results may not be the same even for similar studies. The causal relationship between factors should not be concluded based only on the results of a single study.

Researchers use meta-analysis to estimate a large amount of data, which can effectively improve the accuracy and increase the accuracy of the detection effect. Cooper et al. [23] divided the implementation of meta-analysis into six stages: problem formulation, literature search, data evaluation, data analysis, interpretation results, and result presentation. Each stage has its own importance. Among them, the "data analysis" stage is critical. Because the data analyzed by meta-analysis is not the original but the effect size of past studies. Furthermore, its concept focuses on the variation between studies. Assuming that two continuous variables are correlated, the correlation coefficient in the study is the focus of the analysis. In addition, if there are differences between studies, high heterogeneity occurs. Therefore, meta-analysis is divided into two models, i.e., random and fixed effects. The following subsections introduce three methods in meta-analysis to test heterogeneity.

3-2-1- Subgroup Analysis

In meta-analysis research, subgroups are created based on the value of the research variables [53]. Past studies [54, 55] applied subgroup analysis and found that the research results may be variable for different sample groups. This paper's grouping is based on "identity" and "voluntary". Grouping by identity aims to understand whether samples of different identities could cause between-study variation. On the other hand, this paper refers to Fishbein & Ajzen's [51] "whether the use is voluntary or not" as a factor to group the IT usage as voluntary. Next, investigate whether the variables are related to each other. If the subgroup analysis can explain the effect sizes of the variables, then a fixed effect model can be built, which means that the variables of the subgroup are the variables of the samples. If a random effects model is adopted, the effect sizes are attributed to the between-study variance, which reflects that subgroup variance cannot explain all the variance of the studies.

3-2-2- Heterogeneity Test

Heterogeneity testing is the primary method used in meta-analysis to determine between-study variance. The commonly used methods are Cochrane's Q test and I^2 statistics. Cochrane's Q test obtains the Q-value, and when the Q-value is not significant, it indicates that the studies analyzed are heterogeneous; otherwise, they are homogeneous [56]. However, when the sample size is large, the Q-value is easily significant. Hence, I^2 statistics were adopted in this paper to verify again.

In this paper, I^2 statistics were applied to test heterogeneity according to the suggestion of Higgins et al. [57]. I^2 is obtained through I^2 statistics. It is a value between 0% ~ 100% and is classified as 25% (low), 50% (medium), and 75% (high). In this study, $I^2 > 75\%$ was used as the criterion for heterogeneity. However, the disadvantage of I^2 statistics is that the precision of the degrees of freedom (d.f.) becomes worse when the sample is insufficient [58]. In addition, Legris et al. [39] advocate that the estimate of Q-value should be determined not at $p\text{-value} < 0.05$ but at $p\text{-value} < 0.1$ and that I^2 should be above 80% so that it is statistically significant.

3-2-3- Publication Bias

Researchers can obtain important information from meta-analysis, one of which is publication bias [59]. Publication bias is a phenomenon that can occur in academic publishing. It means that researchers tend to publish significant and positive findings, and journal editors are more receptive to significant, positive, and interesting research findings. As a result, some findings that should be present may not be discovered when the literature is collected [60]. Most of the collected studies have significant and positive results. Biases can occur when using meta-analysis. If this phenomenon occurs to explore medical treatments, the results obtained will be overly optimistic. Currently, a standard method used to explain whether there is a publication bias is the funnel plot. A scatterplot illustrates the relationship between sample size and effect size [61]. Although some scholars consider the use of funnel plots to determine publication bias to be subjective [23], it is easy to draw and understand and is still used by many researchers.

3-3- Meta-Analytic Structural Equation Modeling (MASEM)

The correlation analysis of the meta-analysis only revealed the correlation between the two variables without considering the effect of other variables in the model. To better understand the relationship between TTF and other variables, this paper employs MASEM to analyze and examine the validity of the extended TTF model. MASEM is a research method that combines meta-analysis (MA) and structural equation modeling (SEM). In addition, this paper refers to previous research and adds factors in UTAUT2 and TAM to develop an extended TTF model. For example, individual characteristics [30], perceived ease of use [36], performance expectancy [41], and behavioral intention [40]. It is expected that essential predictors can be found to enhance the explanatory power of the TTF model. Figure 3 is the extended TTF model of this paper.

