On-Site Personnel's Use of Mobile Cloud Computing Applications - A Case Study of An LCD Panel Manufacturing Company

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Abstract

More enterprises are now integrating mobile cloud computing into their operations. This study combines and modifies the Task-Technology Fit theory and the Unified Theory of Acceptance and Use of Technology to form a new model. A questionnaire was administered to the employees of a company that has applied mobile cloud computing. The purpose is to investigate what happens when this new technology is introduced in the workplace and what the influencing factors may be. After confirming the validity and reliability of the instrument through a pilot, 239 formal responses were collected and analyzed using descriptive statistics, one-way ANOVA, and structural equation modeling. It was found that employees' perception of how well the technology fits the nature of their work positively affects their effort expectancy of the technology and their view of the task-technology fit, which in turn affects their performance impact (user satisfaction) and actual technology use. Also, employees' behavioral intention to use this new information technology is affected by their perceived effort expectancy, performance expectancy, and facilitating conditions. The behavioral intention then affects their use behavior and performance impact (user satisfaction).

1. Introduction

Since the start of the COVID-19 pandemic, all enterprises are now faced with a new normal, and the use of mobile devices with cloud computing applications has become a trend in the marketplace (Market Intelligence & Consulting Institute [MIC], April 2020). Gartner Survey Research reported in August 2020 a continuous growing revenue for enterprises that have adopted cloud computing, especially public cloud services. The providers

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of infrastructure as a service (IaaS) are expected to increase their revenue as higher adoption is occurring worldwide; for example, Amazon Web Services earned the largest increased revenue (19.99 billion USD) last year. Even though International Data Corporation [IDC] (June 2020) expects that smartphone shipments are to decline in Q3 2020 due to the pandemic, the first quarter of next year will see the growth return. Forrester Consulting (October 2020) reported that having more cloud computing service providers will further propel cloud application development and delivery to satisfy business needs in Q4 2020. In addition, Infosys (July 2020) indicated that mobile management will continue as one of the trends in manufacturing, driven by innovations in mobile applications. As suggested by Gartner Survey Research (July 2020), during the COVID-19 pandemic, collaboration software, mobile device management, and applications that support remote work functionality are critically needed by more enterprises. Taiwan's manufacturing sector includes many different industries. Among them, liquid crystal display (LCD) materials' output value has always been challenged by global competitions such as factories in China, Korea, and Japan (Taiwan Institute of Economic Research [TIER], August 2019). Specifically, during the pandemic, the output value fell 12% to approximately 1.329 billion USD profit gain (Industrial Economics & Knowledge Center [IEK], May 2020). However, Business Net (April 2020) considered that due to the quarantines in most countries, Taiwan's LCD industry can still expect a promising future. The LCD-panel and related industries employ over a hundred thousand people, who are important for the economic development of Taiwanese society.

Prior studies have stated that work efficiency improvement is positively influenced by cloud technology (Kulkarni et al., 2014; Stieglitz & Brockmann, 2012). The use of mobile cloud computing applications can also improve overall operational efficiency, competitiveness, corporate image, and energy cost reduction (Banerjee et al., 2013; Bauer, 2018; Guerrero-Contreras et al., 2016; He et al., 2019). However, many factors can make or break the adoption process, such as enterprise software, the hardware environment (e.g., network environment), and individual factors (e.g., acceptance of new information systems) (Arinze, 2010; Chiu et al., 2017; Lian et al., 2014).

Most of the studies on operational efficiency utilize the Task-Technology Fit (TTF) theory proposed by Goodhue & Thompson in 1995 (e.g. Cady & Finkelstein, 2014; D'Ambra et al., 2013; Kim & Ammeter, 2014; Lin, 2014). Task-technology fit refers to the degree of match between a technology and a work task. When the two are well-matched (has good fit), the technology supports the tasks to a higher extent, making the user more willing to use the technology and resulting in higher efficiency in completing the task. Therefore, this study uses the TTF to investigate the relationship between mobile cloud computing application and work tasks and how the two affect operational efficiency.

Moreover, recent studies on technology adoption mostly use the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) as their research framework (e.g., Gupta et al., 2019; Lai & Lai, 2014; Wang, 2016; Williams et al., 2015; Oliveira et al., 2014). The UTAUT includes four dimensions: performance expectancy, effort expectancy, social influence, and facilitating conditions. The current study explores users' acceptance of new information technology and the factors of that acceptance. Among these factors, performance expectancy, effort expectancy, and social influence have a direct impact on the intention to use, while use behavior is affected by the intention and facilitating conditions. The enterprise in this study has applied mobile cloud computing to its operations. It is worth using the UTAUT to study the factors that influence its employees' use of new technology.

Overall, the current study combines and modifies the TTF and the UTAUT and formulates a new model to investigate the impact of enterprise adoption of mobile cloud computing on employees' operational efficiency and to find the key factors that influence their task efficiency after adopting the technology.

The scope of this study is limited to companies that manufacture LCD panels and components. These companies are already using cloud computing and are actively encouraging staff members to apply this technology to their work. The employees of these companies are the object of this study. Through a comprehensive analysis, a cohesive set of results are concluded, and specific proposals can be provided to other companies as guidance for future development.

2. Literature review

2.1 Application and development of cloud computing and mobile devices

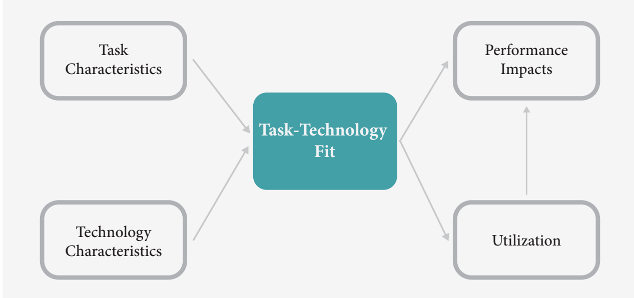
The National Institute of Standards and Technology (NIST) defines cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" (NIST, January 2018 updated). Based on this definition, cloud computing provides three service models, four deployment models, and five essential characteristics. The service models are infrastructure as a service (IaaS), platform as a service (PaaS), and software as a service (SaaS). The deployment models are private cloud, public cloud, community cloud, and hybrid cloud. The essential characteristics are on-demand self-service, broad network access, resource pooling, rapid elasticity, and measured service (NIST, June 2020 updated).

Since cloud computing can operate at any time without restriction, and it accepts requests from anywhere to connect to the company's information service system for data exchange, it can improve the information worker's efficiency and competitive edge (Banerjee et al., 2013; Bauer, 2019). Cloud computing applications are diverse and flexible and are commonly used in the corporate world (Guerrero-Contreras et al., 2016; He et al., 2019; Lee et al. al., 2013; Stieglitz & Brockmann, 2012; Yuan et al., 2010). The development of the cloud has also directly driven the widespread use of mobile devices. As the degree of mobility varies widely among the devices, the applications of cloud computing also vary widely (Chiu et al., 2017; Forrester Consulting, October 2020). In the literature, mobile devices combined with cloud computing applications fall into four categories: mobile enterprise, mobile office, mobile commerce (m-commerce), and bring-your-own-device (BYOD).

BYOD adopts the idea of mobile computing, which refers to using mobile phones at home, in the office, even on the street. Mobile computing is characterized by portability, connectivity, low power, platform independent, and integrated environments (Kulkarni et al., 2014, p.565). BYOD means that employees bring their personal devices to work. The devices may be notebook computers, tablets, smartphones, etc., which are easy to use, can be connected anytime from anywhere, and has low energy consumption and low cost. Kulkarni et al. (2014) researched BYOD from six angles: employee privacy, financial liability, compliance and legal concerns, appropriate device usage, mobile device management (MDM), and mobile device storage (local storage). Overall, the use of BYOD can effectively reduce equipment costs and energy consumption and has a positive impact on the organization's operational efficiency and cost reduction (Banerjee et al., 2013; Guerrero-Contreras et al., 2016; He et al., 2019). One of the four major information technology application development future trends in the manufacturing industry is the emerging cloud and mobile technologies. Therefore, the improvement of mobile computing technology can effectively manage the mobility of factories, after-sales customer service, and tasks such as massive data collection, mobile communication, and collaboration between partners.

