

Assessing the Effectiveness of Smartphone Usage to Interact with Learning Materials in Independent Learning Outside of Classrooms among Undergraduate Students

Sununthar Vongjaturapat^{a,*}, Nopporn Chotikakamthorn^b, Panitnat Yimyam^c

^a Lecturer, Faculty of Humanities, Ramkhamkaeng University, Thailand

^b Associate Professor, Faculty of Information Technology, King Mongkut's Institute of Technology Ladkrabang, Thailand

^c Lecturer, Faculty of Sciences and Social Sciences Burapha University, Sakaeo Campus Sakaeo, Thailand

ABSTRACT

Clearly, the smartphone is increasingly playing a greater role in everyday life, thus providing opportunities to evaluate how well the use of the smartphone meets the requirements of undergraduate students in independent learning outside of a classroom setting. This study used the task-technology fit (TTF) model to explore the effectiveness of smartphone usage to interact with learning materials in independent learning outside of classrooms, the need for smartphone support, and the fit of devices to tasks as well as performance. First, the study used interviews, observation, and survey data to identify what are the most important constructs of smartphones that stimulate students to interact with learning materials in independent learning outside of classrooms. Based on the findings from the exploratory study and Task Technology Fit theory, we postulated the Navigation design, Ergonomic design, Content support, and Capacity as the essential dimension of the smartphone construct. Then, we proposed a research model and empirically tested hypotheses with the structural model analysis. The results reveal a significant positive impact of task and technology on TTF for smartphone usage to interact with learning materials in independent learning outside of classrooms; it also confirmed the TTF and performance have a direct effect on actual use.

Keywords: IT adoption, Mobile technology, Task Technology Fit model, Educational aide, Technology Acceptance, Information and Communication Technologies

I . Introduction

In the era of constantly changing and developing

technology, smartphones are increasingly playing a greater role in everyday life (e.g., Gartner, 2019). Smartphones provide a potential support for users

*Corresponding Author. E-mail: sununthar.v@ru.ac.th

to gain knowledge such as learning tools both inside and outside the classroom (e.g., Scotte et al., 2016). However, the Education Centre for Applied Research findings suggest only 20% of respondents reported that instructors asked them to use their smartphones in-class (Gierdowski, 2019). 70% of nearly 44,000 students reported that instructors banned or discouraged the use of smartphones in the classroom (Brooks and Pomerantz, 2017). This means that the use of smartphones in classrooms still has several issues that can complicate this integration of smartphones in classrooms. For example, interferences such as distraction and reduction in quality of face-to-face interaction (e.g., Anshari et al, 2017; Gierdowski, 2019).

In contrast, independent learning outside of classrooms, students acquiring knowledge in isolation and student interaction with IT without stimulation from the lecturer, the more students could learn on their own. They can interact with IT for long periods of time to gain knowledge and enjoy self-improvement (Sung et al., 2016). Related to this, previous research results show that students mainly perform their independent learning through user interface of a mobile device, namely, iPads, tablets and notebooks, or even stationary-based systems for greater convenience (e.g., Meyer, 2016). However, there are research results which indicate that students still believe in the benefits of smartphone technology such as education apps and access to educational materials (e.g., O'Connor and Andrews, 2018). Although iPad/tablet and smartphones have some resemblance (e.g., handheld touchscreen), they are used somewhat differently and have slightly different interaction-design constraints (Budiu, 2016). For example, using drop down boxes and pickers: both pickers and dropdowns have the disadvantage that they use only a small fragment of the screen on a tablet. The situation

is somewhat better on a smartphone, but even their dropdowns do not cover the full screen. As a result, a long list in a dropdown will require a lot of scrolling. Thus, they utilize dropdown boxes and pickers only when there are limited options available (4-6), or even in some cases, typing would have been faster (Budiu and Nielsen, 2016). This slightly different interaction-design constraint may lead to the promotion or obstruction of the flexibility in usage of smartphones in independent learning outside of classrooms such as multiple-choice online practice exercises, or even reservation or booking courses. What appeals to one user may be exactly what disappoints another. It just means that smartphone usage is more attuned to the contextual information needs that users tend to have during independent learning outside of classrooms. Moreover, smartphones tend to be the preferred platform for users aged between 18 and 34 but for those older or younger than that market sector the tablet is the dominant platform (Interaction design foundation, 2020). While smartphone ownership has been consistently high and nearly every student uses one, tablet use increased slightly or remained stable (Gierdowski, 2019). Thus, this means that the smartphone still has an opportunity increase usage to support a student in independent learning which is conducive to agile tasks such as easy information access (Brooks and Pomerantz, 2017). This is especially so with the COVID-19 pandemic situation, the school learning was conducted online in most countries around the world, including Thailand. Whilst Thailand did not mandate complete learning online, it is increasingly providing a potential support for students to use as an independent learning tool outside the classroom (Scotte et al., 2016). So, smartphones allow users to learn on the go, as they are more mobile than tablets and more likely to be used in a wide variety of locations and scenarios

(Interaction design foundation, 2020).

We know from previous research results that three-factors improved self-regulation of smartphone: avoiding distractions while studying (focus), mindful phone use, and the knowledge of the phone (Hartley et al., 2020). Tao et al. (2018) explained that smartphone use has significant positive effects on self-directed learning and individual impact. Their results suggested that education institutes rationally use technical resources like a smartphone to improve the effect and efficiency of student learning and take effective measures to prevent addiction to digital devices. However, one commonly cited problem with smartphone usage for learning is whenever a smartphone was used to complete an assessment, or even take online home exams, students performed differently than students on a regular computer (Huff, 2015). Students remain reluctant to take quizzes and exams on smartphones because they are concerned about losing access during their task (Liederman, 2019). Thus, while students are using their own devices for educational purposes now more than ever (Lieberman, 2019), it is still unclear exactly how well the fit between independent learning outside of the classroom and smartphone supported learning, and if so which components of smartphones could be more suitable for supporting interaction with learning material in independent learning outside of the classroom (Lieberman, 2019).

Moreover, the sample of the adoption of smartphones for learning is different from adoption of other technologies namely laptops, notebooks, and PCs. The advantage of a smartphone is usage in an environment not conducive to a keyboard and mouse such as lying in bed, standing, or handling with a single hand. This difference indicates the simple usage which makes a smartphone useful for any time and place for learning (Hamidi and Chavoshi,

2018). For example, a touch environment makes navigation easier than the conventional use of a keyboard, mouse or touchpad in certain contexts such as image manipulation, musical, or mouse-oriented infotainment games. Digital painting and image editing are more precise and intuitive than painting or sketching with a mouse. The ability for easier faster entry of data such as diagrams, equations, notations, and symbols. Moreover, some users find it more direct and pleasant to use a stylus, pen or finger to point and tap on objects, rather than use a mouse or touchpad, which are not directly connected to the pointer on the screen (Roebuck, 2013). Therefore, a smartphone has significant implications for education, should be identified as a critical tool and receive deliberate attention from researchers. This research focuses on assessing the effectiveness of smartphone usage to interact with learning materials, especially in independent learning outside of classrooms setting that may a good solution for undergraduate students who own a smartphone.

To support students in developing their own learning goals and helping students become self-motivated and take charge of their independent learning, we need a greater effort to fully understand the nature of the students' task and a smartphone's suitability to enhance independent learning outside of classrooms among undergraduate students. The following questions are important: What are the essential factors of smartphones that promote their use to interact with learning materials in independent learning outside of classrooms? What are the student's perspectives and the technical perspectives integrated in the process of using a smartphone to interact with learning materials in independent learning outside of classrooms? The extant research has tried to explain the importance of the fit between the smartphone characteristics and independent learning

task requirement as well as to help developers to find usability problems and produce better solutions for independent learning activities. The results of this study would help identify the essential factors of smartphones for evaluating improvements in the implementation of mobile learning in independent learning outside of classrooms and optimizing independent learning outside of classrooms for smartphones. This paper contributes in designing guidelines for the recent adoption of the smartphone function that enhance independent learning outside of classrooms among undergraduate students. The proper use of the smartphone may enrich students to have a responsibility and involvement in their learning and manage their own motivation towards learning. Moreover, the observed participant independent learning task should enhance the development and evaluation of future systems.

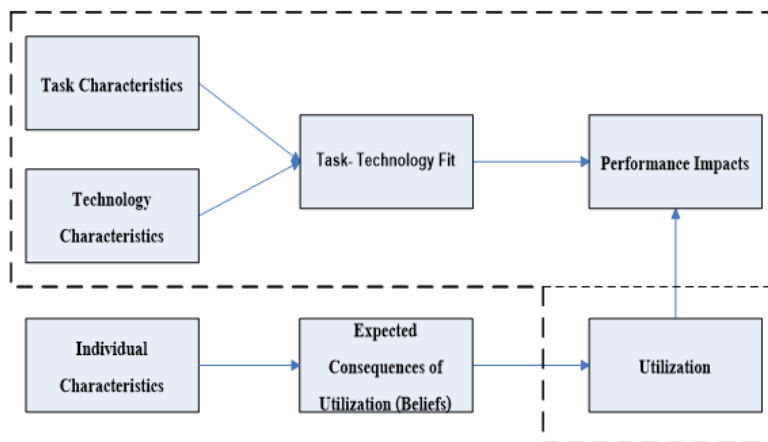
II. Theoretical Background

2.1. Task-technology Fit Theory

We found the conceptual basis of the Task-Technology Fit (TTF) model (Goodhue, 1995; Goodhue and Thompson, 1995). Task characteristics refer to operations performed by users to change the input to output. Technology characteristics are defined as the tools used by users in the execution of their tasks, and the TTF is the level to which a technology can assist users in accomplishing their tasks. The relationship in the model is defined such that the task characteristics (TA) and technology characteristics (TECH) impose the task technology fit (TTF), which result in the adoption and use of the new technology (Goodhue 1995; Goodhue and Thompson 1995). The TTF enables the investigation

of issues of fit of technology to tasks as well as performance (e.g., Lu and Yang, 2014). The TTF can provide guidance for the design of a task or technology (Ambra et al., 2013).

Although the TTF has not been as well developed as the TAM, it has been gradually applied to explore user adoption in various new technology. For example, MOOCs feature, Wu and Chen (2017) found TTF relationship can inform the associations between perceived ease of use, task-technology fit, reputation, social recognition, and social influence that are found to play important roles in predicting continuance intention. The TTF model has also been used to explain user adoption of online learning, the TTF model demonstrated that TTF presents positive influence performance (Isaac et al., 2019). Park et al. (2019) applied the TTF model to the use of multimedia technology for online and blended learning; they found multimedia technology positively affects the adoption of multimedia technology for learning. Moreover, the idea of task-technology fit is an important user evaluation factor in forecasting the utilization of a technology (Yen et al., 2010). Nevertheless, the technology-to-performance chain considered in Goodhue and Thompson (1995) encloses task, technology, and individual characteristics, but only the first two constructs are discussed and assessed in their research. Their findings showed that individual characteristics indicated a vague effect on the TTF. Moreover, from Goodhue's research results (1995), only subsets of the model: TA, TECH, TTF, performance impact, and utilization were empirically tested (see <Figure 1>). As discussed above, this means that individual characteristics have a small role in forecasting the TTF (Goodhue, 1995). Thus, this factor was removed in this study.