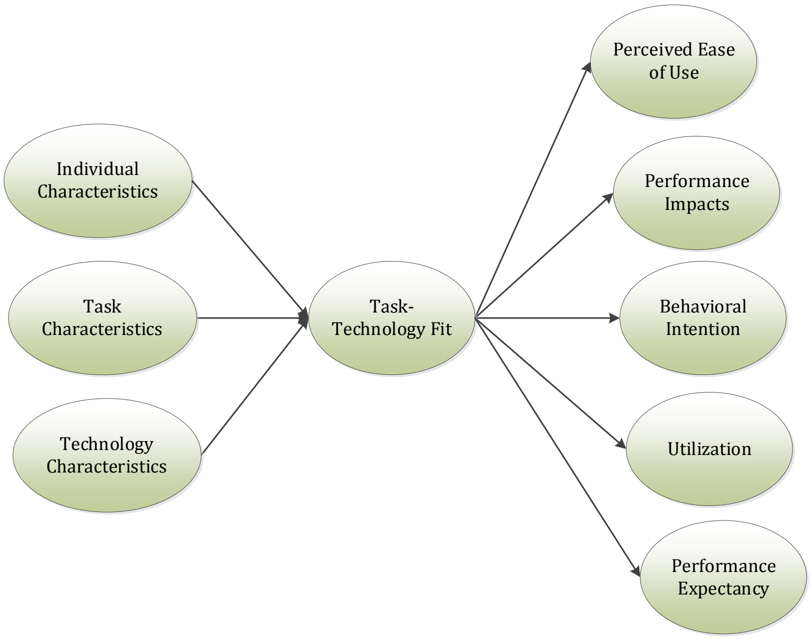

Figure 3. Task-Technology Fit Augmentation Model

4- Research Results

4-1- Meta-Analysis Results

In this paper, CMA (Comprehensive Meta-Analysis) was used as an analytical tool to conduct random-effects analysis, and the results are presented in Table 1. This table has several data, including study number, standard error, point estimate, upper and lower 95% confidence interval, z-value, and p-value.

Table 1. Meta-analysis - random effect

Path	Study Number	Standard error	point estimate	Lower limit	Upper limit	z-value	p-value
IC-TEC	4	0.134	0.384	0.128	0.592	2.874	**
IC-TTF	4	0.088	0.381	0.217	0.524	4.350	***
PI-UT	4	0.158	0.498	0.204	0.709	3.157	**
PEOU-BI	9	0.043	0.570	0.501	0.631	13.113	***
PEOU-PE	14	0.085	0.522	0.375	0.643	6.161	***
PE-BI	9	0.089	0.649	0.513	0.753	7.333	***
TASK-BI	16	0.046	0.433	0.351	0.509	9.342	***
TASK-PI	8	0.066	0.403	0.281	0.512	6.065	***
TASK-PE	14	0.072	0.403	0.270	0.521	5.564	***
TASK-PEOU	13	0.044	0.350	0.269	0.427	7.937	***
TASK-TEC	28	0.041	0.450	0.378	0.517	10.959	***
TASK-UT	6	0.072	0.516	0.392	0.621	7.135	***
TEC-BI	16	0.058	0.519	0.422	0.605	8.982	***
TEC-PI	8	0.094	0.473	0.304	0.613	5.031	***
TEC-PE	13	0.070	0.442	0.317	0.552	6.335	***
TEC-PEOU	12	0.073	0.487	0.358	0.597	6.657	***
TEC-UT	7	0.023	0.547	0.510	0.582	23.424	***
TTF-BI	19	0.051	0.546	0.463	0.619	10.802	***
TTF-PI	12	0.083	0.574	0.436	0.685	6.887	***
TTF-PE	16	0.082	0.494	0.351	0.616	6.039	***
TTF-PEOU	15	0.060	0.475	0.370	0.568	7.918	***
TTF-TASK	31	0.040	0.499	0.432	0.561	12.515	***
TTF-TEC	31	0.042	0.573	0.507	0.633	13.590	***
TTF-UT	11	0.077	0.525	0.393	0.635	6.807	***

Note 1. IC = Individual Characteristics; Task = Task Characteristics; TEC = Technology Characteristics; TTF = Task-Technology Fit; PEOU = Perceived Ease of Use; PI = Performance Impacts; BI = Behavior Intention; UT = Utilization; PE = Performance Expectancy.

Note 2. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

This paper uses the population correlation coefficient estimate (r) proposed by Hunter et al. [62] as an indicator. According to their suggestions, find each piece of literature's correlation coefficient, subtract the sampling error, and then get the true maternal effect. The evaluation criteria for effect size refer to Cohen's [54] recommendations, which are r > 0.1 (low effect), r > 0.3 (medium effect), and r > 0.5 (high effect). Random effect analysis shows that the 95% confidence interval does not contain 0, and the p-values are all less than 0.05. Therefore, the research results are statistically significant (see Table 1).

In addition, the relationship between the variables belonging to the original TTF model (including TASK, TEC, TTF, PI, and UT) was found to be relatively stable. After combining the variables of UTAUT2 (including PEOU, BI, and PE) and IC, all paths were also found to have a medium or high effect. Hence, this paper concludes that TTF is a more mature research model and has accumulated many clear outcomes, so the results indicate that the relationships between the variables have median or high effects. Finally, other variables were included, and the results were medium or high effects. The variables in this research model are essential factors in TTF-related studies.

