Antecedents of Usage Intention of E-hailing Apps in Thailand from Generation-Y & Generation-Z Chinese Independent Tourists' Perspective, an Integration of TTF and UTAUT

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Abstract

E-hailing has gain increased popularity in recent years for some of its advantages. However, very few extant researches examined the usage intention of e-hailing from the perspective of foreign tourists. This research examines the antecedents of usage intention of e-hailing apps by integrating TTF and UTAUT model, by using the case of Gen-Y and Gen-Z Chinese independent tourist. Online survey data were collected from Chinese respondents who has visited Thailand be-fore the outbreak of COVID-19 pandemic or planned to visit Thailand after the end of pandemic (n = 396). The data were analysed by using Covariance Based Structural Equation Modelling (CB-SEM). The key findings showed that tourist's usage intention of e-hailing app is positively affected by the task-technology fit, performance expectancy, effort expectancy, and social influence, which together accounted for 62% of total variation of usage intention in the integrated model. This research also confirmed a positive effect of effort expectancy on performance expectancy.

Keywords: E-hailing, UTAUT, TTF, Usage Intention, Chinese Tourists

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ปัจจัยที่มีอิทธิพลต่อความตั้งใจในการใช้งานแอปพลิเคชัน E-hailing ในประเทศไทยจากมุมมองของนักท่องเที่ยวอิสระชาวจีนเจเนอเรชั่น-Y และเจเนอเรชั่น-Z การบูรณาการ TTF และ UTAUT

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บทคัดย่อ

E-hailing ได้รับความนิยมอย่างมากในช่วงไม่กี่ปีที่ผ่านมา เนื่องจากมีข้อได้เปรียบบางประการ อย่างไรก็ตาม มีงานวิจัยส่วนน้อยที่ยังคงเหลืออยู่ได้สำรวจจุดประสงค์ในการใช้งาน E-hailing จากมุมมองของนักท่องเที่ยวต่างชาติ งานวิจัยครั้งนี้จะเป็นการวิเคราะห์เพื่อหาสาเหตุการใช้งานของแอปพลิเคชัน E-hailing โดยการใช้โมเดล TTF และ UTAUT โดยเลือกกลุ่มทดลองเป็นกลุ่มนักท่องเที่ยวชาวจีนระหว่าง Gen-Y และ Gen-Z จากการรวบรวมข้อมูลการตอบแบบสอบถามออนไลน์ของนักท่องเที่ยวชาวจีนที่เคยมาท่องเที่ยวในประเทศไทย ก่อนเกิดการระบาดของ COVID-19 หรือมีการวางแผนไว้ที่จะมาท่องเที่ยวในประเทศไทย หลังสิ้นสุดของการระบาดใหญ่ (n = 396) ซึ่งได้วิเคราะห์ข้อมูลโดยใช้แบบจำลอง CB-SEM พบว่า จุดประสงค์ในการใช้งานของแอปพลิเคชัน E-hailing ของนักท่องเที่ยว เป็นไปในเชิงบวก ซึ่งมีผลมาจากเทคโนโลยีที่มีความเหมาะสมเฉพาะด้าน การสอดคล้องระหว่างงานและเทคโนโลยีและความคาดหวังในการใช้งานแอปพลิเคชันที่มีประสิทธิภาพและความคาดหวังในเรื่องของความพยายามและอิทธิพลทางสังคม ซึ่งเมื่อรวมผลลัพธ์จะคิดเป็นร้อยละ 62 ของจุดประสงค์ในการใช้งานทั้งหมดซึ่งวิเคราะห์โดยใช้แบบจำลอง งานวิจัยนี้ยืนยันให้รู้ว่าความคาดหวังในเรื่องของความพยายามมีผลกระทบที่เชิงบวกต่อความคาดหวังในการใช้งานแอปพลิเคชันที่มีประสิทธิภาพอีกด้วย