<Figure 1> The Technology-to-performance Chain (TTF Model)

2.2. Adoption of smartphone in Education

There is the research regarding smartphone use in clinical nursing education. For example, O'Connor and Andrews (2018), Sun et al. (2018) indicated that educational apps such as medical dictionaries were used. They appraised benefits of mobile technology such as access to educational materials and reducing their anxiety around learning in practice. Alsayed et al. (2019) concluded that undergraduate nursing students rely heavily on their smartphones for acquiring information and communication. They bear tendency of smartphones appear to be potential recipients for active learning techniques that may fit their educational needs. Willemse et al. (2019) explored the experiences of undergraduate nursing students who participated in an authentic mobile learning enactment. The results showed the themes which provide valuable insights into students' experiences of the authentic mobile learning enactment, such as mobile devices afforded a learning platform. Furthermore, Sung et al. (2016) analyses the effects of mobile-integrated education. In their analysis report, it indicates that the smartphone is widely used, and that students and their teachers have their own

smartphones. From the focus group discussion, Anshari et al. (2017), the study revealed the pros and cons, such as portability, comprehensive learning experiences, whereas interferences included distraction and reduction in quality of face-to-face interactions. Green (2019) indicated that when instructors failed to make course content relatable, understandable, or engaging, the students turned to their smartphones as sources of distraction. This result encouraged instructors to view the teaching methods and the course environments, rather than universal indications of students' distraction or disinterest. Moreover, several studies on integrating smartphones with learning have focused on the application of smartphones to enable students to expand learning (Sung et al., 2016). For example, mobile computing can facilitate conventional lecture-style teaching, information gathering and sharing, and exploratory learning outside the classroom (e.g., Sung et al., 2016). Moreover, Kossey et al. (2015) indicating that camera phones are also used for learning activities such as read QR codes for scanning and downloading additional supplementary learning or reference materials.

In the case of the use of mobile devices, mainly

derived from the physical limitation imposed by the device itself. It is related to the use of mobile devices, where the interactions are necessary to visualize learning materials, students must navigate between different screens to display all related information (Molina et al., 2014), or zoom into more clearly visualize the content (Sanchez and Goolsbee, 2010). In sum, the literature review reveals a smartphone's suitability to enhance learning activity that the lecturer uses to stimulate motivation, and students use the smartphone to participate learning process. However, there are still several issues that can complicate this integration of smartphones in education (e.g., Gierdowski, 2019). Thus, this research focusing on assessing the effectiveness of smartphone usage to interact with learning materials, especially in independent learning outside of classrooms setting that may have different reasons from previous research results and maybe a good solution for undergraduate students owned smartphones with successful independent study.

2.3. Smartphone Technology

The main capabilities of smartphones are voice-centric technology designed to provide voice functions and data content that connects wireless networks on the internet or send and receive SMS or MMS, e-mail, and so on (Ketola and Roykkee, 2001). However, currently, mobile technology is constantly evolving. Many functions that appear in each type of mobile device are similar or can be replaced. For example, Apple has embedded small electronic devices of cellular telephones and MP (Media Player) into iPhones, so customers can listen to music, play videos as well as connect to the internet, and so on. If we analyze and distinguish all characteristics of mobile technology, then we see that there are differences among mobile technology:

First, while tablet-screen sizes are commonly cited as tablets being less mobile than a smartphone and too big to be user friendly in all spaces and immediacy (Interaction design foundation, 2020), smartphones are available at all times (and connected at all times), and smartphones tend to be used for almost anything (Budi and Nielsen, 2016). This difference may greatly affect the immediate access of the interaction with relevant learning material requests over online activity (Liederman, 2019).

Second, when compared to the Kindle, although similarly lightweight, the Kindle is suitable as only an e-book reader or audiobooks (Roebuck, 2013). This slight difference indicates the various functions useful of smartphones for independent learning outside of classroom learning are not available on a Kindle. This may lead to the problem of interacting with each different learning material type and need complete independent learning on a smartphone (Roebuck, 2013).

Third, entering data on laptops and notebooks through a keyboard is similar to a personal computer. However, data is entered on a smartphone and tablet with a virtual keyboard (there is a keyboard that appears on the screen, using touch to type). Touch input allows students to emulate the way actual objects behave and navigate easily. Moreover, students can use an accessory such as a stylus, or even voice input. This difference may increase student perception of effortlessness and self-confidence, as well as belief that a touch screen interface is useful in any situation (Hamidi and Chavoski, 2018).

The main objective of this paper is to investigate the essential factors of smartphones that promote their use to interact with learning materials in independent learning outside of classrooms. Obviously, the definition of a modern tablet is a portable personal computer with a touch screen interface, the tablet

form factor is smaller than a notebook computer but larger than a smartphone, and often uses an on-screen virtual keyboard or digital pen rather than a physical keyboard (Roebuck, 2013). Related to the above characteristics of smartphones and tablets, smartphones largely resemble tablets, the only difference being that tablets are larger than smartphones and some versions of iPad/tablet may not support access to a cellular network (Roebuck, 2013). Thus, we adapted from previous research findings to identify the characteristics of smartphones that could also be applied to tablets.

Based on previous findings, the smartphone characteristics user interface can be put into the three user interface types (Heo et al., 2009; Kiljander, 2004). These types are the graphical user interface (GUI), physical user interface (PUI), and logical user interface (LUI). The GUI graphically presents information that users need to execute their task (e.g., font style and icon). The PUI is tangible components supporting the physical body of the smartphone itself (e.g., microphone). The LUI is the layout and information contents for task execution (e.g., navigation structure) (Heo et al., 2009; Kiljander, 2004). We have also explored some recent studies of smartphone technology which indicate that smartphones have various properties of an interface and are parts and beyond of these three interfaces such as “multiple windows” and “adapting vertical and horizontal position” (e.g., Kim et al., 2014; Molina et al., 2014; Park et al., 2019; Shitkova et al., 2015; Sun et al., 2018). These characteristics of smartphones are discussed in short as follows.

(1) Portability is a characteristic attributed to smartphones that can be carried or moved. However, whenever using such smartphones, any event in the outside environment is more likely to interfere with a student’s study and may demand their attention

and require them to reduce their focus on whatever they were concentrating on the screen. Consequently, attention on a smartphone is frequently shattered and sessions are short.

(2) Multiple windows: allow the user to work with multiple apps.

(3) Adjusting font size is making the font size smaller or larger on a smartphone screen. This property gives users the ability to set the font-size or bold text, rather than the images or media.

(4) Touch screen is layered on the top of the smartphone display. A user can use the touch screen to control the information processing system through simple or multi-touch gestures by touching the screen with a special stylus or one or more fingers (Kaur et al., 2019). It is nevertheless easy to accidentally touch the wrong target.

(5) Connectivity technology such as 4G, 5G, and Wi-Fi have automatic connection ability. Whenever the Wi-Fi features are activated, the smartphone will automatically search for a connection to nearby devices. However, clear/strength signal and stability could be the signal fluctuate when users are inside or outside of buildings.

(6) Software features are the tools users use within a system to execute users’ tasks. Smartphones usually come with various features, which may only offer basic customization options.

(7) Screen resolution is the number of pixels, both horizontally and vertically. More importantly, if the pixel density is high, it will help users see the clarity of the text or content displayed on the screen.

(8) Battery life is a measure of battery performance and longevity. It is important to provide several methods that help users to optimize their app’s battery use.

(9) Storage capacity is the amount of stored data that a storage device can hold. Moreover, it also

refers to cloud storage services that encourage the use of smartphone technology offered by a service provider.

(10) Smartphone camera is a camera phones use to capture images. Nowadays, a smartphone equipped with a camera can read QR codes.

(11) Ram and processing power are components for storing program instruction and process via the CPU. However, there are limits to the benefit of adding more RAM. One restriction is physical; smartphones can only hold a certain amount of RAM.

(12) Accessories refer to physical input/output devices that help users to perform many items of work in a system quickly and conveniently if they offer friendly hardware.

(13) Application is a computer program that is executed in the smartphone and facilitates users to create their tasks.

(14) Graphical design is characteristic of the user interface such as theme fonts, font size, icon, color, and style design on the screen. However, these factors can create a requirement of numerous time and attention.

(15) Menu design such as menu structures is the effectiveness in navigating between screens of smartphones that may lead to facilitating the user's experience contextually and in overcoming the limitations of smartphones.

(16) Ability to adapt the vertical and horizontal position of smartphone: Allows users to customize the orientation in any way user like to view and to fit the content.

(17) Weight: Some smartphones are heavier than others, but heavier is not always better. For example, lightweight is better for carrying.

(18) Ability to adjust lighting: staring at a smartphone for a long period of time is terrible to user's eyes as it may hurt their eyes and become strained.

Hence, if a user works in a shiny reflective office, the ability to adjust light can help alleviate the reflectiveness.

According to the above discussion, smartphones have various properties of an interface. Thus, to provide rich insights into smartphone components such as the 'adjusting lights on smartphone 'adjusting vertical and horizontal position' that may influence on the usage of a smartphone to interact with learning materials in independent learning outside of the classroom. It is more useful to understand user's interactions with smartphones if these constructs were classified by using the term "Navigation design (ND)", "Ergonomic design (ED)", "Content support (CS)" and "Capacity (CP)" respectively. Moreover, the four categories described above can help understand the characteristics of smartphones easier, and they could be an instrument for a further experiment (e.g., Park et al., 2019).

III. Research Model and Hypotheses

3.1. Identification of Smartphone Components and Procedure

We initially identified in the literature factors that could affect smartphone usage to interact with learning materials for independent learning outside of classrooms. The elements include variables of e.g., Wainwright (2017), Anshari et al. (2017), Ketola and Roykkee (2001), and Kaur et al. (2019).

Five undergraduate students were employed as interviewers for data collection. The canteen at Burapha University, Sakaeo Campus, Thailand was chosen because it is a convenient site from which to solicit survey participants. The first question was whether they have had experience with smartphone

usage to interact with learning material for independent learning outside of classrooms. Students who answered “yes” were then chosen for a short interview. During the interview, participants were asked to do 4 independent learning tasks using their own smartphone to interact with learning materials. All participants perform independent learning tasks according to their interests. According to observation, overall, the tasks they performed were download, browse, skim, scan as well as reading learning materials, listen to audio lectures (e.g., listening audio for practicing listening and speaking foreign language such as the English language), and watching video lectures, take-note/annotation and highlighting. Later on, participants were asked to answer the open-ended questionnaire. We also asked them further to select the most important construct of the smartphone which stimulated them to use it to interact with learning materials in independent learning outside of classrooms from the given list of variables. This interview took about 30-40 minutes. However, participants in phase 1 were not included in the main survey (phase 2). In total, 282 volunteers were chosen as participants, interviewed, and observed in this way.