4-2- Subgroup Analysis Results

In this paper, the respondents were divided into identity and voluntary groups. The identity group was divided into employee, individual, and student; the voluntary group was divided into voluntary and non-voluntary. The data in the tables include upper and lower 95% confidence intervals, p-value, study number, point estimate, z-value, and Q-value. CMA is adopted as a tool to conduct the analysis. A subgroup analysis was performed to better understand the differences between TTF-related studies. The results showed that r greater than 0.3 or 0.5 was either a medium or high effect; the 95% confidence interval did not contain 0, indicating that all these paths had a significant effect. Then, observe the overall results of each path in Table 2.

Table 2. Subgroup analysis – identity

Path	Group	Number	Point estimate	Lower limit	Upper limit	z-value	p-value
IC-TTF	Employee	2	0.370	0.084	0.599	2.499	*
	Student	2	0.391	0.131	0.602	2.874	**
				Q-value = 0.015; d.f. = 1			0.904
TASK-TTF	Employee	7	0.414	0.088	0.660	2.453	*
	Individual	16	0.439	0.504	0.565	12.903	***
	Student	8	0558	0.451	0.649	8.572	***
				Q-value = 1.305; d.f. = 2			0.521
TEC-TTF	Employee	7	0.526	0.397	0.634	6.989	***
	Individual	14	0.600	0.483	0.697	8.154	***
	Student	10	0.564	0.463	0.651	9.096	***
				Q-value = 0.837; d.f. = 2			0.658
TTF-PEOU	Employee	3	0.500	0.354	0.622	6.022	***
	Individual	8	0.450	0.287	0.588	5.008	***
	Student	4	0.510	0.366	0.630	6.164	***
				Q-value = 0.386; d.f. = 2			0.824
TTF-PI	Employee	6	0.616	0.447	0.743	5.917	***
	Individual	4	0.580	0.255	0.787	3.232	**
	Student	2	0.412	0.155	0.617	3.045	**
				Q-value = 2.293; d.f. = 2			0.318
TTF-BI	Employee	4	0.648	0.540	0.735	9.020	***
	Individual	8	0.572	0.427	0.689	6.556	***
	Student	7	0.446	0.342	0.538	7.663	***
				Q-value = 8.025; d.f. = 2			0.018
TTF-UT	Employee	3	0.543	0.326	0.705	4.427	***
	Individual	2	0.648	0.402	0.807	4.378	***
	Student	6	0.470	0.273	0.628	4.363	***
				Q-value = 1.550; d.f. = 2			0.461
TTF-PE	Employee	4	0.531	0.296	0.705	4.042	***
	Individual	9	0.479	0.266	0.647	4.104	***
	Student	3	0.497	0.368	0.607	6.716	***
				Q-value = 0.134; d.f. = 2			0.935

Note 1. IC = Individual Characteristics; Task = Task Characteristics; TEC = Technology Characteristics; TTF = Task-Technology Fit; PEOU = Perceived Ease of Use; PI = Performance Impacts; BI = Behavior Intention; UT = Utilization; PE = Performance Expectancy. Note 2. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 2 shows the subgroup analysis based on identity. This subgroup analysis is divided into three groups: employee, individual, and student. Furthermore, in Table 2, these subgroups are associated with different paths proposed in the research framework of the study. It is found that when d.f. = 2, only TTF-BI (p-value = 0.018 < 0.05) is significant. On the other hand, other paths, including IC-TTF (p-value = 0.904), TASK-TTF (p-value = 0.521), TEC-TTF (p-value = 0.658), TTF-PEOU (p-value = 0.824), TTF-PI (p-value = 0.318), TTF-UT (p-value = 0.461), and TTF-PE (p-value = 0.935), were found to have p-values greater than 0.05 and hence were not found to be significant.

Table 3 indicates the results of subgroup analysis on voluntary base groups. The subgroups indicated in Table 3 are divided into volunteer and non-volunteer groups. In Table 3, the subgroups are also associated with various proposed paths of the research model. The overall results of each path in Table 3 show that when d.f. = 1, only IC-TTF (p-value = 0.034 < 0.05) is significant. On the other hand, all the other paths, including TASK-TTF (p-value = 0.157), TEC-TTF (p-value = 0.250), TTF-PEOU (p-value = 0.339), TTF-PI (p-value = 0.347), TTF-BI (p-value = 0.440), TTF-UT (p-value = 0.515), and TTF-PE (p-value = 0.748), were found to have p-values greater than 0.05 and hence were not found to be significant.