คำสำคัญ: E-hailing UTAUT TTF ความตั้งใจในการใช้งาน นักท่องเที่ยวจีน

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Introduction

Background and Problems

Taxi is an important form of transportation that is flexible and can deliver passenger with door-to-door service (Aarhaug & Skollerud, 2014). In more recent years, due to the popularization of smart phones and the advancement in mobile Internet technology and GPS technology, there is rapid growth of e-hailing (also called ride-hailing) platforms that enable passengers to enjoy real-time tailored mobility services, such as Uber, Didi, Grab, Line Taxi (Nguyen-Phuoc et al., 2021; Zhong et al., 2022). By using e-hailing apps, the passengers can choose their destination point and pickup point by just a few clicks (pickup point could also be auto-located by GPS), can make pay-ment via the application, can chat with the driver via the apps, and they can also check the reviews about the driver from previous passengers.

According to Whalen et al. (2013) and Aziz et al. (2018), the sense of safety that passengers perceived is an important determinant of their choice of travel mode. E-hailing seems more ap-pealing and considered to be safer in the context of developing countries than public transporta-tions because public transportations are considered to have high risk of crime and sexual harass-ment problems especially for female passengers (Gardner et al., 2017; Sabogal-Cardona et al., 2021). On the contrary, some other researchers hold opposing view that even though e-hailing have lower crime rate than traditional taxi and public transportations, passengers perceive e-hailing as less secure, because most of e-hailing drivers are not official formal employees of e-hailing com-panies, malicious individuals can easily breach the registration and verification process to be a e-hailing driver; Conversely, drivers of traditional taxi and public transportations are usually offi-cially hired and supervised by local governments especially in Chinese context, which is a stronger indicator of safety for passengers (Liu et al., 2022). Another kind of safety concern is crash risk. Compared with traditional Taxi drivers, e-hailing drivers look more transparent to passengers, be-cause the e-hailing apps will present several information about the driver to passengers, including the average rating, crash history, and total driving distance of the driver, which will render the e-hailing passengers to make better judgement about potential crash risk (Mao et al., 2021).

E-hailing apps (such as Grab and Line Taxi) firstly appeared in Thailand in year 2016, and finally formally legalized by the Department of Land Transport of Thai government in November 2021 (Bangkok Post, 2021; Sopranzetti, 2021). Thailand is well known as a tourist destination country. Before the outbreak of COVID19 pandemic, according to the secretary-general of the Of-fice of the National Economic and Social Development Council in 2019, the Thai government pro-jected that the tourism sector would account for 30% of GDP by 2030, up from around 20% in 2019 (Theparat, 2019). As a common sense, there are generally two broad categories of foreign tourists into Thailand, group tourist and independent tourist. While group tourists don't need to worry about their mode of transportation within Thailand because all details of their trip schedules are well arranged by travel agency, independent tourists do have to make decision about their mode of transportation. For passengers in the leisure trip (namely, tourists), they have increased probability of using e-hailing platforms (Tirachini & del Río, 2019). According to Bi et al. (2021), traveler would prefer e-hailing rather than a bus journey if transfer during the bus journey is inevi-table, because e-hailing can provide door-to-door delivery service without transfer. With e-hailing application, passengers will increase their frequency of trips, which imply that tourists can actually visit more tourist attractions (K. Shi et al., 2021). Besides the crash risk and crime risk mentioned earlier, another risk concern especially from foreign tourists regarding transportation safety is re-lated to potential financial rip-off from traditional taxi drivers in Thailand, which has a negative press image. There were plenty of complaints from passengers about traditional Taxi drivers in Thailand including rejecting passengers, refusing to use the meter to price, failing to take passen-gers to their destinations, and charging abnormally high price to foreign tourists, and other prob-lems that the Department of Land Transportation of Thai government already took a firm stand trying to resolve in year 2014 (Mahitthirook, 2014). Unfortunately, the problem of ripping off lo-cal tourists and especially foreign tourists by traditional Taxi drivers still exist until the early of year 2022, furthermore, in some areas traditional Taxi drivers even gang-up to make e-hailing drivers afraid of serving passengers (Bangkok Post, 2019; Petpailin, 2022). Therefore, considering the very negative image of traditional taxi drivers, foreign independent tourists should carefully consider their choice of mode of transportations during their trips within Thailand.