Though the benefits of surveys are the better route for collecting more quality data (genuine responses), with the COVID19 pandemic obstructing survey data collection, we decided to conduct both interviews and an online survey by beginning the interviews first, and then the online surveys were done to ensure the robustness of the data coming out of the interviews (Duffy and Smith, 2003). We conducted an online survey to collect valuable insights into the 192 undergraduate students. They allow respondents to partake at their convenience to select and give the reasons or other opinions. By this mixed method, participants feel more comfortable providing open and honest feedback. The descriptive statistics for the primary

important characteristics results were analyzed using SPSS 21.0. <Table 1> compares the frequency distribution of responses for the primary characteristics of the smartphone usage to interact with learning materials in independent learning outside of classrooms and the reason for selecting them as well as any other opinions.

<Table 1> shows the frequency distribution of responses for the primary characteristics included 18 items. As shown, period 1, ram and processing power is highly distinctive. A significant portion of responses indicated that software features can be quite important for smartphone usage to interact with learning materials in independent learning outside of classrooms. For period 2, adapting vertical and horizontal position is highly distinctive. This indicated that students willing to make an effort to turn their phone horizontally and tap to expand to full screen. Moreover, during the interview, some participants expressed their opinion about enjoying writing with a smartphone “I also use note-taking apps that are cross-platform, so my notes get synced across all their devices. I can take notes in a variety of formats like text, image and handwriting.” However, the subjects often commented that “I am concerned with the difference of the quality of service of a mobile network, such as high-speed signals and strong signals.” Interestingly, accessories such as pen stylus and earpiece are some of the critical factors that help determine smartphone usage to interact with learning materials in independent learning outside of classrooms. The possible reason is that students may have happily listened to audio and video lectures on the go, students could review and listen to an interesting learning material multiple times.

According to the observation, online learning, if it is not changing the pedagogical approaches teachers use in the classroom, the method of teaching is likely

<Table 1> The Frequency Distribution of Responses for the Primary Characteristics

Variables	Frequency distribution		Reasons and other opinions
	Interview (Period 1) N = 282	Online survey (Period 2) N = 192	
1. Ram and processing power	54 (No.1)	23	-smartphones' processor and ram has more speed and efficiency.
2. Software feature	48 (No.2)	23	-the tool students use within a system to execute their' tasks offers customization options.
3. Application	40 (No.3)	48 (No.2)	-facilitate users to create their tasks.
4. Connectivity	34	28 (No.3)	-automatically search to connect to nearby devices.
5. Accessories	30	20	-help users to perform many items of work in a system that usually take a long period of time. -provide friendly hardware, -annotation and highlight.
6. Menu design	28	17	-overcoming the limitation of smartphone. -facilitate the user's experience of contextually and switching between page.
7. Adapting vertical and horizontal	25	57 (No.1)	-convenient, -comfortable, -a lot of information could be displayed at the same time.
8. Multiple windows	22	16	-fully find the information with to different apps simultaneously, -easy to work with multiple apps.
9. Smartphone camera	22	18	-capture images, -read QR codes facilitate users to access resource.
10. Adjusting lights	20	20	-alleviate the reflectiveness.
11. Adjusting font size	17	21	-making the font size smaller or larger on a smartphone screen permits users to read easier.
12. Portability	15	28	-carrying or move.
13. Touch screen	15	27	-simple or multi-touch gestures by touching the screen with a special stylus or one or more fingers is easy to use.
14. Graphical design	12	19	-the user interface: theme fonts, font size, icon, color, and style design on screen is understandable.
15. Weight	12	23	-some smartphones are heavier.
16. Battery life	10	0	-longevity, -depends on the app's battery use.
17. Storage capacity	10	4	-the amount of stored data that a device can hold, -cloud storage services.
18. Screen resolution	9	8	-pixel density is high; it will help users see the clarity of content displayed on the screen.

different from independent learning. However, during the COVID-19 pandemic, it has provided a potential for blending both independent learning and on-line learning to be easier than before. Moreover, currently, students are familiar with learning technology and could learn already use it (Lieberman, 2019),

which will provide more exposure time (O'Connor and Andrews, 2018).

As shown in <Table 1>, the result of the exploratory study provides a great indication of the drivers influencing smartphone usage in independent learning outside of classrooms. The probable discrepancy in

the variables stimulated further efforts in the form of confirmatory research. In order to explain the divergence theoretically, we employed the TTF theory pioneered by Goodhue (1995), Goodhue and Thompson (1995) to explain how well the smartphone usage met the requirements of undergraduate students in interacting with learning materials in independent learning outside of classrooms. Thus, verifying their relationship in the overall research model was conducted to further establish the trustworthiness of the research results.

3.2. Modeling TTF of Smartphones Usage to Interact with Learning Materials in Independent Learning Outside of Classrooms and Hypotheses

The research framework in this study has been mainly adopted from the TTF model. Furthermore, several new measuring instruments have been made in the current study and were integrated into the research to develop a new model of smartphone usage to interact with learning materials in independent learning outside of classrooms. These were described as follows - first, we used the literature on the adoption of smartphones in education as well as from volunteer opinions as a guideline for Task (TA) and Actual use (AU) construct. This was described in Section 2.2 and 3.1 as well. Second, smartphone characteristics factors derived from e.g., Wainwright (2017), Anshari et al. (2017), and Kaur et al. (2019) (discussion in Section 3.1).

We formulate the following hypotheses. <Figure 2> shows the model relationships and hypotheses.

In the TTF model, a Task is defined as an operation performed by users to change the input to output (Goodhue, 1995; Goodhue and Thompson, 1995). In an exploratory study, e.g., O'Connor and Andrews

(2018), Sun et al. (2018) were used as a guideline for the interviews. The task was constructed from the volunteer perspective also. Moreover, from previous research results, tasks can vary in many statements, e.g., Goodhue (1995), Goodhue and Thompson (1995), the different dimensions and contexts of tasks were used to measure the task constructs such as routineness. Sung et al. (2016), Alsayed et al. (2019) constructed the task as the activities in which students engage as part of their learning activities, for example, access to educational materials and exploratory learning outside the classroom. Therefore, we hypothesize:

H1: Tasks have a positive impact on TTF in the usage of smartphones to interact with learning materials in independent learning outside of classrooms.

Technology is the tool used by workers in the execution of their tasks (Goodhue, 1995; Goodhue and Thompson, 1995). The TTF model has shown that the technology will be accepted by users only if the capabilities of the technology can accomplish the tasks to be conducted (Goodhue, 1995; Goodhue and Thompson, 1995). For example, although smartphones have many advantages, such as ubiquity and immediacy, if the user does not require performance with their independent learning task through the user interface of the smartphone (if they are mostly performing their independent learning task through the user interface of a stationary-based PC or a tablet for greater convenience), they will select traditional methods rather than new a method. A study from Oliveira et al. (2014) found that technology would affect the TTF when users were attracted to technology on the go, and it provided users a ubiquitous, real-time service with a connection protocol. Moreover, as smartphone ownership has been con-

sistently high and nearly every student uses one; the portability is a premium for the real-time independent learning task session (e.g., Anshari et al., 2017; Gierdowski, 2019). Thus, a possible research hypothesis is as follows.

H2: The technology has a positive impact on TTF in the usage of smartphones to interact with learning materials in independent learning outside of classrooms.

According to the definition of TTF, if the smartphone can support the student's independent learning task, students will realize that the smartphone is productive for performing their independent learning tasks (Goodhue, 1995; Goodhue and Thompson, 1995). Furthermore, the TTF model can be used in the context of considering the effect of IT on personal performance (Fuller and Dennis, 2009). Park et al. (2019), Isaac et al. (2019) found that the TTF would affect a user's performance (PE). Moreover, Ambra et al. (2013) showed that high performance indicates a high level of fit. Thus, only when a student's independent learning task demands increased productivity, the fulfillment of independent learning tasks and comfort, do they realize that the smartphone usage to interact with learning materials in independent learning outside of classrooms enriches their performance. Otherwise, other technologies, such as tablets or notebooks, may also be used. Hence, we hypothesize:

H3: The fit between the smartphone and the task has a positive impact on user performance.

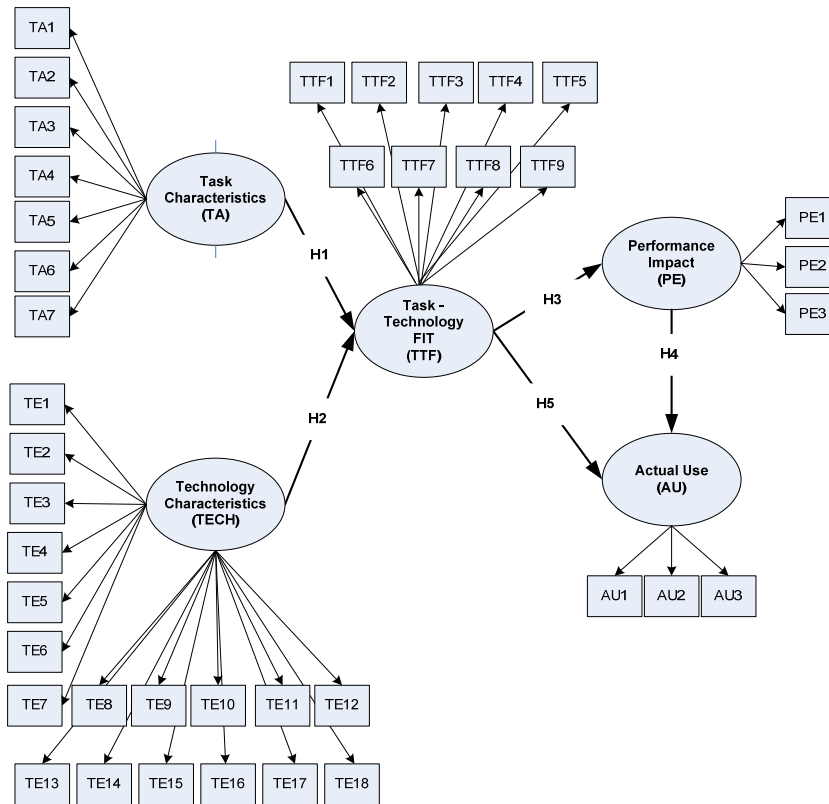
Performance is defined as the level at which individuals believe that using this system will allow them to achieve better performance. It reflects user awareness about performance improvements using

smartphones to interact with learning materials in independent learning outside of classrooms such as accomplishing independent learning tasks more quickly and increasing productivity (Venkatesh et al., 2003). According to the research results of Alasmari and Zhang (2019), if students get the service that best suits their needs and recognize that these services are useful, they will perform the actual use. Hence, we hypothesize:

H4: Performance impact has a positive impact on the actual use of a smartphone to interact with learning materials in independent learning outside of classrooms.