2.2 Task-technology fit

The TTF theory was proposed by Goodhue & Thompson (1995) (Figure 1). The main thesis is the relationship between the information system and the individuals' performance. The TTF theory came from Vessey's (1991) cognitive-fit theory, which explains the mutual influence between the presentation of information and the task. The TTF theory touches upon the cognitive-fit theory, defining it as understanding the degree of fit between a technology's characteristics and the task that it is supposed to support. In other words, when the cognitive-fit model yields a good fit, auxiliary systems or tools can be used to process specific tasks, thereby improving task efficiency (Zhou et al., 2010). The so-called auxiliary systems or tools can be regarded as the use of information technology. The ability of information technology users also affects the extent that technology can support work tasks. If using information technology can significantly support the work tasks, the users will have a positive perception of the technology and use it more habitually (Dishaw & Strong, 1999; Lian et al., 2014; Wang, 2016; Zhou et al., 2010)



[**Figure 1**] The Task-Technology Fit Model

The work tasks of manufacturing LCD panels and components can be divided into three categories: directly related to the production line, indirectly related to the production line, and general operations. The tasks include raw material management, manufacturing and production process control, finished product management, customer management, etc. These tasks have some common characteristics: immediacy, repetitiveness, and unfixed location. Immediacy means that real-time information is needed to perform the task smoothly. For example, equipment engineers need to be able to know the equipment conditions at any given time, so information devices are used to monitor the real-time conditions of the production line equipment. Repetitiveness refers to a work task that has a fixed or standardized operating mode and needs to be performed repeatedly at certain time intervals. For example, the production unit needs to routinely confirm the stock of raw materials. If the safety stock is insufficient, raw materials should be purchased. This type of operation has the characteristics of being cyclical and has a regular and standardized procedure. Unfixed location means that there is no fixed location for the task; rather, it needs to be constantly moved to be completed. For example, the daily inventory operations of warehouse managers require them to go to different locations to take inventory of the various items. For the tasks that are repetitive and with unfixed locations, the combination of cloud computing systems and mobile devices can be applied to execute the tasks to effectively improve the efficiency of the work.

In general, the technology characteristics of mobile devices combined with cloud computing can be matched to the task characteristics, and application programs can be developed accordingly for employees to use in their work. Combining mobile device and cloud computing applications would better reflect the five technology characteristics: portability, connectivity, low power, platform independent, and integrated environments (Kulkarni et al., 2014). Based on this understanding, the following two hypotheses are proposed:

H1 : Task characteristics have a positive impact on the task-technology fit in the LCD panel and component manufacturing industry.

H2 : Technology characteristics of mobile cloud computing application programs have a positive impact on the task-technology fit.

In addition, TTF is mainly used to study the situation where the task characteristics and technology characteristics are appropriately matched, which affect performance and intention to use. Performance impact and use tend to improve with a higher degree of fit (Goodhue & Thompson, 1995). In the past, the literature on TTF included a wide range of research topics such as websites, medical information systems, mobile communications, and e-books (Cady & Finkelstein, 2014; D'Ambra et al., 2013; Kim & Ammeter, 2014; Lin, 2014). More recently, the research topic has shifted toward mobile information technology, and all research results agree that if the task characteristics are effectively supported by the information technology, then the performance impact and use behavior will be impacted significantly (Alyoubi & Yamin, 2019; Tam & Oliveira, 2016; Wang & Lin, 2019). Continuous use also has a significant effect on performance impact. Therefore, this research uses TTF as the theoretical basis to explore the LCD panel and component manufacturing industry, which has begun to introduce the characteristics of mobile cloud computing technology and to examine the performance impact and use behavior of its staff, and the relationship between these two. Performance impact can be regarded as the employees' multi-faceted operational efficiency (D'Ambra et al., 2013; Lin, 2014; Tam & Oliveira, 2016). However, prior studies have pointed out that, in the discussion of organizational behavior and the implementation of information systems, performance evaluation based on user satisfaction is generally accepted (Au et al., 2002; Brown et al., 2008). Therefore, to improve the explanation of variances in operational efficiency, this research uses user satisfaction to measure performance impact. Based on the above discussion, the following three hypotheses are made:

H3 : The task-technology fit of the mobile cloud computing application in the LCD panel and component manufacturing industry has a positive impact on the employees' performance impact (user satisfaction).

H4 : The task-technology fit of the mobile cloud computing application in the LCD panel and component manufacturing industry has a positive impact on the employees' use behavior.

H5 : The LCD panel and component manufacturing industry employees' use behavior of mobile cloud computing application program has a positive impact on their performance impact (user satisfaction).

However, the TTF theory does not take into account the influence of users' personal factors or community factors. Therefore, to make up for the shortcomings of a single structure and strengthen the explanatory power of TTF, Dishaw and Strong (1999) proposed a model that integrated the TTF theory and the technology acceptance model (TAM). To conduct more comprehensive analyses and research, many scholars have chosen to use the TTF-UTAUT integrated model to explore the key factors that affect user behavioral intention and actual use behavior (Lee et al., 2007; Oliveira et al., 2014; Tai & Ku, 2014; Zhou et al., 2010). This new integrated model is the best choice to predict and explain user behaviors. Many studies have used the UTAUT to predict the user's use of the system and have obtained a higher explanatory power than the TAM (e.g., Gupta et al., 2019).

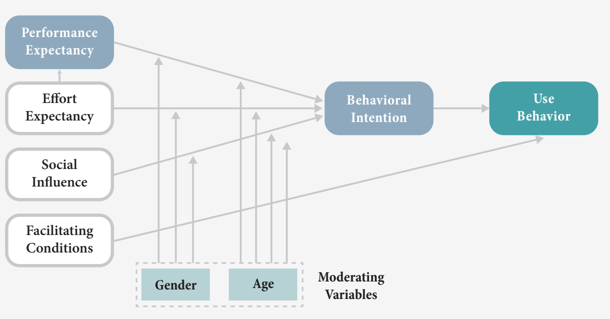
2.3 UTAUT

The UTAUT was developed by Venkatesh et al. (2003) based on two theoretical models: Theory of Reasoned Action (TRA) and Technology Acceptance Model (TAM). Additionally, the UTAUT integrated six other theoretical models: MM (Motivational Model), TPB (Theory of Planned Behavior), C-TAM-TPB (Combined TAM and TPB), MPCU (Model of PC Utilization), IDT (Innovation Diffusion Theory), and SCT (Social Cognitive Theory).

The TRA was published by Fishbein and Ajzen in 1975 to illustrate the causal relationship between an individual's specific behavior intention and the actual behavior; this relationship is affected by two factors—the attitude toward the behavior and subjective norms. Attitude refers to the assessment resulting from beliefs about the consequences of one's behaviors, and it has a positive impact on behavioral intention. Subjective norms refer to external social pressures when performing specific behaviors, and it also directly affects an individual's behavioral intention, which in turn determines the actual behavior of the individual. Davis (1986) proposed the TAM based on the TRA. The TAM introduces two dimensions: perceived usefulness and perceived ease of use. It aims at evaluating user behavior related to the internal information system of an organization. Perceived usefulness is the subjective perception of users when using a specific information system, which can improve performance impact and is affected by external variables and perceived ease of use. Perceived ease of use is the subjective perception of users in learning to use a specific information system. The degree of effort required is affected by external variables; the attitude toward technology use is affected by perceived usefulness and perceived ease of use. The user's positive and negative emotions are affected by their attitude when using a specific information system as an aid, and the attitude affects the use behavior of that technology. Later, in 1989, Davis studied IBM laboratory employees and found that behavioral intention has an impact on use behavior, and perceived usefulness is directly related to behavioral intention. Therefore, the TAM theoretical model was modified again, and behavioral intention was added to the newly proposed TAM2.

It is worth noting that Venkatesh et al. revisited the UTAUT in 2012 and re-integrated the aforementioned eight theories into the theory and proposed the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), into which they added hedonistic motivation, price value, and habit as influencing factors. Although the newly added factors have a significant impact at the individual level, they have a low degree of impact in corporate organizations. As the research participants of this study worked in the LCD panel and component manufacturing industry, factors such as entertainment, price value, and habits are already being controlled as task characteristics and are not affected by the technological characteristics of mobile cloud computing that is introduced in the workplace. Therefore, UTAUT is more suitable for this study than UTAUT2.

As the theory evolved from TRA to UTAUT, behavioral intention has been used to predict the final use behavior of users. However, behavioral intention is affected by various factors, and these influencing factors are mostly derived from the user's cognitive psychology (Vessey, 1991). In other words, individual behaviors are specific outward expressions based on personal expectations. The UTAUT has been used in various fields such as medical care, agriculture and forestry, web services, mobile business, psychology, sociology, and information systems (Gupta et al., 2019; Lai & Lai, 2014; Lee et al., 2013; Oliveira et al., 2014; Wang, 2016; Williams et al., 2015; Zhou et al., 2010). According to the key influencing factors found by previous studies, to analyze user behavioral intention for the research purpose of this study, the modified UTAUT has four independent variables: performance



Source: Revised from Venkatesh, Morris, Davis and Davis, 2003, p. 447.