Table 3. Subgroup analysis – voluntary

Path	Group	Number	Point estimate	Lower limit	Upper limit	z-value	p-value
IC-TTF	Non-volunteer	3	0.331	0.162	0.481	3.740	***
	Volunteer	1	0.502	0.451	0.550	16.253	***
				Q-value = 4.499; d.f. = 1			0.034
TASK-TTF	Non-volunteer	17	0.458	0.347	0.557	7.286	***
	Volunteer	14	0.545	0.479	0.606	13.255	***
				Q-value = 2.007; d.f. = 1			0.157
TEC-TTF	Non-volunteer	15	0.532	0.432	0.620	8.905	***
	Volunteer	16	0.609	0.511	0.691	9.677	***
				Q-value = 1.325; d.f. = 1			0.250
TTF-PEOU	Non-volunteer	8	0.430	0.295	0.548	5.783	***
	Volunteer	7	0.525	0.366	0.654	5.740	***
				Q-value = 0.915; d.f. = 1			0.339
TTF-PI	Non-volunteer	7	0.620	0.472	0.734	6.693	***
	Volunteer	5	0.505	0.267	0.684	3.866	***
				Q-value = 0.883; d.f. = 1			0.347
TTF-BI	Non-volunteer	11	0.569	0.442	0.673	7.388	***
	Volunteer	8	0.510	0.417	0.593	9.248	***
				Q-value = 0.596; d.f. = 1			0.440
TTF-UT	Non-volunteer	5	0.567	0.386	0.707	5.319	***
	Volunteer	6	0.488	0.291	0.645	4.470	***
				Q-value = 0.424; d.f. = 1			0.515
TTF-PE	Non-volunteer	8	0.474	0.220	0.668	3.461	**
	Volunteer	8	0.513	0.410	0.604	8.410	***
				Q-value = 0.103; d.f. = 1			0.748

Note 1. IC = Individual Characteristics; Task = Task Characteristics; TEC = Technology Characteristics; TTF = Task-Technology Fit; PEOU = Perceived Ease of Use; PI = Performance Impacts; BI = Behavior Intention; UT = Utilization; PE = Performance Expectancy.

Note 2. *** p < 0.001; ** p < 0.01; * p < 0.05.

4-3- Results of Publication Bias and Heterogeneity Analysis

The funnel plot is commonly used to detect publication bias [63]. Sterne et al. [64] advocate that there is no publication bias and heterogeneity in the study, and the funnel plot appears similar to symmetric and inverted. In the funnel plot, the standard error (SE) value on the vertical line and at the top is SE = 0. When the points (research samples) fall within the 95% confidence interval of the plot, it indicates heterogeneity; otherwise, it does not. Samples without heterogeneity are distributed inside the funnel plot. Alternatively, if the points scattered within the funnel plot show asymmetry, this may be due to a lack of research samples, which indicates a possible publication bias. Visual inspection is so subjective that the funnel plot is the most vulnerable. Torgerson [63] stated that the asymmetry in the funnel plot can only be seen as a hint of publication bias. Sterne et al. [61] also described two reasons for the asymmetry in the funnel plot. One is that there is real heterogeneity; the other is irregularities in the data. If there is really heterogeneity and data-related factors cause it, it is difficult to find these potential causes in the funnel plot. The funnel plot of all paths in this study is presented in Figure 4. Heterogeneity (I^2) is between 91% and 97%, indicating that the paths are all high in heterogeneity. Thus, it is impossible to determine whether there is any publication bias.