Obviously, a high level of TTF will encourage user adoption of smartphones to interact with learning materials in independent learning outside of classrooms. On the other hand, a low TTF will lead to reducing user's adoption intention (e.g., Goodhue and Thompson, 1995; Zhou et al., 2010). If students use smartphones to interact with learning materials in independent learning outside of classrooms does not meet the students' expectations, the system will not be interesting because students do not benefit from them (Isaac et al., 2019). Previous research also shows the significance of TTF on user adoption. For example, Wu and Chen (2017) indicated that the TTF affects user's utilization of IT. Thus, as discussed in the TTF model, the best TTF will encourage user adoption of smartphones to interact with learning materials in independent learning outside of classrooms (Goodhue and Thompson, 1995; Goodhue et al., 2000). Thus, we postulate.

H5: TTF has a positive impact on AU of the usage of smartphones to interact with learning materials in independent learning outside of classrooms.



<Figure 2> The Research Model Exhibits the Relationship between ○ Constructs and □ Measurements and Path Relationship between Constructs.

As shown in <Figure 2>, the research model is based on the TTF model (Goodhue 1995; Goodhue and Thompson 1995). The structure model is set with two parts. The independent variables include task (TA), and smartphone technology (TECH). The dependent variables include the Task Technology Fit (TTF), performance (PE), and Actual use (AU).

IV. Research Methodology

4.1. Instrument Development

First, we conducted the first survey to develop

the initial component and items for these constructs. An identifying of a smartphone component that may affect user adoption was described in Sec 3.1. Moreover, we used the literature on the adoption of smartphones in education as well as from volunteer opinions as a guideline for Task (TA) and Actual use (AU) construct. Then, based on three expert reviews of all items, we revised some items as their recommendation. Next, we conducted a pilot test before the official commencement of the main survey. For more details of pilot test procedures see section 5.1. Finally, we gathered data and conducted a confirmatory factor analysis (CFA) to refine the items. We also tested the reliability of these constructs.

Following four steps, we achieved new items for task characteristics (TA), smartphone characteristics (TECH), and actual use (AU). These factors are explained further below.

4.2. Procedures and Research Sampling

The data was collected at Burapha University (BUU) Sakaeo Campus, Thailand from undergraduate students. The questionnaire was administered to 343 students. Subjects were chosen randomly around campus, and they were asked whether they had experience with using a smartphone to interact with learning materials in independent learning outside of classrooms. Then, these undergraduate students were asked to fill out questionnaires based on their usage.

4.3. Measurement Methodology

4.3.1. Independent Variables

(1) Task Characteristics (TA)

We adapted from 7 measurement tool of smartphone adoption in education and from the perspective of the primary user's assumption of the independent learning task. These tasks reflect: download learning materials, watch a video lecture, annotate, browsing/skimming/scanning learning materials, read, listen to audio, and highlight learning materials. (e.g., O'Connor and Andrews, 2018; Alsayed et al., 2019).

(2) Smartphone Characteristics (TECH)

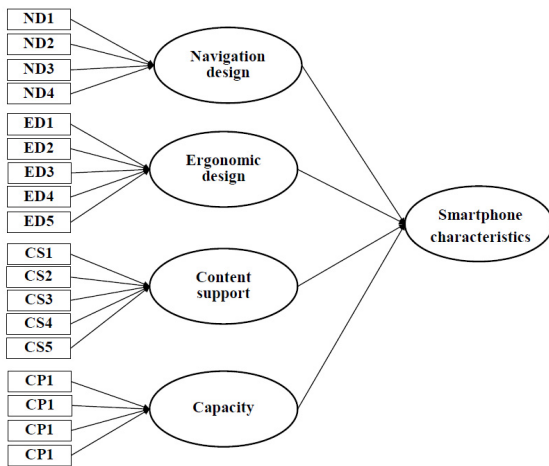
The smartphone characteristics variable represents the multi-dimensional concept of an interface that

<Table 2> Indicator Variables of Smartphone Characteristic

Characteristics of smartphone		Source
1	Portability	Adapted from e.g., Anshari et al. (2017)
2	Adapting vertical and horizontal position	Adapted from e.g., Park et al. (2019)
3	Adjusting font size	Adapted from e.g., Sanchez and Branaghan (2011)
4	Touch screen	Adapted from e.g., Kim et al. (2014)
5	Connectivity	Adapted from e.g., Ketola and Roykkee (2001)
6	Software features	Adapted from e.g., Sun et al. (2018)
7	Screen resolution	Adapted from e.g., Molina et al. (2014)
8	Battery life	Adapted from e.g., Chang et al. (2009)
9	Storage capacity	Adapted from e.g., Budiu (2016)
10	Smartphone camera	Adapted from e.g., Kossey et al. (2015); Wainwright (2017)
11	Ram and processing power	Adapted from e.g., Budiu (2016)
12	Accessories	Adapted from e.g., Kaur et al. (2019)
13	Application	Adapted from e.g., O'Conner and Andrews (2018)
14	Graphical user interface	Adapted from e.g., Wainwright (2017)
15	Menu design	Adapted from e.g., Molina et al. (2014)
16	Multiple windows	Adapted from e.g., Shitkova et al. (2015)
17	Weight	Adapted from e.g., Wainwright (2017)
18	Adjusting lights	Adapted from e.g., Doyle (2001)

is offered through smartphones. The number of indicator variables is in <Table 2>.

To bridge the unitary nature of the smartphone, we decided to employ higher-order factor analyses to explain the causal construct of the impact of the first-order factor. (Hair et al., 2010). We consider the first-order constructs as indicators of the second-order construct. The model depicts a CFA model where a second-order factor, smartphone characteristics, is introduced as the cause of the four first-order factors (Navigation design, Ergonomic design, Content support, and Capacity) each measured by four reflective items. Depicts our proposed extension of smartphone characteristics viewed as a second-order factor by the first-order dimension (<Figure 3>)



<Figure 3> Second-order for Smartphone Characteristics

4.3.2. Dependent Variables

(1) TTF reflects 9 items measuring: getting data accurately and reliably, gathering data, searching across full text, authorization to access data, operate the results, completing independent learning tasks

smoothly, easy to learn how to use a smartphone, performing learning tasks immediately and meeting the learning task requirements (Adapted from Goodhue, 1995; Goodhue and Thompson 1995).

(2) Performance reflects three measures: usefulness, accomplishment, and increase productivity (Adapted from Venkatesh et al., 2003).

(3) Actual Use includes to participate in independent learning activities, to improve IT skills, and to further explore topics. These items were adapted from relevant literature on the adoption of smartphones in education (e.g., Alsayed et al., 2019; O'Connor and Andrews, 2018) as well as the items were customized by volunteers during the interview and using smartphones to interact with learning materials in independent learning outside of the classroom.

The above constructs constituted 40 items of the questionnaires. Each item was measured with a four-point Likert scale, whose answer choices range from 'strongly disagree' to 'strongly agree'. We decided to exclude the midpoint to avoid respondents to choose it as the "dumping ground" answer (Kulas et al., 2008; Worcester and Burn 1975) as well as to avoid reporting what they see as a less socially acceptable answer (John, 2010). Moreover, it has been shown that the issue about both use and non-use of a midpoint is acceptable because the midpoint may not really affect the reliability and validity (Daw, 2001).

V. Research Results

5.1. Questionnaire Test and Procedures

We proceeded with a pilot test with thirty-nine 4th year students to review and purify all items. The

reliability analysis results for the pilot test ($N = 39$) rate between 0.78 and 0.83. These Cronbach's α values are all above 0.7 (Hair et al., 1998; Nunnally, 1978). This suggests that the instruments were reliable. Moreover, test-retest reliability analysis results reveal 0.77** for the total TTF model, where p-values are all smaller than 0.05.

5.2. Main Survey Sampling Source and Data Analysis

A total of 343 surveys were answered. We obtained 328 valid responses. The demographic profile of the respondents is shown in <Table 3>.

<Table 3> Descriptive Statistics Respondents ($n = 328$)

Variables	Classification	Number of samples	Percentage (%)
Gender	Male	163	49.6
	Female	165	50.0
Department	1. Information Technology	39	11.89
	2. Computer of Business	57	17.37
	3. Logistics and Cross Border Trade Management	63	19.20
	4. Human Resource Management	57	17.37
	5. Natural Resource and Environment	42	12.80
	6. General Administration	70	30.48
Experience of using the smartphone	1-5 Years	23	7.01
	6-10 Years	163	49.65
	11-15 Years	142	43.29

<Table 4> Result of KMO and Factor Analysis

Construct	KMO	Eigenvalue	Alpha
Task technology fit (TTF)	0.925	5.364	0.903
Performance (PE)	0.739	2.610	0.869
Actual use (AU)	0.732	2.763	0.859
Task (TA)	0.834	3.931	0.862
Technology (TECH)	0.927		
Navigation design (ND)		2.359	0.875
Ergonomic design (ED)		3.515	0.909
Content Support (CS)		3.392	0.768
Capacity (CP)		2.661	0.794

5.3. Factor Analysis

A) Cronbach's Alpha, the adopted approach of the Task Technology Fit (TTF) model was proposed by Goodhue and Thompson (1995), but since this study used the exploratory factor analysis for smart-phone technology (TECH), task (TA), and actual use (AU). Hence, before testing factor analysis, it was useful to test the reliability of the scale used to insist on its consistent reflection of the scale they were measuring (Field, 2005). <Table 4>, reliability analysis of all factors is acceptable, all above 0.70 (Nunnally, 1978).

B) Kaiser Meyer Olkin (KMO) and Bartlett's Test of Sphericity, these tests are a measure of the appropri-

ateness of the data for running factor analysis, and sampling adequacy for each variable in the model. The KMO statistic varies between 0.5 and 0.7 which are considered middling, while values between 0.8 and 1 indicate the sampling is adequate (Kaiser, 1974). As shown in <Table 4>, the KMO measure of sampling adequacy exceeded the threshold values of 0.5 and significance at 0.05. While Bartlett's test of sphericity can be used to verify the assumption that variances are equal across groups. To ensure the appropriateness of running a factor analysis, Bartlett's test of sphericity is significant (that is $p < 0.05$).