[Figure 2] The Modified UTAUT

expectancy, effort expectancy, social influence, and facilitating conditions, and two moderating variables: gender and age (Figure 2). Detailed descriptions of these four independent variables are as follows.

Performance expectancy refers to the degree to which an individual can use a specific system to improve operational efficiency (Venkatesh et al., 2003). It is similar to TAM's perceived usefulness. Users' subjective perceptions about the use of a specific information system can improve their performance impact and affect their intention to use (Zhou et al., 2010). This research proposes the following hypothesis:

H6 : LCD panel and component manufacturing employees' performance expectancy of mobile cloud computing application program has a positive impact on their behavioral intention to use the technology.

Effort expectancy refers to how easy it is for an individual to use a specific system (Venkatesh et al. 2003). It is similar to TAM's perceived ease of use, which means that the user's subjective perception about learning a system. For information systems, the degree of effort required has an impact on the user's behavioral intention (Zhou et al., 2010). According to the correlation between TAM's perceived usefulness and perceived ease of use, it can be deduced that effort and expectation will have a positive effect on the behavioral intention of using the technology (Lee et al., 2007). The technology characteristics in the TTF model correspond to the five technology characteristics of mobile cloud computing applications (i.e., portability, connectivity, low power, platform independent, and integrated environments). Users (workers in the LCD panel and component manufacturing industry) will have expectations about the effort required for a specific system due to these characteristics. Their expectations will have positive effects on their behavioral intention (Lee et al., 2007). Therefore, this research proposes the following hypothesis:

H7 : LCD panel and component manufacturing employees' effort expectancy about mobile cloud computing applications has a positive impact on their behavioral intention.

Social influence refers to the degree to which an individual believes that he or she should use a new system because someone important also uses it (Venkatesh et al., 2003). The concept is similar to the subjective norm concerning behavior mentioned by the TRA, which means that when a specific behavior is performed, external social pressure affects the user's behavioral intention to use the system (Zhou et al., 2010). This research proposes the following hypothesis:

H8 : LCD panel and component manufacturing employees' social influence about mobile cloud computing application has a positive influence on their behavioral intention.

Facilitating conditions refer to "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system," which directly affects whether an individual adopts the system (Venkatesh et al., 2003). Facilitating conditions are similar to the idea of perceived behavioral control in the Theory of Planned Behavior (TPB) proposed by Ajzen (1985, 1991). Perceived behavioral control refers to the ability to control one's behavior and is affected by one's capabilities and external resources (Zhou et al., 2010). In the context of mobile cloud computing applications, users need to have some basic skills to operate the application systems, as well as external factors that support the data networks. Otherwise, users would not adopt this system. In addition, according to several studies on mobile commerce, facilitating conditions positively affect behavioral intention (Lai & Lai, 2014; Lee et al., 2007; Oliveira et al., 2014; Zhou et al., 2010). The current study thus proposed the following hypothesis:

H9 : The facilitating conditions of mobile cloud computing's application in LCD panel and component manufacturing positively affect employee's behavioral intention.

Performance expectancy, effort expectancy, and social influence positively affect the behavioral intention, which in turn affects the user's use behavior of the new technology (Venkatesh et al., 2003). Ajzen and Fishbein (1980) and Davis (1989) have pointed out that the intention of use indeed impacts actual system use. Behavioral intention is defined as an individual's inclination to take a certain action. This study proposed the following hypothesis:

H10 : LCD panel and component manufacturing employees' behavioral intention to use cloud computing application programs positively affects their use behavior.

Due to the advantage of mobile cloud computing being easy to operate and having simple system interfaces, users would find it convenient to use. Consequently, mobile cloud computing's technology characteristics are positively related to effort expectancy (Zhou et al., 2010). When the users' work demands ubiquitous, fast, and convenient services, they may perceive that the system could increase their efficiency. The users would then determine that the effort associated with adopting mobile cloud computing may have a positive impact on their performance (Bauer, 2018). Thus, two hypotheses were proposed:

H11 : LCD panel and component manufacturing employees' effort expectancy positively affects their performance expectancy.

H12 : The technology characteristics of cloud computing application programs positively affect the effort expectancy of LCD panel and component manufacturing employees.

The UTAUT includes four moderators; their impact on the intention of use had been confirmed through cross-analysis. The moderators are gender, age, experience, and voluntariness of use (Venkatesh et al., 2003; Venkatesh & Davis, 2000). However, the current study's research scope is within the sector of LCD panel and component manufacturing, which had just in recent years started to require employees to use cloud computing application programs in their operations. Therefore, experience and voluntariness of use are not applicable to this study. The other two variables are detailed as follows: (1) Gender is dichotomized as male or female. The literature indicates that gender plays an important role in the process of technology adoption (Venkatesh et al., 2003; Venkatesh & Davis, 2000). Females tend to be impacted by social influence more so than males when using innovative technology. They are affected more by social factors than individual factors when making decisions. They also have higher levels of computer anxiety than their male counterparts. (2) Age has been confirmed by previous studies as a factor that, alongside gender, affects user perception of specific information technologies by having a moderating effect (Tai & Ku, 2014). Some scholars have pointed out that age and gender have a positive impact on behavioral intention; moreover, the facilitating conditions' impact on the use behavior is affected by the moderating effects of age (Venkatesh et al., 2012; Yu, 2012). Therefore, this study proposed the following seven hypotheses:

H13a : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' gender (particularly female corporate employees) indirectly affects their performance expectancy, which in turn affects their behavioral intention.

H13b : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' gender (particularly female corporate employees) indirectly affects their effort expectancy, which in turn affects their behavioral intention.

H13c : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' gender (particularly female corporate employees) indirectly affects the social influence, which in turn affects their behavioral intention.

H14a : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' age indirectly affects their performance expectancy, which in turn affects their behavioral intention.

H14b : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' age indirectly affects their effort expectancy, which in turn affects their behavioral intention.

H14c : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' age indirectly affects the social influence, which in turn affects their behavioral intention.

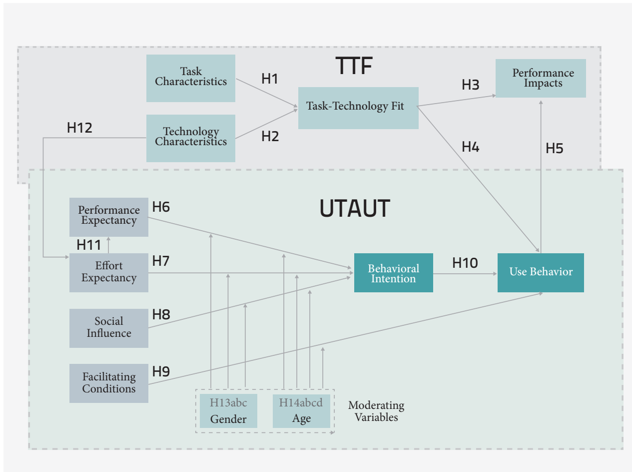
H14d : In the context of mobile cloud computing applications in LCD panel and component manufacturing, the employees' age indirectly affects the facilitating conditions, which in turn ffect their use behavior.

3. Methodology

3.1 Instrument

For our research purpose, this study integrated TTF and UTAUT to build a research model that includes ten constructs and two moderator variables (Figure 3). Table 1 lists the operational definition and measurement items of all the variables. All items were measured with a five-point Likert scale. In the questionnaire, we asked for the respondents' demographic information, such as gender, age, education, department in the case company, job title, years of work experience, and years of using mobile cloud computing systems. We used both online and paper questionnaires to gather data and then utilized SPSS 17.0 and AMOS 20.0 to conduct structural equation modeling to verify this new research model.