Chinese tourist is an important tourist source for the Thai tourist markets. With 10,997,338 tourists in a single year of 2019, China accounted for 27.5% of all tourist arrivals into Thailand in year 2019, before the outbreak of COVID-19 epidemic and the following travel limitation since early 2020 (National Statistical Office, 2020). Among those Chinese tourists and tourists to come, two age groups of them raise the interest of the author regarding the usage intention of e-hailing apps, that is, Generation Y (also called Millennials) and Generation Z groups, namely, tourists that were born in year 1980 or later. A well-known classification of different generations of people is whether they are digital natives or digital immigrants (Prensky, 2001a, 2001b). While digital na-tives had access to digital products since their childhoods, digital immigrants started to use digital technology after they grown up. Generation Y/Millennial (and later generations of course) are commonly believed to be digital native or net generation (Lippincott, 2012; Oblinger & Oblinger, 2005; Zimerman, 2012). Because digital natives had early access to digital technologies in their childhood, they can learn and use digital technology better than digital immigrants (Kesharwani, 2020). As digital natives have high intensity of information technology usage, they are more likely to adopt e-hailing applications (Fu, 2020). Besides, since digital natives are relatively younger in age than the older generations, younger travelers are naturally drawn to e-hailing technology, they have higher monthly usage frequency of e-hailing apps, and they representhe largest group of e-hailing users (Shen et al., 2020; H. Shi & Sweet, 2021; Tirachini & del Río, 2019). For the argu-ments mentioned above, the usage intention about e-hailing apps of Generation Y and Generation Z Chinese independent tourists has research value from the perspective of Thai tourist markets.

There are a number of extant researches that proposed various models regarding the deter-minants of usage intention for individual acceptance of technologies. Venkatesh et al. (2003) pro-posed the unified UTAUT model, in which Performance Expectancy, Effort Expectancy and Social Influence are direct determinants of Behavioral Intention of using information technology. Howev-er, according to the TTF model by Goodhue and Thompson (1995), when the technology character-istics of a new technology cannot match the task requirements from users, the technology is less likely to be adopted. Even though users may perceive a technology as being advanced, they do not adopt it if they think it's unfit with their tasks (Junglas et al., 2008; Zhou et al., 2010). Therefore, it's not sufficient to focus merely on user perceptions and attitudes related constructs, but better to combine the UTAUT and TTF model together to examine user's usage intention of technology from perspectives of both models. Therefore, the author integrated UTAUT model and TTF model in this research to examine the antecedents for usage intention of e-hailing apps among Chinese tourists in Thailand.

Research Gaps

Despite those researches mentioned above, however, to the best of our knowledge, there were very few studies explaining usage intention of e-hailing from both perspectives of UTAUT and TTF. Moreover, there were extremely limited researches that used tourist as the subject for the research topic of usage intention of e-hailing technology. Thus, this research was designed to fill this research gap.

Research objectives

The objective of this research is to examine the antecedents of usage intention of e-hailing apps by integrating TTF and UTAUT model, by using the case of Gen Y and Gen Z Chinese inde-pendent tourist who has visited Thailand before the outbreak of COVID-19 pandemic or planned to visit Thailand after the end of pandemic