C) Factor Analysis, to accept the results reported above, we were able to conduct with the factor analysis. Kaiser (1960) recommended retaining all constructs with an eigenvalue of data > 1 . <Table 4>, eigenvalues of data exceeded the cutoff values 1.0. This reveals the 40 items were grouped into 8 constructs and selected for the next run of factor analysis (Kaiser, 1960). Besides, an exploratory factor analysis of 40 items with a varimax rotation yielded 8 factors based on an eigenvalue cutoff > 1 . The initial instrument was 18 items for the TECH construct, in which Navigation design (ND) contains 4 items, Ergonomic design (ED) contains 5 items Content support (CS) contains 5 items and Capacity (CP) contains 4 items, Task construct (TA) contains 7 items, Performance construct (PE) contains 3 items, Actual Use (AU) contains 3 items and TTF construct contains 9 items. Moreover, the results of the rotated solution show that all factor loading exceeded $+0.40$, considered significant at 0.05 for a sample size of 200 or greater (<Appendix A>) (Hair et al., 2010). This means that 40 items were loaded to each construct.

5.4. First-order and Second-order Model Test

To detect that smartphone characteristic were introduced as the cause of the four first-order factors: Navigation design (ND), Ergonomic design (ED), Content support (CS), and Capacity (CP) construct were each measured by four reflective items. First-order CFA often tests a second-order factor that comprises two layers of latent constructs. All items are much higher than all cross loadings, which loaded well on their factors (0.71 - 0.85 for ND, 0.61 - 0.85 for ED, 0.64 - 0.83 for CS, and 0.69 - 0.86 for CP) (<Table 5>). We constructed the second - order model to test, using the CFA procedure in LISREL. The results of the second-order analysis show $X^2 = 229.824$, $df = 952$, Root Mean Square Error of Approximation (RMSEA) = 0.075, Comparative Fit Index (CFI) = 0.980, Normed Fit Index (NFI) = 0.967, Non-Normed Fit Index (NNFI) = 0.968, Goodness of Fit Index (GFI) = 0.901, Adjusted Goodness of Fit Index (AGFI) = 0.821. These fit indices were higher than the recommended value. This indicated a good fit between the model and the data (Campbell and Fiske, 1959; Gefen et al., 2000). Standardized factor loadings were 0.747, 0.930, 0.925 and 0.896 respectively (see <Appendix B>). This indicates that four factors were elements of smartphone characteristics.

To detect multicollinearity, the variance inflation factor (VIF) was used as an outcome and presented in <Table 6>. A small VIF value indicates low correlation among variables. If the VIF value is under 4.0, then there is no problem with multicollinearity (Hair et al., 2010). However, it is acceptable if it is less than 10 (Hair et al., 2019).

Moreover, these research results suggest that among the four components, users pay attention to Ergonomic design (ED). The possible reason might be that smartphone is an innovation that attracts them. For example, the design of a smartphone with

<Table 5> First-order and Second-order Model Test for Technology Characteristic: Standardized Item Loading, t -value, and R^2

Factor	Item	Loading (First-order)	t -Value	Loading (Second-order)	R^2
Technology characteristics (TEC)				0.747	0.557
Smartphone characteristic					
– Navigation design (ND)					
1. Graphical user interface	ND1	0.693	10.525		
2. Smartphone camera	ND2	0.621	9.190		
3. Menu structure	ND3	0.747	11.553		
4. Multi windows	ND4	0.825	13.098		
Smartphone characteristic				0.930	0.864
– Ergonomic design (ED)					
1. Portability	ED1	0.768	7.723		
2. Touch screen	ED2	0.609	8.951		
3. Screen resolution.	ED3	0.600	8.790		
4. Accessories	ED4	0.729	10.993		
5. Smartphones weight	ED5	0.914	14.076		
Smartphone characteristic				0.925	0.855
– Content support (CS)					
1. Adapting vertical and horizontal position	CS1	0.694	6.091		
2. Adjusting the font size	CS2	0.545	7.895		
3. Software features	CS3	0.561	8.179		
4. Application	CS4	0.744	11.333		
5. Adjusting lights	CS5	0.914	14.260		
Smartphone characteristic				0.896	0.803
– Capacity (CP)					
1. Connectivity	CP1	0.797	12.778		
2. Battery life	CP2	0.864	14.185		
3. Storage capacity	CP3	0.627	9.457		
4. Ram and processing	CP4	0.625	9.414		

lighter weights, slimmer shape, and multi-touch screen interface (e.g., Kim et al., 2014), this ergonomic design is significant which can be the critical factor that supports ease of use in balance and portability (e.g., Anshari et al., 2017). Thus, user's perceptions of ease of use can be improved. Besides, Content Support (CS) such as "Feature support" and "Adjusting lights on the smartphone" would ensure that users can expand independent learning regardless of the platform (Luo and Li, 2015).

5.5. The Measurement Model

To approve validity at the construct level- convergent validity and discriminate validity were assessed (Campbell and Fiske, 1959). First, we examined the composite reliability (CR), where we evaluated the construct reliability and the internal reliability for each set of measures. As shown in <Table 5>, CR indicated that all constructs exceeded the cutoff value of 0.07 (Bagozzi and Yi, 1988). This shows extensive evidence of the reliability of the data existed.

<Table 6> Variance Inflation Factor (VIF) of the Second-order Factor

Outer VIF Values		Inner VIF Values	
Item	VIF	Constructs	VIF
ND1	2.232	Navigation design	2.257
ND2	2.079		
ND3	2.020		
ND4	3.558		
ED1	1.600	Ergonomic design	7.352
ED2	1.798		
ED3	2.083		
ED4	2.283		
ED5	3.703		
CS1	2.036	Content support	6.896
CS2	2.409		
CS3	1.694		
CS4	2.617		
CS5	3.246		
CP1	3.401	Capacity	5.076
CP2	3.731		
CP3	1.934		
CP4	2.217		

(Park et al., 2019). Then, we examined an average variance extracted (AVE), which compares the amount of variance obtained from indicators with variance due to measurement error (Fornell and Bookstein, 1982). The acceptance value of AVE is 0.5 or higher, which indicated that 50% or more variance of the indicators is accounted for by the construct (Park et al., 2019). <Table 5> shows that AVE by the measurements ranges from 0.500 to 0.699, which met the acceptable value. This testifies to the validity of the instrument for further analysis. In another measurement, we evaluated the convergent validity that shows whether each factor can be reflected by its own item and its associated construct should exceed the error variance (Gefen et al., 2000). To find this condition, a high standardized loading for each factor model should be greater than 0.5 or higher, and ideally 0.7 or higher, t-value exceeds the recommended value of 0.7 and is significant at

0.001 (<Table 7>), all the standardized loading exceeded this recommendation.

The second part of the measurement model was to evaluate the discriminant validity. The discriminant validity is the square root of the AVE for each construct and should exceed the correlation shared between the construct and other constructs in the research model (Fornell and Larcker, 1981). As shown in <Table 8>, all AVEs (the diagonal elements) is greater than the correlations between the latent construct and all other constructs, indicating discriminant validity. Hence, the discriminant validity criterion was also met for the CFA model, providing further confidence in the adequacy of the measurement model. Therefore, the derived CFA model was incorporated into the analysis of a structural equation model (SEM) with latent variables (Boudreau et al., 2001).

<Table 7> Confirmatory Factor Analysis for the Survey Instrument Validity

Factor	Item	Loading	t-Value	AVE	CR
Task Technology Fit (TTF)					
1. I can get data that are accurate and reliable.	TTF1	0.513	6.671	0.500	0.898
2. I can gather data that meets the information need.	TTF2	0.658	10.242		
3. I can search across full text.	TTF3	0.697	11.137		
4. I have the authorization to access data.	TTF4	0.720	11.633		
5. I can operate the result on the smartphone.	TTF5	0.705	11.311		
6. I can use a smartphone to complete interaction with learning materials independent learning outside of classroom smoothly.	TTF6	0.741	12.125		
7. I can easily learn how to use a smartphone to interact with learning materials independent learning outside of classroom.	TTF7	0.750	12.333		
8. I can use a smartphone to interact with learning materials independent learning outside of classroom immediately.	TTF8	0.736	12.006		
9. Overall, smartphone usage to interact with learning materials outside of classroom meets the independent learning task requirement.	TTF9	0.797	13.468		
Performance (PE)					
The usage of smartphones...					
1. is useful to interact with learning materials in independent learning outside of classrooms.	PE1	0.853	15.161	0.699	0.874
2. help me to accomplish an interaction with learning materials in independent learning outside of classrooms more quickly.	PE2	0.841	14.304		
3. increases my productivity of interaction with learning materials in independent learning outside of classrooms.	PE3	0.814	13.635		
Actual use (AU)					
I often use a smartphone to...					
1. participate in the process of interaction with learning materials in independent learning outside of classrooms.	AU1	0.836	14.644	0.680	0.864
2. improve IT skills.	AU2	0.856	14.554		
3. further explore topics relevant learning materials, I am interested in independent learning outside of classrooms.	AU3	0.781	12.765		
Task (TA)					
1. I want to download learning materials.	TA1	0.826	7.550	0.500	0.872
2. I want to watch videos lecture.	TA2	0.732	8.440		
3. I want to annotate regarding the learning materials.	TA3	0.767	11.132		
4. I want to browse, skim and scan relevant learning materials.	TA4	0.673	9.235		
5. I want to read learning materials.	TA5	0.727	10.238		
6. I want to listen to the audio lecture.	TA6	0.624	8.884		
7. I want to highlight a learning material.	TA7	0.560	7.773		
Smartphone characteristic					
- Navigation design (ND)					
The core attraction of smartphone that stimulates you to interact with learning materials in independent learning outside of classrooms is:					
1. Graphical user interface	ND1	0.693	10.525	0.526	0.815
2. Smartphone camera	ND2	0.621	9.190		
3. Menu structure	ND3	0.747	11.553		
4. Multiple windows	ND4	0.825	13.098		

<Table 7> Confirmatory Factor Analysis for the Survey Instrument Validity (Cont.)