A pilot for the questionnaire was conducted, and a total of 33 valid pilot questionnaires were collected. Four experts were invited to establish the content validity of the instrument. They modified items A1, A2, B2-B5, B7-B9, B10-B11, B13-B15, D3, and I1 to make the item read more smoothly and easier to understand. Then, reliability analysis was carried out using Cronbach's α reliability coefficient, item-to-total correlation, and "alpha if item deleted" (Nunnally & Bernstein, 1994). To confirm the construct validity of the scale, after the item analysis was completed, exploratory factor analysis was performed as a verification step, using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1974), and Bartlett's test of sphericity and other methods to evaluate the results. The principal axis factoring method was used for factor analysis; factor loading was determined based on the recommendations of DeVellis (2012), and community was judged based on the recommendations of Hair, et al. (2010). As a result, the α coefficient after deleting item B1 was 0.727, greater than the original scale α coefficient (0.633). Besides, the community and factor loading of this item were both lower than the standard (<0.5 and <0.7, respectively), so it was deleted from the scale. For B7, B13, D1, E2, F1, G3, H2, and J3, the α coefficient after removing the items was greater than the original scale α coefficient, but the reliability coefficients of these items were all greater than 0.7, and the sample size of the pilot analysis was not quite representative of the population, thus, these items were temporarily retained. Although the KMO values of G1-G3 (<0.6) were lower than the standard, the community and factor loading were both higher than the standard, and the pilot sample size cannot represent the population, so these were also temporarily retained. There were 44 items in the entire questionnaire, and it was expected that at least 220 valid questionnaires would be collected (Hair et al., 2010).



[Figure 3] Research Model

3.2 Mobile cloud computing applications in the case company

The current study's respondents were the employees at all levels in a corporate enterprise. The company uses four types of platforms: the Citrix Xen app, the Microsoft Remote app, Microsoft Exchange, and

[Table 1] The operational definition and measurement items of all constructs

Constructs	The operational definition and measurement items
Task characteristics	The characteristics of the tasks that employees are responsible for, namely, immediacy, repetitiveness, and unfixed work locations (Goodhue & Thompson, 1995).
	A1. I often need to monitor in real-time the tasks that I am responsible for. A2. I often need to manage in real-time the tasks that I am responsible for. A3. Processing the tasks that I am responsible for requires repetitive procedures. A4. The tasks that I am responsible for remain mostly static. A5. The tasks that I am responsible for do not occur in a fixed location but require that I move around.
Technology characteristics	In the context of LCD panel and component manufacturing, when employees use mobile cloud computing to carry out their tasks, the five main technology characteristics of mobile computing are portability (B2-B3), network connection, low power (B4-B6), platform independent (B7-B9), and integrated environments (B10-B12) (Kulkarni et al., 2014, p.565).
	B1. I think that mobile cloud computing devices, such as tablets and phones, can be carried around easily (Note: This item was removed after the pilot analysis.). B2. I think that the mobile cloud computing devices provided by the company, such as tablets or cell phones, can be used easily when I'm on the move. B3. I think that the portability of the mobile cloud computing devices provided by the company, such as tablets or cell phones, do not interfere with my completing the tasks at work. B4. I think that the mobile cloud computing provided by the company has high network-connection speed. B5. I think that the mobile cloud computing provided by the company offers a convenient way of connecting to the network (such as WiFi or 3G). B6. In the area that I am in charge of, the signal strength of the network connection is enough to let me use my company's mobile cloud computing application system. B7. I think that the battery life of the mobile cloud computing devices provided by the company, such as tablets or cell phones, should match what the tasks require. B8. I think that the battery life of the mobile cloud computing devices provided by the company, such as tablets or cell phones, are more energy-saving than other information technology equipment (e.g., laptops, desktop computers, etc.). B9. I think that the battery life of the mobile cloud computing devices provided by the company, such as tablets or cell phones, can help the company lower its energy consumption. B10. I think the mobile cloud computing provided by the company can be easily installed with popular cell phone operating systems, such as Android and IOS. B11. I think the mobile cloud computing provided by the company is convenient because it can be used with popular cell phone operating systems. B12. I think the mobile cloud computing provided by the company can be easily executed with popular cell phone operating systems. B13. I think the mobile cloud computing provided by the company is convenient because it can be used in combination with peripheral information technology equipment (e.g., scanners, printers, etc.). B14. I think the mobile cloud computing provided by the company can be easily used in combination with peripheral information technology equipment (e.g., scanners, printers, etc.). B15. I think the mobile cloud computing provided by the company can be efficiently combined with peripheral information technology equipment (e.g., scanners, printers, etc.).
Task-technology fit	The degree of fit when applying mobile cloud computing to the tasks (Goodhue & Thompson, 1995; Zhou et al., 2010)
	C1. Mobile cloud computing provides me with the information I need for work. C2. Mobile cloud computing provides me with real-time information I need for work. C3. Mobile cloud computing is beneficial to the execution of my tasks.

Constructs	The operational definition and measurement items
Performance impact (user satisfaction)	The relationship between the LCD panel and component manufacturing employees' performance impact (user satisfaction) and their use behavior and the task-technology fit (Au et al., 2002; Brown et al., 2008).
D1. I am satisfied with using mobile cloud computing for my tasks. D2. I am satisfied with the results that mobile cloud computing has given me. D3. I am satisfied with how using mobile cloud computing has affected my job performance.	
Performance expectancy	The LCD panel and component manufacturing employees' perception of the degree to which applying mobile cloud computing may increase their operational efficiency (Venkatesh et al., 2003; Zhou et al., 2010)
E1. I think mobile cloud computing can increase work efficiency. E2. I think mobile cloud computing can reduce workload. E3. I think mobile cloud computing can increase the task processing speed.	
Effort expectancy	The LCD panel and component manufacturing employees' perception of the amount of effort required to use the mobile cloud computing systems (Venkatesh et al., 2003; Zhou et al., 2010)
F1. I am proficient at using mobile cloud computing. F2. I can quickly learn how to use mobile cloud computing. F3. I can easily learn how to use mobile cloud computing.	
Social influence	The degree to which the LCD panel and component manufacturing employees' perceptions of applying the mobile cloud computing systems are influenced by their co-workers and supervisors (Venkatesh et al., 2003; Zhou et al., 2010)
G1. My colleagues think that I should apply mobile cloud computing to my work. G2. My supervisor thinks that I should apply mobile cloud computing to my work. G3. My company encourages employees to apply mobile cloud computing to their work.	
Facilitating conditions	The degree to which the LCD panel and component manufacturing employees' perceptions of applying the mobile cloud computing systems are influenced by their co-workers and supervisors (Venkatesh et al., 2003; Zhou et al., 2010)
H1. I think I know what resources are needed to apply mobile cloud computing to my work. H2. I think I have the necessary knowledge for applying mobile cloud computing to my work. H3. There is dedicated staff in the company that can help me when I have trouble applying mobile cloud computing to my work. H4. There is a dedicated department in the company that can help me when I have trouble applying mobile cloud computing to my work.	
Behavioral intention	The LCD panel and component manufacturing employees' intention to apply mobile cloud computing to their work (Ajzen & Fishbein, 1980; Venkatesh et al., 2003)
I1. I will continue to use mobile cloud computing. I2. I may continue to use mobile cloud computing in the future. I3. I plan to continue to use mobile cloud computing.	
Use behavior	The frequency and experience of the LCD panel and component manufacturing employees' use o mobile cloud computing for work (Oliveira et al., 2014; Tai & Ku, 2014)
J1. I have positive experiences with applying mobile cloud computing to my work. J2. I often apply mobile cloud computing to my work. J3. I think that it is beneficial to apply mobile cloud computing to one's work.	

others (38 different services). The Citrix Xen app and Microsoft Remote app share similar functionalities. They can provide mobile cloud computing services by establishing a connection through the mobile cloud computing application platform without making any changes to any of the systems or web services provided by the company. Users can connect to the system services required by the cloud computing application platform's web pages or application software. In addition, the Citrix Xen app provides application software that supports various mobile devices, which is easier to use than the Microsoft Remote app. The setup cost is relatively high, so it is mainly used by the executives and business departments higher than the manufacturing level. The Microsoft Remote app is mainly used by the officials above the division level and personnel with relevant business needs. Microsoft Exchange is the mail server, which provides functions such as sending and receiving mail messages, online contact lists, and calendars. Users can connect and use Microsoft Exchange through the browser of the mobile device or the mail application software. Mobile cloud services provided are Outlook Web App and Exchange ActiveSync. The Outlook Web App service can be connected and used with a browser on any mobile device. The service is provided for all corporate members. Exchange ActiveSync is an application program and mail server accessed through the mobile device. It is more complete and more convenient than Outlook Web App and mainly provides officials above the department level and personnel with relevant business needs.

Finally, the other mobile cloud computing application systems were developed by the company based on its internal operating requirements. For example, the "WHMS" warehouse management system is a mobile cloud computing application system combined with a wireless scanner device. It was developed mainly for inventory operations and can be integrated with other peripheral devices (such as printers) through a wireless network to produce paper-based outputs. This service is mainly provided for the warehouse team. Other mobile cloud computing applications and the teams they provide service for are not listed here.