Literature Review

Effect of Task Characteristics on Task-Technology Fit

This research proposes that task characteristics required by e-hailing passengers has nega-tive effect on the task-technology fit of e-hailing apps. According to Goodhue and Thompson (1995), individuals carry out actions in order to turn inputs to outputs, and the actions are generally defined as tasks. Task characteristics composed of things that will make people who uses the in-formation technology to dependent on higher degree on some aspects of it (Goodhue & Thompson, 1995). According to Goodhue and Thompson (1995), when task characteristics required by users become more demanding, the gap between what users required and what the technology can offer widen, so there will be a decrease in task-technology fit. Especially when the tasks are non-routine, people are often forced to use the technology to solve new problems, the effect of task characteris-tics on fit will be the strongest, because the more demanding non-routine task would make people more aware of the shortcomings of the technology, which would widen the gap. In the context of adopting e-hailing apps by foreign tourists, it's a kind of non-routine task, because foreign tourists are generally not familiar with the travel route and the e-hailing apps prevalent in the destination country. Zhou et al. (2010) confirmed the negative effect of task characteristic on task-technology fit when explaining user adoption of mobile banking technology, which contended that as tasks be-come more difficult and complex (e.g., simultaneous batch processing), there would be lower fit because some limitation in mobile banking technologies would make it hardly to satisfy the task demand. H. Wang et al. (2020) contend that if the task to be completed by using healthcare weara-ble devices is of higher complexity and time criticality, the task-technology fit will be lower. However, the negative relationship between task characteristic and fit is controversial. Some other researchers found positive relationship between task characteristic and fit, but to the best of our knowledge, there seems lack of enough logical reasoning to explain the positive relationship (Fa-qih & Jaradat, 2021; Hsieh & Lin, 2020; Khan et al., 2018). Considering all of the prior researches mentioned above, the author prone to the negative relationship for the reason of more abundant logical reasoning available, and the following hypothesis is presented:

Hypothesis H1: Task Characteristics has negative effect on Task-Technology Fit of e-hailing apps among Chinese tourists in Thailand.

Effect of Technology Characteristics on Task-Technology Fit

This research proposes that technology characteristics offered by e-hailing apps has posi-tive effect on the task-technology fit of e-hailing apps. When individuals are carrying out their tasks, they need to use some tools which are referred to as technologies. Technology characteris-tics mean the characteristics of both the IT system itself (software, hardware, and data) and service that support users in performing tasks (training, etc.)

(Goodhue & Thompson, 1995). According to Goodhue and Thompson (1995), if the technology provides less functionality, there would be a de-crease in task-technology fit, because the technology can not satisfy the requirements by tasks, the gap between what task required and what technology can offer would widen. Inversely, if the tech-nology characteristic is very advanced, the gap would narrow, and there would be better fit. This positive relationship was confirmed by many other researches. For example, Zhou et al. (2010) contended that mobile banking technology has the characteristic to provide ubiquitous and real-time services, which is more advantageous for mobile users who has on-the-go task requirements, therefore there is a higher task-technology fit. X. Wang et al. (2021) claimed that shopper-facing technologies possess the right characteristics that can minimizing social contacts or enabling shopping from home, which satisfy shopper's desire of avoiding social contacts during COVID-19 pandemic, therefore result in better task-technology match. Khan et al. (2018) also confirmed that technology characteristics of MOOCs technology (accessibility, affordability, and open enroll-ment) will positively influence task-technology fit of it. However, Junglas et al. (2008) warned that technology should not offer too much functionality than what the majority users required, other-wise this "over-fit" will waste users too much time overwhelmed by unneeded functionality and make users feel overall unsuccessful about the technology. Considering the prior researches men-tioned above about the effect of technology characteristic on task-technology fit, the following hy-pothesis is presented:

Hypothesis H2: Technology Characteristics has positive effect on Task-Technology Fit of e-hailing apps among Chinese tourists in Thailand.