Factor	Item	Loading	t-Value	AVE	CR
Smartphone characteristic - Ergonomic design (ED) The core attraction of smartphone that stimulates you to interact with learning materials in independent learning outside of classrooms is:				0.537	0.849
1. Portability	ED1	0.768	7.723		
2. Touch screen	ED2	0.609	8.951		
3. Screen resolution.	ED3	0.600	8.790		
4. Accessories	ED4	0.729	10.993		
5. Smartphones weight	ED5	0.914	14.076		
Smartphone characteristic - Content support (CS) The core attraction of smartphone that stimulates you to interact with learning materials in independent learning outside of classrooms is:				0.500	0.824
1. Adapting vertical and horizontal position	CS1	0.694	6.091		
2. Adjusting the font size	CS2	0.545	7.895		
3. Software features	CS3	0.561	8.179		
4. Application	CS4	0.744	11.333		
5. Adjusting lights	CS5	0.914	14.260		
Smartphone characteristic - Capacity (CP) The core attraction of smartphone that stimulates you to interact with learning materials in independent learning outside of classrooms is:				0.541	0.822
1. Connectivity	CP1	0.797	12.778		
2. Battery life	CP2	0.864	14.185		
3. Storage capacity	CP3	0.627	9.457		
4. Ram and processing	CP4	0.625	9.414		

<Table 8> The Square Root of AVEs and Factor Correlation Coefficients

	TTF	PE	AU	TA	ND	ED	CS	CP
TTF	0.707							
PE	0.393	0.836						
AU	0.360	0.082	0.824					
TA	0.208	0.316	-0.647	0.707				
ND	0.456	0.199	0.019	0.632	0.725			
ED	0.335	0.127	0.300	0.025	-0.339	0.732		
CS	0.313	0.119	0.115	-0.126	-0.495	0.081	0.707	
CP	0.189	0.038	0.080	0.452	0.137	0.130	0.276	0.735

5.6. The Structural Path Model Analysis

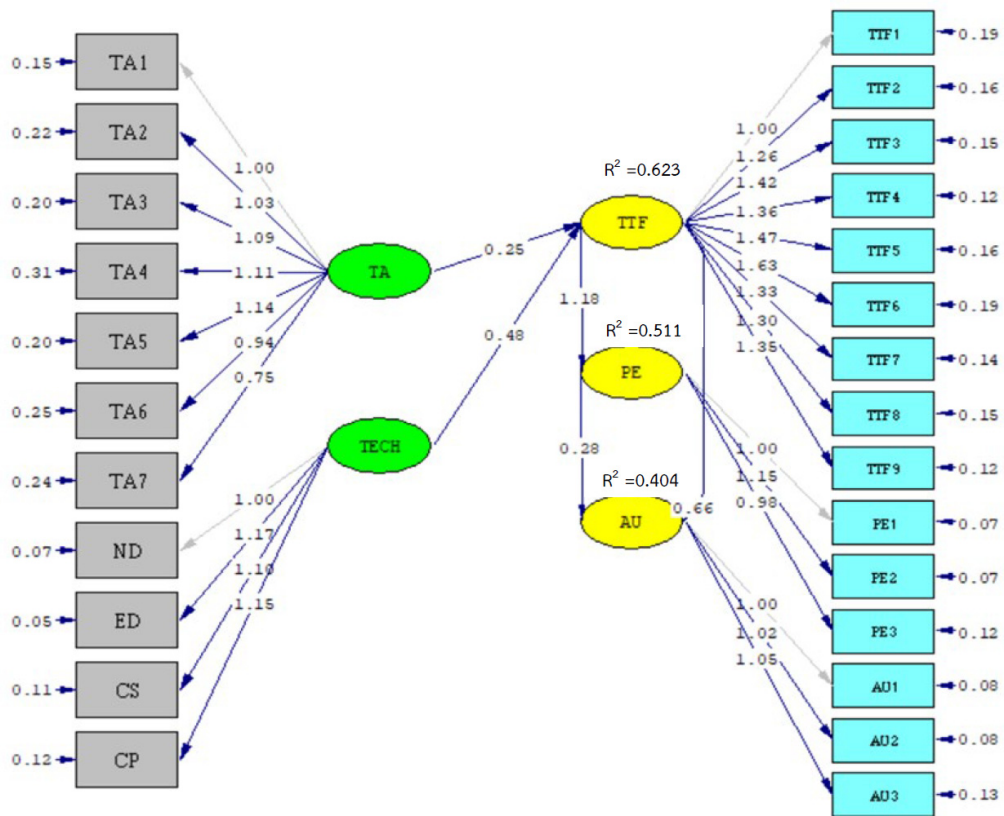
The sample size was 328 respondents, and this

was large for LISRES (Hau et al., 2004). Standardized path coefficients and significant levels were used to assess the research hypothesis (Zhou et al., 2010).

The structural model results are shown in <Figure 4>. As shown in the <Table 9>, except for GFI, the actual values of other fit indices were better than the recommended values. This demonstrated a good fit between the model and the data (Hau et al., 2004; Marsh et al., 2004).

As shown in <Table 10>, the results show that the 5 hypotheses proposed in the model have been supported. Both task characteristics and smartphone characteristics have a significant positive relationship

with the TTF ($\beta = 0.249$, $t = 5.079$ and $\beta = 0.482$, $t = 6.131$, $p < 0.01$ for $TA \rightarrow TTF$ and $TECH \rightarrow TTF$, respectively). Hypotheses H1 and H2 are supported. Both TA and TECH are significant predictors of the TTF. The results also show correlations between TTF constructs and performance impact. The significance of TTF on PE is observed ($\beta = 1.178$, $t = 6.298$, $p < 0.01$). Thus, hypothesis 3 was supported. Performance impact also meaningfully predicts actual use, therefore hypothesis 4 was supported with



<Figure 4> Structural Model Results

<Table 9> The Recommended and Actual Values of Fit Indices

Fit index	χ^2/df	GFI	AGFI	CFI	NFI	NNFI	RMSEA
Recommended value	< 3	> 0.90	> 0.80	> 0.90	> 0.90	> 0.90	< 0.08
Actual value	1.76	0.852	0.809	0.979	0.958	0.974	0.056

<Table 10> Structural Model Results

Path	Hypotheses	β^a	t-Statistics	Result of Hypotheses testing
H1	TA \rightarrow TTF	0.249**	5.079	Supported
H2	TEC \rightarrow TTF	0.482**	6.131	Supported
H3	TTF \rightarrow PE	1.178**	6.298	Supported
H4	PE \rightarrow AU	0.280*	2.506	Supported
H5	TTF \rightarrow AU	0.665**	3.327	Supported

Note: ^a Standardized beta coefficient. * Significant at $p < 0.05$, ** Significant at $p < 0.01$

$\beta = 0.280$, $t = 2.506$, $p < 0.05$, and the TTF meaningfully predicts impacts on actual use, and hence H5 is confirmed with $\beta = 0.665$, $t = 3.327$, $p < 0.01$.

The squared multiple correlations (SMC), which were explained variances (R^2) of task technology fit (TTF), performance expectancy (PE), and actual use (AU) were 0.623, 0.511, and 0.404 respectively. The explanatory power of this research model can be evaluated by the final dependent construct, the actual use (AU), indicated that the research model accounts for 40.1% of the variance in the usage of smartphones to interact with learning materials in independent learning outside of classrooms.

The total effects on actual use were 0.280 for PE, 1.659 for TTF, 0.247 for TA, and 0.480 for TECH (see <Table 11>). The results showed that TECH has the strongest total effect among the exogenous variables on the actual use for accepting smartphones to interact with learning materials through TTF and PE. Thus, the design of smartphone characteristics

is a key determinant in popularizing the smartphone usage to interact with learning materials in independent learning outside of classrooms.

VI. Discussion

The outcome of the study strongly supports hypothesis 1 and hypothesis 2, which indicates that both task characteristics/smartphone characteristics and the TTF are positively associated with each other. In other words, the TTF is in a concordance of technology and tasks in achieving the objective of interaction with learning materials in independent learning outside of classrooms. It provides instant access that improves the delivery of a variety type of learning material to individuals, improving their responsibility and motivation (Oliveira et al., 2014). This provides support for previous research findings (Yen et al., 2010; Zhou et al., 2010). However, technology charac-

<Table 11> Direct, Indirect and Total Effect in Predicting Actual Use

Dependent variable	Actual Use-		
Independent variable	Direct	Indirect	Total
PE	0.280	--	0.280*
TTF	0.665	0.994	1.659**
TA		0.247	0.247**
TECH		0.480	0.480**

teristics have a stronger direct effect on the TTF than task characteristics. One of the reasons is that tasks may be too large and complicated for smartphone technology to provide appropriate support (Goodhue, 1995; Goodhue and Thompson, 1995).

Hypothesis 3 is accepted and supported; The results also show correlations between TTF constructs and performance impact. Zhou et al. (2010) found that Task-Technology Fit can result in performance. If users meet their needs, they will realize that these services are useful and effective.

Hypothesis 4 is supported and accepted; it states that an important way to increase performance is a good Task Technology Fit which further determines actual use. These results correspond to previous findings (e.g., Zhou et al., 2010). One of the possible reasons is the student perception of the accomplishment of the independent learning task, and that smartphones are the preferred method for communication by the lecturer regarding content. Thus, when students realize that their smartphone can improve their independent learning, they will be willing to adopt the smartphone to interact with learning materials for independent learning outside the classroom.

Hypothesis 5 was supported, as forecast, the TTF has a significant direct effect on actual use, which showed that the better fit between task and technology impacted on user adoption. This is consistent with previous research findings (e.g., Yen et al., 2010). One possible reason is that whenever IT provides adequate support, that is fit improves as task requirements increase, as IT functionality increases, fit increases; then students will willing to adopt smartphones to interact with learning materials for independent learning outside the classroom (Goodhue, 1995; Goodhue and Thompson, 1995). Moreover, it was also shown that TTF has an indirect effect on actual use through performance impact. This is

in line with previous studies (Isaac et al., 2019). This finding demonstrates that the more fit between task and technology offers responsiveness, authority to access data, ease to perform independent learning outside of classrooms, the more students are pleased about updated knowledge and increase their productivity by interacting with learning materials in independent learning outside of classrooms. This is because students view smartphones as aligned with their individual needs and lifestyles (Isaac et al., 2019).

Among the exogenous variables, smartphone technology characteristics were determined to be the primary antecedent with the most major effects on the interaction with learning materials for independent learning outside of classrooms among undergraduate students. Although smartphone users ultimately rely on interaction with each of part/components (Park et al., 2019), it has certain quality characteristics that may affect the academic performance of students and their work priorities (O'Connor and Andrews, 2018). This study suggested that ergonomic design, content support, capacity, and navigation design are prominent aspects of smartphones respectively. Thus, on the academic performance of students, especially for independent learning outside of classrooms, developer and institutes/pedagogical universities must be aware of positive evaluations on prominent aspects of smartphones that may be a key aspect for the interaction with learning materials in independent learning outside of classrooms.

VII. Conclusion and Contribution

First, we found that both the task-technology fit (TTF), and performance (PE) have a significant effect on actual use (AU). Moreover, we also found that the TTF has an effect on PE. This indicates that

Task Technology Fit (TTF) deserves further attention. Developers and institutes/pedagogical universities need to improve the task technology fit. For example, lecturers can provide some online independent learning activities such as listen to audio textbooks online as well as some independent learning tools for students to use outside of classrooms, such as self-study audio, workbooks with answer keys. Developers can provide more advanced functions on smartphone app first in order to meet different independent learning task demands so as to improve user acceptance of smartphone usage to interact with learning materials for independent learning outside of classrooms. Thus, the collaboration between developers and the learning project team is important for the deployment and operation of new or extensively revised independent learning activities that correspond to new features in smartphones.