3.3 Research scope

The scope of this research is limited to the LCD panel and component manufacturing industry. The case company specializes in the production of color filters. It is one of the 500 largest manufacturing companies in Taiwan and has nearly 1,000 employees. It has already adopted mobile cloud computing, and the employees are already using this technology in their work. Therefore, the sample of this study is limited to the data of the company's employees who use mobile cloud computing applications. This will help to understand the impact of the company's adoption of mobile cloud computing, the key factors for such adoption, and their impact on the operational efficiency of the staff.

4. Results

In this study, 239 valid responses were returned (a response rate of 74.22%). The demographic of all valid responses is listed in Table 2. One-way ANOVA was first used to analyze the within-group and between-group variances. The homogeneity of gender, age, work experience, and other variables was confirmed. Next, the Games-Howell test was used to verify that there were no significant differences between the following variables: education (behavioral intention), department (effort expectancy), job title (task characteristics, technology characteristics, task-technology fit, user satisfaction, performance expectancy), experience in using mobile cloud computing (performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, use behavior), frequency of using mobile cloud computing system (effort expectancy, social influence, facilitating conditions, use behavior). In the end, the homogeneity of these variables was confirmed.

Subsequently, this study used Harman's one-factor test of common method variance. Also, following the suggestion of Podsakoff and Organ (1986), principal factor analysis was conducted for all 44 items across the constructs. Eleven factors were extracted that had a characteristic value of >1. The cumulative variance explained was 72.242%, with the first factor accounting for 31.494% of the variance (<50%). It was concluded that common method variance was not a significant problem in the current study.

The results of the descriptive statistical analysis are shown in Table 3. As for the results of the reliability analysis, first, we determined the critical ratio between the high-scoring group (top 27% of the total score) and the low-scoring group (bottom 27% of the total

[Table 2] Demographics of all valid responses (N=239)

Demographic	Group	Number	Percentage
Gender	Male	164	68.62%
	Female	75	31.38%
Age	21 and below	50	20.92%
	31~40	161	67.30%
	41 or above	28	11.72%
Education	High school	17	7.11%
	Associate degree	31	12.97%
	College	136	56.90%
	Graduate school	55	23.01%
Department	Biotechnology manufacturing	133	55.65%
	Management-related	78	32.64%
	Information-related	28	11.72%
Job title	On-site personnel	79	33.05%
	Engineer	94	39.33%
	Manager	38	15.90%
	Supervisor	28	11.72%

Demographic	Group	Number	Percentage
Work experience	Less than 1 year	19	7.95%
	1 to 3 years	45	18.83%
	4 to 6 years	67	28.03%
	7 to 9 years	47	19.67%
	10 years or more	61	25.52%
Year of using mobile cloud computing systems	1 year or less	86	36.00%
	2 to 3 years	99	41.49%
	4 to 5 years	37	15.50%
	6 years or more	17	7.10%
Frequency of using mobile cloud computing systems	Every day, each time taking > 1 hour	98	41.00%
	Every day, each time taking < 1 hour	65	27.20%
	Not every day, but more than 5 times a week	30	12.55%
	Seldom, no more than 5 times a week	46	19.25%

score) for each of the 44 items in the measurement scale. Performing the t-test on the critical ratio showed that all t-values were greater than 3, ranging from 8.85 to 23.45, indicating that all items have good discrimination. Secondly, the item-total correlation values were at least 0.3, ranging from 0.3 to 0.78. This means that the internal homogeneity of the items in the questionnaire was adequate. The Cronbach's α reliability value of each construct was also greater than 0.7, ranging from 0.71 to 0.83, indicating that the various constructs being studied have a certain degree of stability and consistency. Judging from the three reliability analyses and measurement standards, we conclude that the questionnaire in this research has good credibility (Table 3).

Before conducting a path analysis for the overall model, it was necessary to effectively measure the latent variables to correctly estimate the path coefficients in the overall model. A confirmatory factor analysis was performed to confirm whether the questionnaire data can measure the latent variables and verify the appropriateness of the various constructs and items of this research. As for the model's basic appropriateness, item removal based on the modification index (MI) can help achieve the highest explanatory power and improve the model's goodness of fit. The maximum MI value and the absolute value of the maximum "par change" value should be used when modifying the model. In addition, according to Hair et al. (2010), before evaluating the model's goodness of fit, it is necessary to check whether there is any offending estimate and check that the error variance is not a negative value, and the standardized coefficient is not greater than 0.95. In this study, A3-A5, B4, B7, B10, B13, C1, D1, E1, F1, G1, H1, H4, I1, J1 were deleted from the questionnaire. The final 28 measurement items in the research model all had a positive error variance, and the factor loadings were between 0.679 and 0.931. Hence, there was no violation of statistical assumptions.

The main indicators for the overall model fit are absolute fit measures, incremental fit measures, and parsimonious fit measures (Hair et al., 2010). The results of the overall fit of the model in this study yielded the following absolute fitness indexes: RMSEA = 0.079, RMR = 0.036, GFI = 0.8, and AGFI = 0.757, all of which met the standards. Then, the incremental fit measures yielded NFI = 0.800 and CFI = 0.869. Finally, the parsimonious fit measures yielded PNFI = 0.583 and PCFI = 0.576. Although not all indexes exceeded the ideal values, the overall model was still deemed as acceptable.

Construct validity is divided into convergent validity and discriminant validity. The results of the analysis of convergence validity showed that the average variance extracted (AVE) for the constructs ranged from 0.529 to 0.788. All AVE values were >0.5. Next, factor loading of the questionnaire items showed that, except for item E2, which had a value of 0.679, all other items' factor loadings were greater than 0.7. As a factor loading of 0.6 or above is considered acceptable by Hair et al. (2010), the factor loading of the items was regarded as meeting the criterion. Finally, the composite reliability values of all the constructs ranged from 0.6913 to 0.9627, which were all greater than 0.6, indicating that this model has convergent validity. The other validity, discriminant validity, measures whether there is a degree of differentiation between the items under different variables. According to Hair et al. (2012), the square root of the AVE of each construct should be greater than its correlation coefficient with all other constructs to be considered as having sufficient discriminant validity. Such was the case

[Table 3] Descriptive statistical analysis results of all valid responses (N=239)

Item	Mean	Standard deviation	Factor loading
A1	4.12	0.75	0.756
A2	3.98	0.67	0.882
A3	3.96	0.78	-
A4	3.78	0.91	-
A5	3.60	1.07	-
Overall A	**3.89**	**0.58**	
B2	3.64	0.96	0.851
B3	3.86	0.80	0.764
B4	3.58	0.91	-
B5	3.44	0.96	0.792
B6	3.38	1.08	0.87
B7	3.49	0.88	-
B8	3.57	0.85	0.823
B9	3.49	0.85	0.786
B10	3.72	0.83	-
B11	3.73	0.91	0.824
B12	3.67	0.87	0.923
B13	3.71	0.88	-
B14	3.44	0.92	0.931
B15	3.47	0.88	0.912
Overall B	**3.59**	**0.14**	
C1	3.54	0.915	-
C2	3.86	0.790	0.857
C3	3.99	0.756	0.818
Overall C	**3.80**	**0.67**	
D1	3.94	0.70	-
D2	3.66	0.71	0.891
D3	3.67	0.76	0.848
Overall D	**3.76**	**0.63**	
E1	3.72	0.65	-
E2	4.02	0.60	0.679
E3	3.91	0.72	0.773
Overall E	**3.88**	**0.53**	
F1	3.92	0.77	-
F2	3.63	0.84	0.923
F3	3.74	0.77	0.851
Overall F	**3.76**	**0.65**	
G1	3.58	0.784	-
G2	3.55	0.665	0.793
G3	3.58	0.734	0.72
Overall G	**3.57**	**0.60**	
H1	3.58	0.789	-
H2	3.58	0.773	0.821
H3	3.35	0.861	0.849
H4	3.77	0.795	-
Overall H	**3.57**	**0.62**	
I1	3.87	0.668	-
I2	3.97	0.604	0.86
I3	3.97	0.597	0.819
Overall I	**3.94**	**0.51**	
J1	3.93	0.65	-
J2	4.01	0.58	0.757
J3	3.85	0.65	0.743
Overall J	**3.93**	**0.54**	

for all the constructs in this study. It was therefore concluded that this model has adequate discriminant validity (Table 4). Once the research model was confirmed as having a good fit, path coefficient testing, moderating variable analysis, and path effect analysis were conducted using the statistical software AMOS to observe the causal relationships between the variables and the latent variables. Table 5 and Figure 4 present the path coefficients and the results of hypothesis testing.