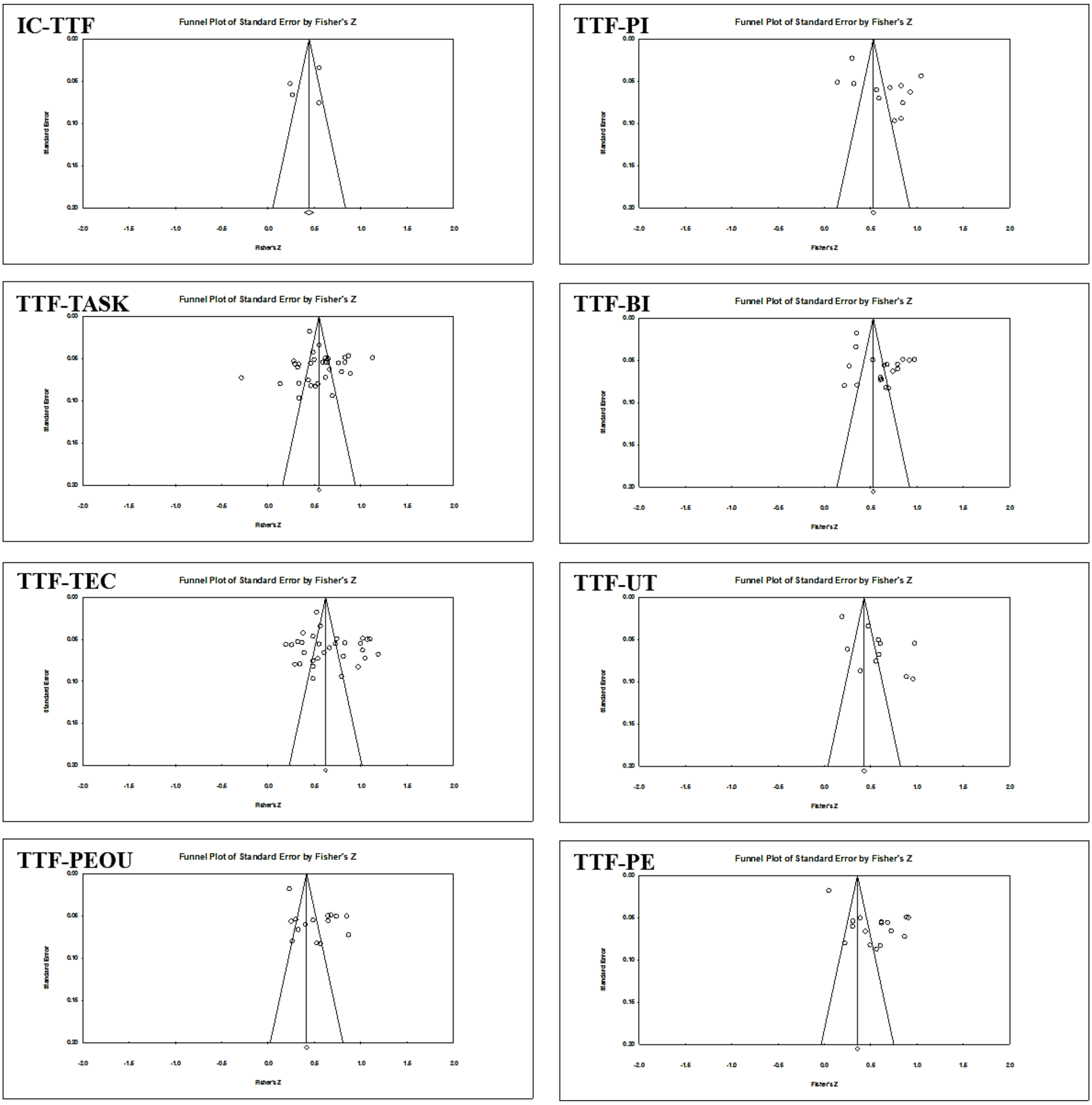

Figure 4. Funnel Plot (Note: IC = Individual Characteristics; Task = Task Characteristics; TEC = Technology Characteristics; TTF = Task-Technology Fit; PEOU = Perceived Ease of Use; PI = Performance Impacts; BI = Behavior Intention; UT = Utilization; PE = Performance Expectancy).

In order to accurately judge whether there is publication bias, this paper adopts the Fail-Safe Number (FSN) tests to detect it. Rosenthal [65] suggested calculating the FSN value, then integrating this amount of literature with no significant effect into the analysis. This approach turned the initially significant integration effect into a non-significant one ($p > 0.05$). The larger the FSN, the less publication bias. However, this method focuses on whether the p-value meets the standard rather than the interference effect and confidence interval. Therefore, it is not suitable for medical research [66]. The detection results of heterogeneity and publication bias are shown in Table 4.

Table 4. Heterogeneity and publication bias

Group	Number	Q-value	D (f)	p-value	I^2	FSN
IC-TEC	4	81.800	3	***	96.333	258
IC-TTF	4	34.702	3	***	91.355	263
PI-UT	4	82.639	3	***	96.370	239
PEOU-BI	9	70.581	8	***	88.666	3699
PEOU-PE	14	636.779	13	***	97.958	6063
PE-BI	9	336.302	8	***	97.621	4715
TASK-BI	16	216.068	15	***	93.058	4670
TASK-PI	8	66.342	7	***	89.449	725
TASK-PE	14	423.785	13	***	96.932	2978
TASK-PEOU	13	130.379	12	***	90.796	2179
TASK-TEC	28	517.278	27	***	94.780	6242
TASK-UT	6	38.690	5	***	89.077	671
TEC-BI	16	401.999	15	***	96.269	7378
TEC-PI	8	128.576	7	***	94.556	926
TEC-PE	13	338.098	12	***	96.451	2938
TEC-PEOU	12	332.642	11	***	96.693	3420
TEC-UT	7	7.804	6	-	23.113	1259
TTF-BI	19	435.983	18	***	95.871	1813
TTF-PI	12	426.477	11	***	97.421	4653
TTF-PE	16	719.171	15	***	97.914	5413
TTF-PEOU	15	355.378	14	***	96.061	5202
TTF-TASK	31	608.646	30	***	95.071	4335
TTF-TEC	31	772.170	30	***	96.115	3741
TTF-UT	11	301.596	10	***	96.684	2960

Note 1. IC = Individual Characteristics; Task = Task Characteristics; TEC = Technology Characteristics; TTF = Task-Technology Fit; PEOU = Perceived Ease of Use; PI = Performance Impacts; BI = Behavior Intention; UT = Utilization; PE = Performance Expectancy. Note 2. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

4-4- Results of MASEM

The results of the bivariate correlation matrix analysis show that the overall TTF expansion model paths are all positively correlated. The path coefficients are IC-TTF = 0.137, TAST-TTF = 0.288, TEC-TTF = 0.492, TTF-PE = 0.710, TTF-PEOU = 0.649, TTF-PI = 0.755, TTF-UT = 0.744, and TTF-BI = 0.786. Construct reliability (CR) is between 8.282 and 49.543. The p-values were less than 0.001, which was statistically significant. The results of MASEM are shown in Figure 5.