Second, we proposed new measurements that can be used to identify the important factors to promote the smartphone usage to interact with learning materials in independent learning outside of classrooms. For example, adjusting font size helps students to feel most comfortable reading and varied their viewing distances voluntarily. Another example is adapting a smartphone vertically and switch it to the horizontal position. Students naturally adjust their viewing according to different media; with a vertically, students hold the phone vertically, and with a video format students adopted a horizontal position. Moreover, accessories such as pen stylus and earpiece are some of the critical factors that help determine the smartphone usage to interact with learning materials in independent learning outside of classrooms.

Third, by re-specifying the TTF model to the independent learning context, the re-specific model can present an essential function of the smartphone that promotes the use of smartphones to interact

with learning materials in independent learning outside of classrooms. Moreover, we will extend the extant research in the assessment of smartphones by employing higher-order factor analyses for incorporating a wide number of factors that constitute the current context of the usage of smartphones to interact with learning materials in independent learning outside of classrooms. The higher-order helps explain the causal factor that impacts the first-order factor and these 6 relationships with 4 factors loading (Hair et al., 2010). The model describes a CFA model where a second-order factor, Technology Characteristics (TECH), is introduced as the cause of the 4 first-order factors (Ergonomic design, Content support, Capacity, and Navigation design), each measured by 4 reflective items. The correlation between any two measures is highly positive and internal consistency is significant. Therefore, individual measures can be removed to improve construct validity without affecting content validity (Ambra and Wilson, 2013). This demonstrates better than the combined set of first-order constructs (Hair et al., 2010).

VIII. Practical Implications

The research results indicate that among four core smartphone characteristics (Navigation design, Ergonomic design, Content support, and Capacity), Ergonomic design has the strongest effect. This implies that computer hardware engineers, computer science, or electrical engineering should be aware of the practical application of their ideas such as accessories and smartphone weight.

Moreover, although Content support has a lower effect, developers and the learning project team need to reduce students' concerns about owning a smartphone that may not interoperate with other systems.

For example, whenever developers create apps, they should be aware that learning materials are optimized for use on smartphones. One of the most important factors of the IT is the kind of technology with the potential problem of interoperability, namely programming frameworks, application programming interfaces, and data formats. These technology types indicate the means for accomplishing interoperability, and ultimately directly affect the end user. (Gebregiorgis and Altmann, 2015; Haile and Altmann, 2018; Rezaei et al., 2014). Thus, focus on the level of interoperability that relates to platform users is extremely important.

Actual use is the most important for IT adoption research (Ajzen, 1991). Our findings showed that smartphones increase participation in the process of interaction with learning materials in independent learning outside of classrooms, improving information technology skills, and further explore topic relevant learning materials in independent learning outside of classrooms. Thus, developers and academic institutes should take the effective interaction of smartphone functions with the different learning ma-

terials and learning activities into consideration. Providing a specific extension software customized to the individual needs of departments, schools, and colleges are probably required.

IX. Limitation and Future Direction

Even though we included exploratory, quantitative, and qualitative, data collection was only one university that may impact the interpretation of the results. Futures researches should consider the limitation of this study by including using an event sampling, and/or diary methods, to name some possibilities as well as usage logs, which would also enhance the validity of research findings. Moreover, the results did not determine whether there are differences in smartphone adoption in the classroom and outside the classroom and if so, which one is an important factor among undergraduate students? Thus, the research on how different between smartphone adoption for learning in classrooms and outside of classrooms is a salient issue.

<References>

- [1] Ajzen, I. (1991). The theory of planned behaviour. *Organizational behaviour and human. Decision Processes*, 50(2), 179-211.
- [2] Alasmari, T., and Zhang, K. (2019). Mobile learning technology acceptance in Saudi Arabian higher education: An extended framework and a mixed-method study. *Education and Information Technologies*, 24, 2127-2144.
- [3] Alsayed, S., Bano, N., and Alnajjar, H. (2019). Evaluating practice of smartphone use among university students in undergraduate nursing education. *Health Professions Education*, 6(1), 238-246.
- [4] Ambra, J. D., Wilson, C. S., and Akter, S. (2013). Application of the task-technology fit model to structure and evaluate the adoption of E-books by Academics. *Journal of the American Society for Information Science and Technology Archive*, 64(1), 48-64.
- [5] Anshari, M., Almunawar, M. N., Shahrill, M., Wicaksono, D. K., and Huda, M. (2017). Smartphones usage in the classrooms: Learning aid or interference? *Educ. Inf. Technol.*, 22, 3063-3079.
- [6] Bagozzi, R. P., and Yi, Y. (1988). On the evaluation of structural equation model. *Journal of Academy of Marketing Science*, 16(1), 74-94.
- [7] Botella, F., Moreno, J. P., and Penalver, A. (2015). Comparing the efficiency of performing complex tasks with a tablet and a smartphone. *DYNA*, 82(193), 202-211.

- [8] Boudreau, M. C., Gefent, D., and Straub, D. W. (2001). Validation in information system research: A state-of-the art assessment. *MIS Quarterly*, 25(1), 1-16.
- [9] Brooks, D. C., and Pomerantz, J. (2017). *ECAR study of undergraduate students and information technology*. Research Report, Louisville, CO: ECAR.
- [10] Budiu, R. (2016). *Mobile user experience: Limitations and strengths*. Retrieved from <https://www.nngroup.com/articles/mobile-ux>.
- [11] Budiu, R., and Nielsen, J. (2016). *Tablet website and application UX: Design guidelines for improving the usability of websites viewed on tablets and tablet-specific apps*. Retrieved from <http://www.nngroup.com/reports/tablets/>.
- [12] Campbell, D. T., and Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, 56(2), 81-105.
- [13] Chang, Y. F., Chen, C. S., and Zhou, H. (2009). Smartphone for mobile commerce. *Computer Standards and Interfaces*, 3, 740-747.
- [14] Daw, J. (2001). Comparing data gathered using five point vs eleven point scales. *Bridging Marketing Theory and Practice*, 1, 1-8.
- [15] Doyle, S. (2001). *Understanding information and communication technology for AS level*. Nelson Thornor Ltd.: United Kingdom.
- [16] Duffy, B., and Smith, K. (2003). Comparing data from online and face-to-face surveys. *International Journal of Market Research*, 47(6), 615-639.
- [17] Field, A. (2005). *Discovering statistics using SPSS*. California, CA: SAGE Publication.
- [18] Fornell, C., and Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*, 19(4), 440-452.
- [19] Fornell, C., and Larcker, D. F. (1981). Evaluating structural equation models with unobservable and measurement error. *Journal of Marketing Research*, 8(1), 39-50.
- [20] Fuller, R. M., and Dennis, A. R. (2009). Does fit matter? The impact of task-technology fit and appropriation on team performance in repeated tasks. *Journal Information Systems Research Archive*, 20(1), 2-17.
- [21] Gartner Inc. (2019). *Gartner forecasts flat worldwide device shipments until*. Retrieved from <http://www.gartner.com/newsroom/id/3560517>.
- [22] Gebregiorgis, S. A., and Altmann, J. (2015). IT service platforms: Their value creation model and the impact of their level of openness on their adoption. *Comput. Sci.*, 68, 73-187.
- [23] Gefen, D., Straub, D. W., and Boudreau, M. C. (2000). Structural equation modelling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, 4(7), 1-70.
- [24] Gierdowski, D. C. (2019). *ECAR study of undergraduate students and information technology*. Research Report, Louisville, CO: ECAR.
- [25] Goodhue, D. L. (1995). Understanding user evaluations of information system. *Management Science*, 41(2), 827-1844.
- [26] Goodhue, D. L., and Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213-236.
- [27] Goodhue, D. L., Klein, B. D., and March, S. T. (2000). User evaluations of information system as surrogates for objective performance. *Information and Management*, 38(2), 87-101.
- [28] Green, M. (2019). Smartphones, distraction narratives, and flexible pedagogies: Students mobile technology practices in networked writing classroom. *Computers and Composition*, 52, 91-106.
- [29] Haile, H., and Altmann, J. (2018). Evaluating investments in portability and interoperability between software service platforms. *Future Generation Computer Systems*, 78, 224-241.
- [30] Hair, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. (1998). *Multivariate data analysis*. Englewood Cliffs, NJ Prentice Hall.
- [31] Hair Jr, J. F., Anderson, R. E., Tatham, R. L., and Black, W. C. (1995). *Multivariate data analysis* (3rd ed.). New York: Macmillan.

- [32] Hair, J. F., Black, W. C., Babi, B. J., and Anderson, R. E. (2010). *Multivariate data analysis*. Englewood Cliffs, NJ Prentice Hall.
- [33] Hair, J. F., Risher, J. J., Sarstedt, M., and Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.*, 31, 2-24.
- [34] Hamidi, H., and Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics*, 35(4), 1053-1070.
- [35] Hartley, K., Bendixen, L. D., Olafson, L., Gianoutsos, D., and Shreve, E. (2020). Development of the smartphone and learning inventory: Measuring self-regulated use. *Education and Information Technologies*, 25, 4381-4395. doi:10.1007/s10639-020-10179-3.
- [36] Hau, K. T., Wen, Z., and Chen, Z. (2004). *Structural equation model and its applications*. Beijing Educational Science Publishing House.
- [37] Heo, J., Ham, D. H., Park, S., Song, C., and Yoon, W. C. (2009). A framework for evaluating the usability of mobile phones based on multi-level, hierarchical model of usability factors. *Interacting with Computers*, 21(4), 263-275.
- [38] Huff, K. C. (2015). The comparison of mobile devices to computers for web-based assessments. *Computers in Human Behavior*, 49, 208-212.
- [39] Interaction Design Foundation (2020). *What you need to know about smartphones vs. tablet use of the mobile internet*. Retrieved from <https://www.interaction-design.org>.
- [40] Isaac, O., Aldholay, A., Abdullah, Z., and Ramayah, T. (2019). Online learning usage within Yemeni higher education: The role of compatibility and task-technology fit as mediating variables in the IS success model. *Computers and Education*, 136, 113-129.
- [41] Johns, R. (2010). *Likert items and scale*. Retrieved from <https://www.surveynet.ac.uk/sqb/datacollection/likertfactsheet.pdf>.
- [42] Kaiser, H. F. (1960). The application of electronic computer to factor analysis. *Educational and Psychological Measurement*, 20, 141-151.
- [43] Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, 39(1), 31-36.
- [44] Kaur, G., Kaur, L., and Kaur, R. (2019). *Elements and digitization of computer*. Education Publishing, India.
- [45] Ketola, P., and Roykkee, M. (2001). Three facets of usability in mobile handsets, *In Proceeding of CHI 2001 Workshop Mobile Communication: Understanding User Adoption and Design*, Seattle, WA: ACM.
- [46] Kiljander, H. (2004). *Evolution and usability of mobile phone interaction styles*. Unpublished Ph.D. Dissertation, Helsinki University of Technology.
- [47] Kim, J. H., Aulck, L., Bartha, M. C., Harper, C. A., and Johnson, P. W. (2014). Differences in typing forces, muscle activity, comfort, and typing performances among virtual, notebook, and desktop keyboards. *Applied Ergonomics*, 45(6), 1406-1413.
- [48] Kossey, J., Berger, A., and Brown, V. (2015). *Connecting to educational resources online with QR codes*. Retrieved from <https://www.fdla.com/wp-content/uploads/2015/04/connecting-to-educational-resources-online-with-qr-codes.pdf>.
- [49] Kulas, J. T., Stachowski, A. A., and Haynes, B. A. (2008). Middle response functioning Likert-responses to personality items. *Journal of Business and Psychology*, 22(3), 51-259.
- [50] Lieberman, M. (2019). Students are using mobile even if you aren't. *Inside Higher Ed*, Retrieved from <https://www.insidehighered.com/>.
- [51] Lu, H. P., and Yang, Y. W. (2014). Toward an understanding of the behavioral intention to use a social networking site: An extension of task-technology fit to social-technology fit. *Computers in Human Behavior*, 34, 323-332.
- [52] Luo, Y., and Li, M. (2015). The application and research of information technology of cloud computing in colleges and universities. *In International Conference on Materials Engineering and Information Technology Applications (MEITA 2015)*, 1011-1013.
- [53] Marsh, H. W., Wen, Z., and Hau, K. T. (2004).