Additionally, moderating variable analysis was performed to verify whether gender and age have an impact on each construct. Gender was divided into two groups, male and female. Each group's parameters were set in AMOS, and the hypotheses were specified in Manage Models for the analysis (A1 = A2; B1 = B2; C1 = C2). Age was also divided into two groups: 30 years old and under, and over 30 years old. Similarly, each group's parameters were set in AMOS, and the hypotheses were specified in Manage Models for the analysis (A1 = A2; B1 = B2; C1 = C2; D1 = D2). The overall analysis results are shown in Table 6. As shown in Figure 5, the female group's explanatory power (R^2 =0.704) is greater than that of the male group (R^2 =0.374). Figure 6 shows that the younger age group had an explanatory power of behavioral intention (R^2 = 0.853) that was greater than that of the older group (R^2 =0.414). Besides, the explanatory power of the older group for use behavior was as high as R^2 =0.801.

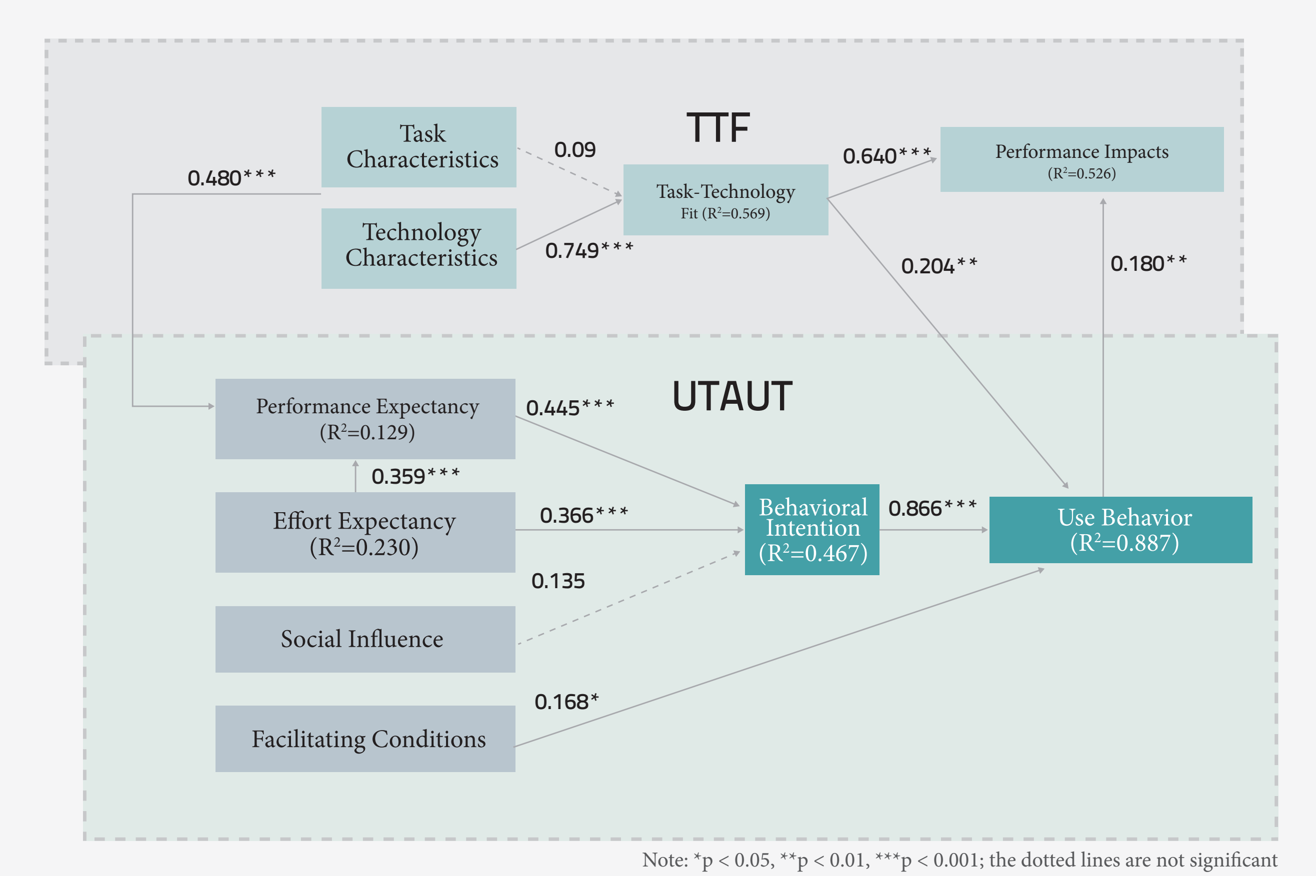
[Table 4] Results of correlation coefficient analysis results and discriminant validity

Constructs	AVE	C.R.	Technology characteristics	Facilitating conditions	Social influence	Task characteristics	Effort expectancy	Performance expectancy	Behavioral intention	Task-technology fit	Use behavior	User satisfaction
Technology characteristics	0.722	0.963	**0.850**									
Facilitating conditions	0.697	0.822	0.172	**0.835**								
Social influences	0.574	0.729	0.217	0.587	**0.758**							
Task characteristics	0.675	0.805	0.042	0.596	0.582	**0.822**						
Effort expectancy	0.788	0.881	0.247	0.326	0.465	0.378	**0.888**					
Performance expectancy	0.529	0.691	0.212	0.393	0.324	0.388	0.264	**0.727**				
Behavioral intention	0.705	0.827	0.189	0.198	0.233	0.281	0.308	0.403	**0.840**			
Task-technology fit	0.702	0.825	0.196	0.397	0.298	0.323	0.300	0.568	0.291	**0.838**		
Use behavior	0.563	0.720	0.204	0.296	0.320	0.295	0.465	0.463	0.328	0.293	**0.750**	
User satisfaction	0.757	0.861	0.250	0.457	0.400	0.451	0.439	0.506	0.371	0.413	0.731	**0.870**

[Table 5] Path coefficients of the structural equation model and the corresponding research hypotheses

Hypotheses	Latent variable	Estimated unstandardized weighted regression coefficient	Standardized weighted regression coefficient (path coefficient)	S.E.	C.R. (t-value)	Sig.	Supported
H1	Task characteristics → Task-technology fit	0.107	0.090	0.076	1.402	0.161	No
H2	Technology characteristics → Task-technology fit	0.860	0.749	0.109	7.906	***	Yes
H3	Task-technology fit → Performance impact (user satisfaction)	0.593	0.640	0.078	7.638	***	Yes
H4	Task-technology fit → Use behavior	0.126	0.204	0.040	3.171	0.002	Yes
H5	Use behavior → Performance impact (user satisfaction)	0.270	0.180	0.101	2.684	0.007	Yes
H6	Performance expectancy → Behavioral intention	0.405	0.445	0.086	4.697	***	Yes
H7	Effort expectancy → Behavioral intention	0.239	0.366	0.049	4.858	***	Yes
H8	Social influences → Behavioral intention	0.130	0.135	0.083	1.568	0.117	No
H9	Facilitating conditions → Use behavior	0.110	0.168	0.044	2.488	0.013	Yes
H10	Behavioral intention → Use behavior	0.707	0.866	0.068	10.348	***	Yes
H11	Effort expectancy → Performance expectancy	0.258	0.359	0.061	4.242	***	Yes
H12	Technology characteristics → Effort expectancy	0.636	0.480	0.106	5.998	***	Yes

Note : N = 239 *p < 0.05 **p < 0.01 ***p < 0.001



[Figure 4] Path coefficient diagram of the structural equation model

5. Discussions and conclusions

The current study developed a conceptual framework by integrating the TTF theory and the revised version of the UTAUT. Using this framework as the theoretical foundation, the study explored mobile cloud computing application systems' effect on user performance impact, as well as the key factors that affect such systems' adoption.