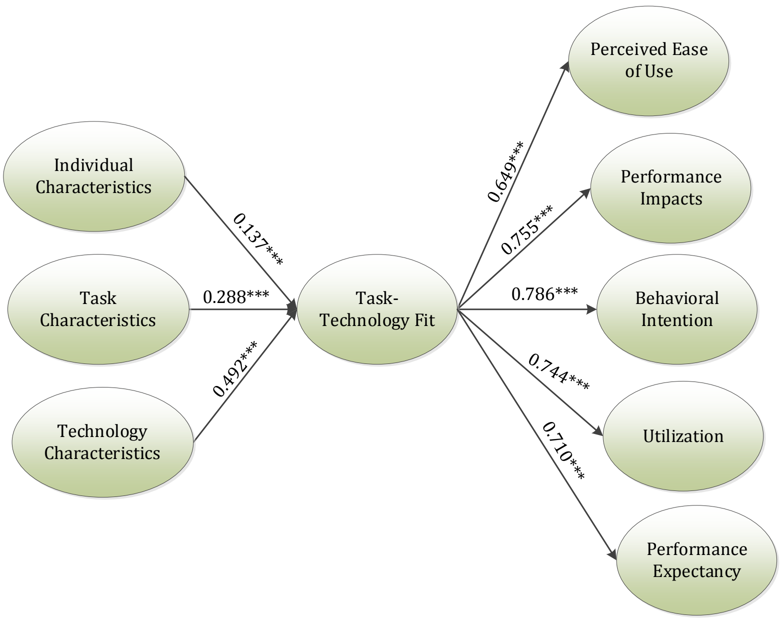

Figure 5. MASEM results of extended TTF model

Analyzing the extended TTF model shows that all path coefficients are significant. Many scholars employ TTF to measure the fit between users, task requirements, and IT, but their results are different. The variables discussed in this study have also been applied to research in various fields. For example, IC is applied to mobile networks and customer satisfaction and is considered to replace the function of TASK in the future [37, 67]. TASK and TEC are typical factors in the TTF model, which are adopted in quite a few fields. For example, Omotayo & Haliru [68] analyzed the fit of library IT and tasks, and Yamin & Alyoubi [69] discussed the fit of medical system technology during the epidemic. The impact of TTF on PEOU and PE has also been applied to empirical mobile payment technology risks [28] or to explore the important factors of product technology adoption [36]. Tam & Oliveira [40] investigate the relationship between the willingness to use mobile banking IT and the improvement of personal performance, i.e., the impact of TTF on BI. PI and UT are applied to test the important efficiency factors in the TTF model. Hsieh & Lin [70] used these two factors to examine the UT of the epidemic prevention cloud. Moreover, Yi et al. [71] employed them to examine students' views on the performance of smartphones. From the above literature review, the factors discussed in this paper have been extensively studied in recent years. The results obtained in this paper more clearly validate the extended TTF model. At the same time, understanding these factors is essential for TTF-related research.

5- Discussion

According to the present study's results, TTF significantly impacts PEOU. This study result can be compared to a previous study conducted by Mustafa et al. [14]. Mustafa et al.'s [14] study employed TTF and TAM to assess the concept of gamification. According to Mustafa et al.'s [14] study, gamification in learning and education will help the students' motivation for engagement in learning tasks and activities. Hence, the purpose of Mustafa et al.'s [14] research was to connect both TTF and TAM to measure the BI of teachers in developing economies to use gamification tools in education. Their study collected and analyzed data from various institutions in Africa. According to Mustafa et al.'s [14] results, TTF was discovered to have significant relationships with perceived usefulness and PEOU. Furthermore, subjective norms, facilitating conditions, and computer anxiety were found to impact the attitude of users adversely.

In addition, according to the present study, TTF significantly impacted the BI of users. The current result of this study is somewhat comparable to an earlier study conducted by Kim et al. [16]. Kim et al.'s [16] study employed TAM and TTF to analyze the BI of users regarding the employment of massive open online courses (MOOCs). Kim et al.'s [16] study used TTF and teaching presence as exogenous variables for the measurement of BI and employed both PEOU and perceived usefulness as mediators. Kim et al.'s [16] study employed a survey methodology and gathered the data from learners in Korea. According to their results, PEOU significantly impacted perceived usefulness but did not have any impact on BI. However, teaching presence was found to impact BI significantly but had no significant impact on PEOU. In addition, TTF was found to be significantly associated with BI, PEOU, and perceived usefulness. Finally, PEOU and perceived usefulness were found to be significant mediators for the relationship between teaching presence and BI.