Effect of Task-Technology Fit on Usage Intention

This research proposes that task-technology fit has positive effect on the usage intention of e-hailing apps. Goodhue and Thompson (1995) proposed that task-technology fit (TTF) is the ex-tent that a technology helps a person to perform the tasks of the person, and it's the correspond-ence between the requirements of task, the abilities of individuals, and the functionality of the technology. Even though the earlier TTF models does not include the utilization construct because they were developed from work adjustment theory, most researches later on assumed a direct ef-fect of TTF on utilization (Dishaw & Strong, 1999; Howard & Rose, 2019; Zigurs & Buckland, 1998; Zigurs & Khazanchi, 2008). Task-technology fit will influence people's expected conse-quence of using the technology, such as more useful, more important, or give more relative ad-vantage, all of which will predict the utilization of the technology (Davis, 1989; Goodhue & Thompson, 1995; Hartwick & Barki, 1994). Dishaw and Strong (1999) contended that technology that offer sufficient advantage will enable users to complete the task with net benefit (a signal of fit), and the technology that provide the greatest net benefit is more likely to be choose by rational users. Some other researchers proposed a mediated point of view that task-technology fit will posi-tively affect perceived usefulness, which will further positively affect usage intention of technolo-gies, such as hotel information system and digital textbook (Kim et al., 2010; Rai & Selnes, 2019). The positive effect of task-technology fit has been supported by many empirical researches. For example, Faqih and Jaradat (2021) found positive relationship between task-technology fit and adoption intention of augmented reality technology. Lin and Huang (2008) confirmed positive re-lationship between fit and usage intention of knowledge management system. Zhou et al. (2010) found that a good fit will promote the user adoption of mobile banking technology. H. Wang et al. (2020) found positive relationship in the context of healthcare wearable devices. X. Wang et al. (2021) found positive relationship in the context of shopper-facing technologies. Therefore, the following hypothesis is presented:

Hypothesis H3: Task-Technology Fit has positive effect on Usage Intention of e-hailing apps among Chinese tourists in Thailand.

Effect of Performance Expectancy on Usage Intention

This research proposes that performance expectancy has positive effect on the usage inten-tion of e-hailing apps. According to Venkatesh et al. (2003), performance expectancy is someone's belief about the degree of how using the technology will aid this individual to increase job perfor-mance. In other word, performance expectancy refers to the degree of believing that the individual using the technology will perform higher (Ayaz & Yanartaş, 2020). There are some similar con-structs from other models of individual adoption of technologies, such as perceived usefulness construct from the Technology Acceptance Model, extrinsic motivation construct from the Moti-vational Model, job-fit construct from the Model of PC Utilization, the relative advantage con-struct from the Innovation Diffusion Theory, and the outcome expectations construct from the So-cial Cognitive Theory (Venkatesh et al., 2003). According to Venkatesh et al. (2003), compared with other similar constructs in earlier models such as perceive usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectation, the performance expectancy construct is the strongest predictor of behavioral intention. Especially for young men, the effect would be stronger, because performance expectancy put emphasis on accomplishing tasks and men are generally task-oriented. Smyth et al. (2021) proposed a different angle of view that the effect of performance ex-pectancy on usage intention is mediated by the attitude towards using technology, which means that PE positively influence attitude, and attitude positively influence usage intention. Most of pri-or researches applying UTAUT model support a direct positive relationship between performance and usage intention of technology. For example, Andrews et al. (2021) found that performance ex-pectancy has direct positive effect on librarians' intention to adopt artificial intelligence technolo-gy. Jiang et al. (2019) contended positive relationship of performance expectancy (more benefits and utilities) on usage intention of online insurance platform to purchase life insurance. H. Wang et al. (2020) proposed that in the context of healthcare wearable devices, when users believe the technology to increase healthcare effectiveness (higher performance expectation), the technology is more likely to be adopted. For the context of e-hailing, Ooi et al. (2020) found that performance expectancy positively affect user's behavioral intention to adopt mobile taxi. Surya et al. (2021) contended that performance expectancy has positive effect on user's usage intention of certain fea-ture of e-hailing apps. Therefore, the following hypothesis is presented:

Hypothesis H4: Performance Expectancy has positive effect on Usage Intention of e-hailing apps among Chinese tourists in Thailand.