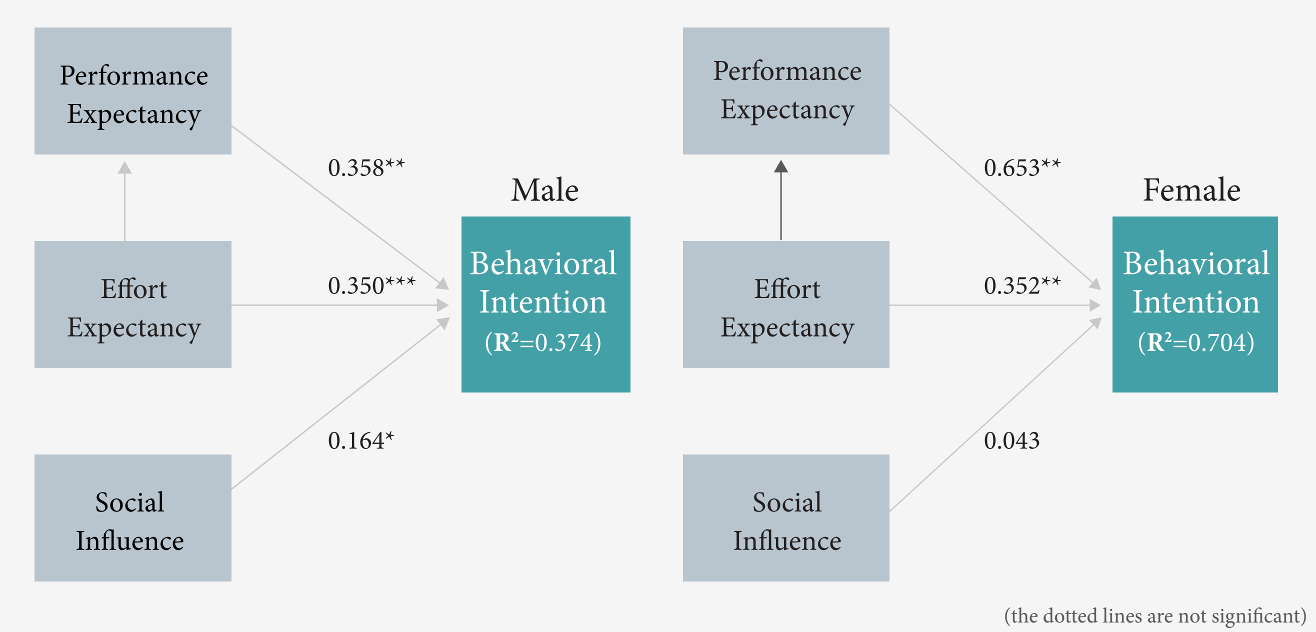
5.1 Academic implications

First, we used the TTF model proposed by Goodhue & Thompson (1995) to explore the impact of the fit between the user's tasks and mobile cloud computing application system on their work performance. The analysis results showed that task-technology fit has a significant positive effect on performance impact ($\beta = 0.640$, $p < 0.001$), which verifies the argument of Zhou et al. (2010) that when the cognitive fit reaches a certain threshold, specific auxiliary systems or tools can be used to help process tasks more efficiently. Dishaw & Strong (1999) have also pointed out that the abilities of information technology users also affect how well the tasks are supported by the technology. If information technology can positively support the task, users will have a positive perception of the technology,

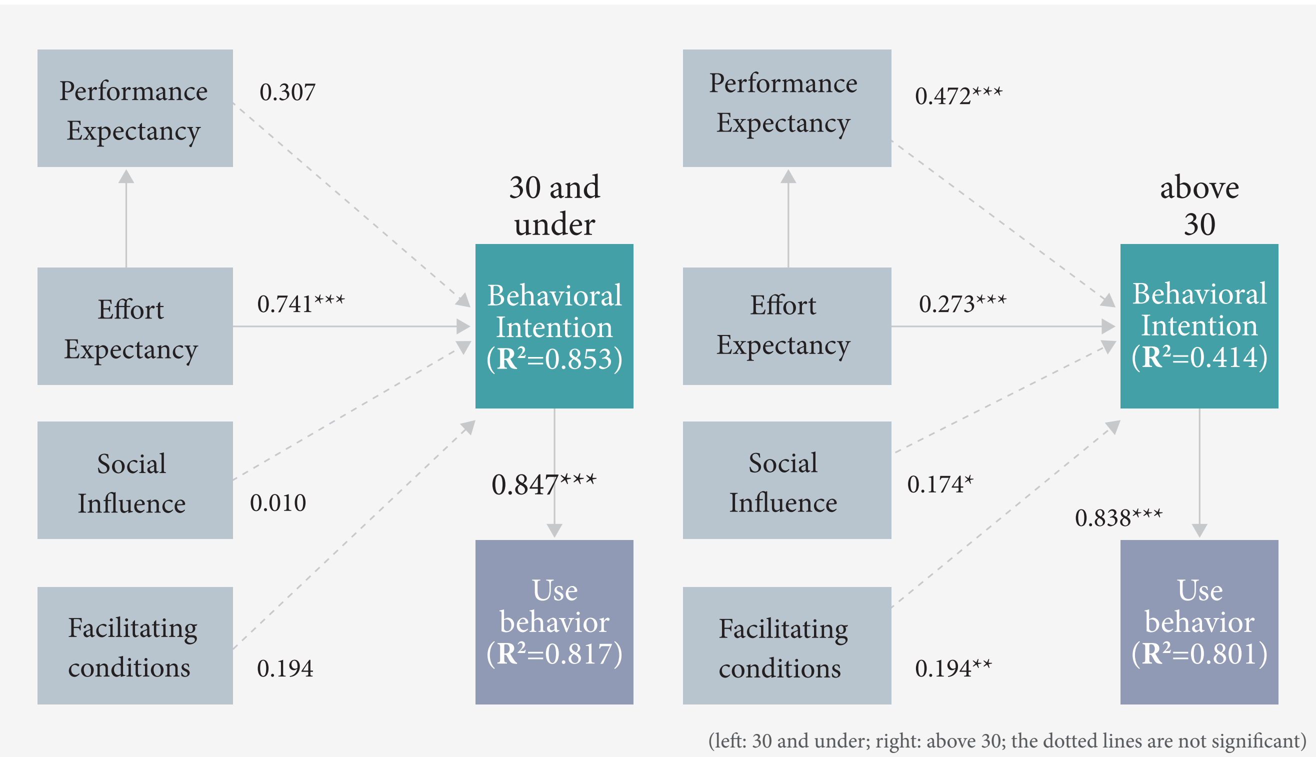
[Table 6] The effect analysis of the adjustment variables of the structural equation model and the corresponding research hypotheses

Hypotheses	Latent variable	Gender / Age	Estimated unstandardized weighted regression coefficient	Standardized weighted regression coefficient (path coefficient)	S.E.	C.R. (t-value)	Sig.	Supported
H13a	Performance expectancy → Behavioral intention	Male	0.325	0.358	0.099	3.273	0.683	No
		Female	0.598	0.749	0.153	3.911		
H13b	Effort expectancy → Behavioral intention	Male	0.244	0.35	0.062	3.906	0.226	No
		Female	0.204	0.352	0.067	3.049		
H13c	Social influences → Behavioral intention	Male	0.201	0.164	0.097	2.061	0.122	No
		Female	0.008	0.043	0.116	0.065		
H14a	Performance expectancy → Behavioral intention	<= 30	0.246	0.307	0.132	1.861	0.019	Yes
		> 30	0.429	0.472	0.097	7.349		
H14b	Effort expectancy → Behavioral intention	<= 30	0.451	0.741	0.116	3.900	0.192	No
		> 30	0.178	0.273	0.051	0.2475		
H14c	Social influences → Behavioral intention	<= 30	0.002	0.010	0.122	0.014	0.352	No
		> 30	0.178	0.174	0.089	2.035		
H14d	Facilitating conditions → Use behavior	<= 30	0.111	0.194	0.059	1.885	0.024	No
		> 30	0.124	0.194	0.048	2.606		

Note 1: GMale: N = 164; Female: N = 75
Note 2: 30 and under : N = 50; Above 30 : N = 189
Note 3: *p < 0.05 **p < 0.01 *** p < 0.001



[Figure 5] The analysis results of the effects of gender as a moderating variable



[Figure 6] The analysis results of the effects of age as a moderating variable and they will become accustomed to using it. Therefore, it was not surprising that this study also found that task-technological fit had a significant and positive impact on use behavior ($\beta = 0.204$, $p < 0.01$), which is consistent with what scholars have concluded (Dishaw & Strong, 1999). Some scholars have pointed out that because mobile cloud computing is not limited by time or space constraints and can connect to the company's information service system to exchange data, it effectively increases operational efficiency and a company's competitive edge (Banerjee et al., 2013; Bauer, 2018). Due to mobile cloud computing's diverse and flexible operation modes, it has been widely adopted by enterprises (Guerrero-Contreras et al., 2016; Kulkarni et al., 2014; Stieglitz & Brockmann, 2012; Yuan et al., 2010). The current study found from the path analysis that technology characteristics significantly affected task-technology fit directly and significantly affected performance impact indirectly. These findings indicate that the diversity and flexibility of mobile cloud technology can indeed increase the task-technology fit when applied to workplace operations. The increased fit then improves operational efficiency. This finding also agrees with the literature. Thus, it can be concluded that the task-technology fit model is appropriate for analyzing enterprise mobile cloud computing applications.