Furthermore, according to the present study, TTF significantly impacted utilization. This result can be compared with a study conducted by Tripathi & Jigeesh [72]. Tripathi & Jigeesh's [72] study was based on the importance of cloud computing technologies and the way these technologies are aiding internet support services, storage services, and software tools from remote data centers. Tripathi & Jigeesh's [72] study aimed to analyze the impact of cloud technologies in organizations; hence, their study combined TTF with utilization models and employed a technology-performance chain (TPC) framework. Tripathi & Jigeesh's [72] study employed a survey methodology and collected data from multinational firms associated with the information technology sector. The data for their research was collected from the senior project managers of these firms, and according to their results, it was found that the firms supported the use of cloud technologies in their organizations. Furthermore, PEOU, training, automation, and system reliability were found to impact the performance of organizations via CCT significantly. Finally, TTF was found to significantly impact the utilization of CCT via precursors of utilization.

Additionally, the current study found a significant impact of TTF on PE. The current study's results are somewhat similar to those of an earlier study conducted by Al-Rahmi et al. [21]. Al-Rahmi et al.'s [21] study targeted the teaching and learning aspects of social media related to higher education. Al-Rahmi et al.'s [21] study employed TTF and UTAUT theories to analyze the BI of students regarding learning, which in turn is related to their academic performance. This research proposes relationships of BI and TTF with PE, technological characteristics, social characteristics, and effort expectancy. The data was collected with the help of a quantitative methodology. Al-Rahmi et. al.'s [21] study employed questionnaires to collect data from students of higher education. According to their results, BI, social characteristics, and task characteristics were correlated with TTF. Furthermore, PE and effort expectancy were also found to be correlated with TTF.

Lastly, according to the present study's outcomes, TTF was significantly related to PI. The result of the present study can be compared to a recent study conducted by Cheng [18]. Cheng's [18] study targeted medical professionals from medical institutions in Taiwan and determined the impact of cloud-based e-learning platforms on their job tasks. Hence, Cheng's [18] study coined and employed a new concept of learning technology fit (LTF), ECM, and TTF to analyze the

BI and PI of using cloud-based e-learning platforms by medical professionals. Cheng's [18] study employed a quantitative methodology and conducted a survey with the help of a questionnaire. The data for their study was collected from medical professionals, and according to their results, TTF and LTF significantly impacted the BI and PI. Furthermore, learning was found to have a significant impact on medical professionals' tasks.

Finally, the present study used MASEM and sub-group analysis, and according to the results of volunteer-based subgroup analysis, the IC relationship with the TTF path was the only significant path. Furthermore, according to the identity-based subgroup analysis, the relationship between TTF and BI was the only significant path. The results of the current study can be compared to a study conducted by Zaremohzzabieh et al. [24]. Zaremohzzabieh et al.'s [24] study targeted the use and acceptance of MOOCs in learning. Their study employed TTF, UTAT, and the theory of planned behavior (TPB) to analyze the factors impacting the use and acceptance of MOOCs. Zaremohzzabieh et al.'s [24] study employed the MASEM approach to analyze the data from 43 previous studies. According to their results, TTF, PE, and effort expectancy were found to significantly influence the BI to use MOOCs via several other technologies and task characteristics.

5-1- Theoretical Implications

This study has several theoretical and academic contributions. This study has theoretically proved the soundness and robustness of the research framework built on the combination of TTF, TAM, and UTAUT designed to analyze the BI and PI of users. Furthermore, besides providing a robust model, this study provides a novel and testable methodology related to applying MASEM [73]. Consequently, this study theoretically contributes to the literature on MASEM methodology and proposes a new testable methodology for other scholars to use in various fields. In addition, this research's framework has proposed and analyzed various new paths, offering insights and contributions for other research scholars.

Moreover, this research contributes to the literature on TTF and goes beyond the traditional role of TTF, which was based on the notion that PI and technology acceptance are only based on task and technology fit [25]. This study offers a new perspective on the use of TTF in organizations. Hence, this research demonstrated the combination of TTF with TAM and UTAT concepts and stressed their importance in improving the overall PI. This study inferred that a good fit between a task and technology will lead to increased performance, whereas a poor connection between task and technology will lead to a reduction in employment of new technologies and poor performance [25, 74].

5-2- Practical Implications

This study provides several practical implications for decision-makers. This study can help decision-makers understand TTF's underlying significance for the effective use and adoption of technologies to improve the PI [25, 75]. In addition, this study suggests to decision-makers the dynamic nature of TTF. Hence, the organizational decision-makers are proposed to continuously evaluate the organizational and technological changes to adapt to the changes in TTF. According to several studies, a good fit between technology and task should be re-ensured by the organizational readiness for future technological changes [74–76].