- Structural equation models of latent interactions: Evaluation of alternative estimation strategies and indicator construction. *Psychological Methods*, 9, 275-300.
- [54] Meyer, B. (2016). Mobile devices and spatial enactments of learning: ipads in lower secondary schools. In *The 12th International Conference on Mobile Learning 2016*, Vila Moura, Algarve, Portugal, 9-11.
- [55] Molina, N. A., Mahan, R. P., and Illingworth, A. J. (2014). Establishing the measurement equivalence of online selection assessments delivered on mobile versus nonmobile devices. *International Journal of Selection and Assessment*, 22(2), 124-138.
- [56] Nunnally, J. C. (1978). *Psychometric theory*. McGraw-Hill, New York.
- [57] O'Connor, S., and Andrews, T. (2018). Smartphones and mobile applications (apps) in clinical nursing education: A student perspective. *Nurse Education Today*, 69, 172-178.
- [58] Oliveira, T., Fariaa, M., Thomas, M. A., and Popovic, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, 34, 689-703.
- [59] Park, C. W., Kim, D., Cho, S., and Han, H. J. (2019). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior*, 92, 288-296.
- [60] Radhakrishna, R., Ewing, J., and Chikthimmah, N. (2012). *TPS (Think, Pair and Share) as an active learning strategy*. NACTA Journal. Retrieved from <https://www.nactateachers.org>
- [61] Rezaei, R., Chiew, T. K., Lee, S. P., and Aliee, Z. S. (2014). Interoperability evaluations model: A systematic review. *Computer in Industry*, 65(10), 1-23.
- [62] Roebuck, K. (2013). *Tablet computer: High-impact emerging technology-What you need to know: Definition, adoption, impact, benefits, maturity, vendors*. San Bernardino: CA.
- [63] Sanchez, C. A., and Branaghan, R. J. (2011). Turning to learn: Screen orientation and reasoning with small devices. *Computer in Human Behavior*, 27, 793-797.
- [64] Sanchez, C. A., and Goolsbee, J. Z. (2010). Character size and reading to remember from small displays. *Computers and Education*, 55(3), 1056-1062.
- [65] Shitkova, M., Holler, J., Heide, T., Clever, N., and Becker, J. (2015). Towards Usability guidelines for mobile websites and applications. In *The 12th International Conference on Wirtschaftsinformatik*, Osnabruck, Germany, 1603-1617.
- [66] Sun, S., Xiong, C., and Chang, V. (2018). Acceptance of information and communication technologies in education: An investigation into university's students intentions to use mobile educational apps. *International Journal of Enterprise Information Systems*, 15(1), 24-44.
- [67] Sung, Y. T., Chang, K. E., and Liu, T. C. (2016). The effects of integrating mobile devices with teaching and learning on students' learning performance: A meta-analysis and research synthesis. *Computers and Education*, 94, 252-275.
- [68] Scott, K. S., Sorokti, K. H., and Merrell, D. M. (2016). Learning 'beyond the classroom' within an enterprise social network system. *The Internet and Higher Education*, 29, 75-90.
- [69] Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 245-478.
- [70] Wainwright, C. (2017). *How to make a QR code in 7 easy steps*. Retrieved from <http://www.blog.hubspot.com/blog/tabid/6307/bid/29449/how-to-create-a-qr-code-in-4-quick-steps.aspx>.
- [71] Willemse, J. J., Jooste, K., and Bozalek, V. (2019). Experiences of undergraduate nursing students on an authentic mobile learning enactment at a higher education institution in South Africa. *Nurse Education Today*, 74, 69-75.
- [72] Wagoner, A., and Myrick, A. (2020). *Best keyboards for android 2020*. Retrieved from <https://www.androidcentral.com/best-keyboard-android>.
- [73] Worcester, R. M., and Burn, T. R. (1975). A statistical

- examination of the relative precision of verbal scales. *Journal of the Market Research Society*, 17(3), 181-197.
- [74] Wu, B., and Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in Human Behavior*, 67, 221-232.
- [75] Yen, D. C., Wu, C. S., Cheng, F. F., and Huang, Y. W. (2010). Determinants of user's intention to adopt Wireless technology: An empirical study by integrating TTF with TAM. *Computer in Human Behavior*, 26, 906-915.
- [76] Tao, Z., Yang, X. Y., Lai, I. K. W., and Yin, K. C. (2018). A research on the effect of smartphone use, student engagement and self-directed learning on individual impact: China empirical study. In *The 3rd International Conference Symposium on Educational Technology*, Osaka, Japan, 1-6.
- [77] Zhou, T., Lu, Y., and Wang, B. (2010). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26(4), 760-767.

<Appendix A> Result of Exploratory Factory and Analysis of Research Model : Cross-loading Matrix

	Component							
	TTF	PE	AU	TA	ND	ED	CS	CP
TTF1	.604	-.004	.229	.077	.218	.143	.027	0.112
TTF2	.739	.041	.141	.185	.199	.177	-.015	0.114
TTF3	.639	.199	.046	.208	.225	.214	.138	0.007
TTF4	.717	.137	.118	.137	.252	.162	.130	0.079
TTF5	.576	.043	.182	.351	.136	.293	.109	-0.031
TTF6	.546	.294	-.032	.241	.061	.303	.224	0.043
TTF7	.624	.300	.094	.108	.082	.247	.104	0.072
TTF8	.598	.261	.101	.166	.001	.194	.269	0.060
TTF9	.676	.294	.170	.189	-.025	.185	.103	0.111
PE1	.336	.623	.328	.125	.153	.242	.087	0.216
PE2	.350	.651	.169	.140	.199	.263	.125	0.176
PE3	.359	.686	.216	.040	.169	.167	.070	0.098
AU1	.245	.216	.736	.212	.147	.101	.161	0.016
AU2	.171	.227	.736	.166	.186	.133	.164	0.064
AU3	.207	.115	.710	.381	.102	.117	.087	-0.048
TA1	.323	-.125	.308	.598	.105	.197	.129	0.008
TA2	.114	.086	.261	.792	.067	.166	.027	0.048
TA3	.249	.137	.152	.739	.178	.169	.042	-0.020
TA4	.160	.130	.076	.688	.177	.137	.032	0.005
TA5	.323	.014	.069	.613	.122	.273	.272	0.079
TA6	.095	.432	.042	.488	.248	.096	.338	-0.019
TA7	.261	.344	.178	.460	.260	-.051	.481	0.031
ND1	.124	.205	.278	.154	.517	.087	.450	0.020
ND2	.180	.086	-.014	.201	.723	.183	.074	0.033
ND3	.151	.225	.139	.106	.676	.132	.201	0.092
ND4	.147	.146	.349	.129	.588	.250	.314	0.030
ED1	.121	.135	.063	.095	.357	.728	-.052	0.096
ED2	.281	-.037	.228	.266	.332	.488	.151	-0.044
ED3	.271	-.184	.268	.145	.428	.438	.277	0.070
ED4	.108	.172	-.042	.323	.348	.662	-.118	0.069
ED5	.182	.043	.048	.207	.351	.669	.208	-0.020
CS1	.085	.005	.063	.305	.259	.473	.423	0.017
CS2	.210	-.035	.143	.213	.312	.241	.506	-0.020
CS3	.302	-.020	-.117	.111	.061	.335	.557	0.063
CS4	.227	.275	.125	.067	.182	.074	.647	0.055
CS5	.251	.237	.131	.148	.101	.138	.759	-0.001
CP1	.234	.063	.210	.115	.187	.070	0.269	.752
CP2	.320	.286	.138	.189	.091	.141	0.266	.703
CP3	.271	.133	.220	.056	.171	.314	0.265	.621
CP4	.154	.133	.244	.044	.147	.451	0.228	.578

<Appendix B> Path Coefficients, SEs, and t-tests

Path in the research model	Path coefficients	t-Statistics
Technology → Navigation design (ND)	0.747**	8.201
Technology → Ergonomics design (ED)	0.930**	9.030
Technology → Content support (CS)	0.925**	10.426
Technology → Capacity (CP)	0.896**	12.349
Task → TTF	0.249**	5.079
TECH → TTF	0.482**	6.131
TTF → PE	1.178**	6.298
PE → AU	0.280*	2.506
TTF → AU	0.665**	3.327

◆ About the Authors ◆



Sununthar Vongjaturapat

Sununthar Vongjaturapat Ph.D. (Information Technology), King Mongkut's Institute of Technology Ladkrabang, Thailand. Lecturer, Faculty of Humanities, Ramkhamhaeng University, Thailand. Her research interests include IT adoption, Human-Computer interaction (HCI) and Electromyography (EMG). Her research work have been published in the *Journal of Information and Knowledge Management*, *Science & Technology Asia*, and *Journal of Science and Technology Maharakham University*.



Nopporn Chotikakamthorn

Nopporn Chotikakamthorn Ph.D. (Electrical and Electronic Engineering), Imperial College, University of London, London, UK. Assoc. Prof., Faculty of Information Technology, King Mongkut's Institute of Technology Ladkrabang, Thailand. His research interests include human-computer interaction, learning technologies, multimedia computing, and signal processing.



Panitnat Yimyam

Panitnat Yimyam Ph.D. (Computing and Electronic Systems), University of Essex, UK. Lecturer, Faculty of Sciences and Social Sciences Burapha University, Sakaeo Campus, Sakaeo, Thailand. Her research interests include computer vision and image processing.

Submitted: September 12, 2020; 1st Revision: December 4, 2020; Accepted: January 22, 2021