This study also used the UTAUT to explore the user's behavioral intention and use behavior of mobile cloud computing application systems and explored their effect on performance impact. Venkatesh et al. (2003) have stated that behavioral intention is affected by performance expectancy, effort expectancy, and social influence, and it affects the use behavior of new technologies. From the results, we can conclude that the behavioral intention to use the technology has a significant impact on use behavior ($\beta = 0.866$, $p < 0.001$). Unlike social influence, performance expectancy ($\beta = 0.445$, $p < 0.001$) and effort expectancy ($\beta = 0.366$, $p < 0.001$) did have a significant impact on behavioral intention. The reason for the insignificant impact of the social influence dimension is due to the research object being a corporate company, where all employees were required to implement the company's new policies, regardless of individual users' willingness. While this conjecture should be further observed and verified, on the whole, it agrees with the arguments that Venkatesh et al. (2003) have made. Zhou et al. (2010) have defined perceived behavioral control as the ability to control one's behavior and is affected by one's capabilities and external resources. Similarly, the results showed that the facilitating conditions ($\beta = 0.168$, $p < 0.05$) have a significant impact on use behavior, which is consistent with the arguments of some scholars (Lai & Lai, 2014; Lee et al., 2007). The model that combines task-technology fit UTAUT also verifies that behavioral intention, facilitating conditions, and task-technology fit all have a significant impact on use behavior, which is also in line with the findings of Oliveira et al. (2014).

Regarding the moderating variables, the study found that age affected only performance expectancy and did not significantly affect effort expectancy, social influence, or facilitating conditions. The research participants were mainly in two age groups, with 88.1% of the participants falling in either the 21-30 years old group (20.8%) or the 31-40 years old group (67.3%). Since the respondents' ages had a small range, this variable's effect on the various dimensions was not discernable. The other moderating variable, gender, had a similar issue. Women accounted for 31.38% (75 people) of the participants. Of these, only 9.3% (7 people) were on-site personnel. The vast majority of the female employees were not on-site personnel, and they mainly used mobile cloud computing application systems such as Microsoft Remote App to connect to the system service. The only notable difference was the connection login method; once the system connection was complete, the mode of operation was no different from working on a PC. Thus, due to the limitations of the respondents' characteristics, the moderating variables' effects on the dimensions of performance expectancy, effort expectancy, and social influence were consequently not significant.

The above analyses lead to the conclusion that our model, which integrates the TTF and the UTAUT, can be used to research mobile cloud computing applications as an effective analytical framework for the impact of enterprises' adoption of mobile cloud computing application systems.

5.2 Practical implications

The study indicated that performance impact was affected more by task-technology fit than by use behavior in a practical situation. This was probably because the respondents were all employees in the same company. Therefore, when the enterprise requires the use of the new information technology system to complete the work tasks, all employees had to follow the policy. Thus, the impact of use behavior was limited. Additionally, when the new technology is adopted and meets the needs of the tasks that it is supposed to support, it increases the operational efficiency (Bauer, 2018; Guerrero-Contreras et al., 2019). Therefore, the task-technology fit has more influence in the workplace than the other factors do. The technology characteristics' effects on task-technology fit were found to be significant, but the task characteristics were not. This is probably because when the enterprise was visited for the study, it was still in the early phase of adopting cloud computing application systems and not in a mature phase. The tasks were therefore still not fully in line with the needs of the users (employees). Technology characteristics had a significant impact on effort expectancy, while effort expectancy had a significant impact on performance expectancy and behavioral intention. In practice, when users are aware that mobile cloud computing is simple and easy to use and when they are willing to learn, they will also be looking forward to this new information technology as a means to increase productivity. On the questionnaire, the overall average score of performance expectancy was higher than that of the performance impact. Respondents indicated that they had high expectations that mobile cloud computing would increase operational efficiency, which in turn increased their willingness to learn and use it at work to make their company more competitive.

The study also found that facilitating conditions allowed users to be willing to continue using mobile cloud computing. With sufficient resources, knowledge, and assistance, users can be encouraged to continue to use it. It was found that performance expectancy was positively related to the 31-and-above group and that people in this age group were more willing to use mobile cloud computing. The 30-and-below group accounted for about 79% of respondents. This indicates that the employee age is significant when the age is above 30, meaning that this factor can strengthen awareness of performance expectancy and effectively enhance the behavioral intention for the majority of the company employees in this age group.

The above analyses demonstrate that the integration of TTF and UTAUT is effective in studying cloud computing applications and in implementing such applications in enterprises.

Drawing from the results, it can be concluded that mobile cloud computing applications indeed have a positive effect on operational efficiency. Consequently, the following suggestions are made based on the key influencing factors for companies that plan to adopt the technology in the future:

① **Focus on communication and interaction with the users before adopting the systems (improving the impact of task characteristics on task-technology fit)**

Before introducing a mobile cloud computing application system, it is necessary to communicate with the users and evaluate their current operations to find a method that is acceptable to the user to ensure that the system is feasible. Afterward, a small-scale test is recommended. Once the test results meet the basic requirements of the operation and can effectively improve the efficiency, the system can then be formally introduced and deployed. After the adoption, the user's work situations should be tracked, and improvements can be made accordingly until the system can meet the operational needs of most users and can effectively increase the operational efficiency, that is, until it reaches the system maturity period.

② **Improve the hardware environment (strengthening the technology characteristics of mobile cloud computing)**

As stated in the results section, technology characteristics have the greatest impact on operational efficiency. Therefore, it is recommended that the technology characteristics of mobile cloud computing application systems be first enhanced before the system enters the maturity period. Doing so can maximize the increase in operational efficiency. One example is connectivity. The coverage of the company's internal wireless network should be enhanced so that users will not find themselves unable to use mobile cloud computing systems due to signal problems at certain work locations. Other examples are portability and integrated environments. For the case company in this study, it used to be necessary to go to the existing factory to take the inventory manually and record the numbers on paper, and then use a personal computer to enter the data into the inventory system, then print out the reports. The process was complex and the data might be incorrect due to paperwork errors. The company has since adopted mobile cloud computing. In the early stage of development, a tablet computer combined with a wireless scanner was used for inventory operations. The inventory was uploaded to the cloud. However, printing still had to be done from a personal computer. In a single inventory operation, two mobile devices had to be carried and used at the same time. Therefore, although the operation efficiency was improved, it was still inconvenient. At present, the technology characteristics of mobile cloud computing have been improved in both portability and integrated environments. It now takes just one wireless scanner to complete the inventory and printing operations, which greatly improves operational efficiency. The single-person inventory operation has proven to be problem-free. For the company, this means that it can effectively reduce the number of people needed.

③ **Improve users' awareness**

As seen from the results related to performance expectancy and facilitating conditions, strengthening these two factors can effectively improve performance impact. Therefore, seminars, training, and consulting services can be held to provide users with information, resource, and assistance to use the mobile cloud computing application systems. At the same time, strengthen the users' understanding of how mobile cloud computing applications can improve operational efficiency. This will enhance users' willingness to use the new system and their attitude toward use behavior, which will increase the company's tangible benefits and its competitive edge.

5.3 Limitations and future research

The results can be used as a reference for enterprises before adopting mobile computing applications in the future. However, two limitations should be considered when referring to this study's results. The first is the data collection source. This study only sampled the employees in the case company to collect the data on mobile cloud computing application systems. However, as the number of companies using mobile cloud computing application systems is gradually increasing, the results may lack broader meaning due to this limited research sample. It is suggested that follow-up research can enlarge the sample in the same industry to enhance the objectivity of the current findings. Future studies can also research different types of industries to explore whether their users have different perceptions of mobile cloud computing application systems. The second limitation is the data collection methods. The sample of data in this research was investigated through questionnaires, which is a quantitative research method. It is recommended that future studies employ qualitative research methods instead and use in-depth interviews to discuss the users' feelings about mobile cloud computing application systems so that the data is more complete and can reach into the core of the issue.

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