In addition, many firms benefit from their employees adopting new technologies, which was done previously only with the employment of TAM in organizations. Hence, this research provides decision-makers with a suggestion to use TAM in combination with TTF to analyze new insights into employees' intentions to accept or reject a technology. According to previous research, many workers reject new technologies related to the improvement of organizational tasks because they find themselves unfamiliar with them [77].

Additionally, TTF and UTAUT are found to analyze the BI of users' technology adoption. Hence, it can help decision-makers in the business-to-customer and business-to-business industries. For instance, in the case of business-to-customer industries, decision-makers can compare their service adoption by users with that of competitors. In the case of business-to-business industries, decision-makers can compare the employees' adoption and use of current technologies in comparison to the use and adoption of prior technologies in the organization.

Lastly, this study recommends that decision-makers include more technological features because including little features can impact users' utilization and BI. For instance, in the future, companies need to consider including enough technological attributes rather than including too many features as a barrier. Users can employ the technologies with too many technological attributes with difficulty, but eventually they will be able to perform their activities effectively. In contrast, if there are too few technological features, the users might immediately notice the lack of features and stop using the technology [78].

5-3- Research Limitations and Future Research Suggestions

This paper is as rigorous as possible, but there are still shortcomings. Various publishers collect the research as a sample, and the year and research field are the selection criteria. In addition, due to the different ways CMA is applied to medical research, this paper must exclude medical-related research. Finally, the literature as a sample should be more than 20 articles to facilitate the analysis and avoid excessively subjective results.

In the field of IT, some theories have made great contributions to human behavior. For example, TAM, UTAUT2, and TTF are used to explore the impact of IT on human behavior. However, some believe that motivation rather than technology drives people to engage in activities and tasks. If there is too much emphasis on technology and too little attention to motivation, human behavior will be distorted, and the role of technology will be misunderstood. On the other hand, technological advances are most evident in IT. As a result, the network service system has changed dramatically, and the scope of the system has become more extensive [79]. Many studies have demonstrated that technology has positive (e.g., bringing benefits to the company) and negative (e.g., affecting physical and mental health, personal privacy, and information security) effects on people. In particular, when individuals use technology selfishly or inappropriately, it can negatively impact IT and harm the value and benefits created by other users. The challenge is to use the TTF's sustainability and its ability to evaluate performance, combined with other perspectives, to estimate the impact of IT and IS. Furthermore, in addition to the commonly discussed variables, creating new variables and enhancing the explanatory power of TTF for other variables are issues and directions for future research.

In addition, this study employed TTF and TAM together to provide deeper insights regarding the behavioral aspect. However, there are some limitations regarding capturing cultural and individual characteristics [80]. Hence, future researchers are advised to include TPB and system usability scales to study the cultural context [73].

6- Conclusion

According to the research results, as the TTF increases, the characteristics of the technology also directly affect PEOU. Because of the advancement of technology, users feel the convenience of use has improved. In other words, TTF-PEOU is affected by TEC-TTF, as found by Yen et al. [27]. In addition, TTF is an important indicator for predicting users' intentions. When technology makes it easier for users to complete tasks, it causes them to prefer and rely on it, and then their behavioral intentions increase [27]. Similarly, an increase in TTF will also affect UT, PE, and PI. For example, users expect to use information equipment to quickly and easily complete tasks to meet health management requirements. As a result, users will have significantly positive expectations and improve their health management requirements through utilization, thereby increasing work efficiency. Observing the research field regarding IS/IT in recent years, whether it is to explore the efficiency of use or to influence the fit between technology and use, TTF plays a crucial role.

This paper compiles TTF-related research from the last 20 years and analyzes the extended TTF model through random effects. The results show that there is a significant positive effect between the variables. This means that the extended TTF model is supported. Next, using subgroup analysis, the results showed that in the voluntary group, IC-TTF was significant and other paths were not; in the identity group, only TTF-BI was significant. There is a significant difference between voluntary and non-voluntary technology users in terms of the effect of IC on TTF. This paper infers that voluntary is related to individual characteristics, so the difference in the results is apparent when the group is classified as voluntary or non-voluntary. It indirectly shows that IC is an important variable when validating IT. On the other hand, grouping by employee, individual, and student, there are significant differences in the impact of TTF on BI by identity. In other words, research on different identity groups has different results on the impact of TTF on BI. Therefore, TTF-BI should be more discussed and verified.

7- Declarations

7-1- Author Contributions

Conceptualization, T.C., Y.L., and S.C.; methodology, T.C., Y.L., and S.C.; validation, A.K. and S.C.; formal analysis, T.C. and Y.L.; resources, S.C.; data curation, T.C.; writing—original draft preparation, T.C., Y.L., A.K. and S.C.; writing—review and editing, T.C., Y.L., A.K., and S.C.; visualization, A.K. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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