Effect of Effort Expectancy on Usage Intention

This research proposes that effort expectancy has positive effect on the usage intention of e-hailing apps. The widely accepted definition of effort expectancy was given by Venkatesh et al. (2003) as the degree of ease to use a technology. There are three similar constructs from other earlier models related to individual adoption of technologies, including the perceived ease of use con-struct from the Technology Acceptance Model, the complexity construct from the Model of PC Utilization, and the ease-of-use construct from the Innovation Diffusion Theory. According to Venkatesh et al. (2003), effort expectancy is one the direct determinant of user's behavioral inten-tion of technology. When users are facing a new technology at the very first stage, the influence of effort-related constructs on intention are believed to be stronger, because users need to overcome some hurdles of using the unfamiliar technology (Davis et al., 1989; Szajna, 1996; Venkatesh et al., 2003). According to Venkatesh and Morris (2000), the behavior intention of female users would be more significantly influenced by effort expectancy than male users because of different gender roles, and older users would be more significantly influenced by effort expectancy than younger users because of the difficulty to handle complexity. When users perceive a technology is easy to use, it's more likely for them to adopt the technology. Most of extant researches support the positive relationship between effort expectancy and usage intention. For example, Smyth et al. (2021) found that effort expectancy positively affect user's attitude towards using driver state monitoring systems for automated vehicles, which is an indicator of usage intention of the tech-nology. Jiang et al. (2019) found that if people perceive online life insurance platform as easy to use, then they are more likely to use online platform to purchase life insurance products. Faqih and Jaradat (2021) found that for advanced technology such as augmented reality technology which is challenging to use, effort expectancy has positive influence on user's usage intention for the tech-nology. However, there are also a few researches that proposing a positive relationship in the be-ginning while statistical results negate later on (Ooi et al., 2020; Surya et al., 2021). Considering all of the prior researches mentioned above, we decide to follow the majority research findings and propose the following hypothesis:

Hypothesis H5: Effort Expectancy has positive effect on Usage Intention of e-hailing apps among Chinese tourists in Thailand.

Effect of Effort Expectancy on Performance Expectancy

This research proposes that effort expectancy has positive effect on performance expectan-cy of e-hailing apps. Several extant researches supported a positive relationship between effort ex-pectancy and performance expectancy. For example, in the context of mobile banking technology, Zhou et al. (2010) contended that when users feel this technology does not require much effort and is easy to use (which indicate higher effort expectancy), users will have higher expectation about attaining their expected performance from using it. In the context of home telehealth services technology, Cimperman et al. (2016) found that user's perceived ease to learn and use (analogous to effort expectancy) of this technology positively influence their perception of usefulness (analo-gous to performance expectancy) of the home telehealth services technology, which means effort expectancy positively affect performance expectancy. Smyth et al. (2021) found that the effect of effort expectancy on performance expectancy is positive for context of driver state monitoring technology for automated vehicles. H. Wang et al. (2020) also found that effort expectancy posi-tively affects performance expectancy for the context of healthcare wearable devices. As for the context of e-hailing technology, we believe that when users perceive e-hailing apps as easy to use, they would have higher expectation about the functionalities and performance of using the apps. Therefore, the following hypothesis is presented:

Hypothesis H6: Effort Expectancy has positive effect on Performance Expectancy of e-hailing apps among Chinese tourists in Thailand.

Effect of Social Influence on Usage Intention

This research proposes that Social Influence has positive effect on Usage Intention of e-hailing apps. According to Venkatesh et al. (2003), social influence is the degree that a person feel about his or her important others' expectation about whether this person should use or reject a technology. It's the social pressure from external surrounding environment (such as the opinions of relatives, friends, and supervisors) and could possibly influence a person's perception and behavior (Tarhini et al., 2016). There are some similar constructs to social influence from other models re-lated to usage intention of technologies, such as the subjective norm construct from the Theory of Reasoned Action, the social factors construct from the Model of PC Utilization, and the image construct from the Innovation Diffusion Theory, all of which capture user's perception about how others will view them by using the technology. When adopting new technology and innovation, there are certain level of uncertainty facing the users, therefore people would interact with their social network (e.g., friends and relatives) to consult some opinion about usage decision (Jiang et al., 2019; Tarhini et al., 2016). For e-hailing technology, even though many Chinese people are familiar with it because of the popularity of Didi app in China, but Chinese people as foreign tour-ists are generally not familiar with local e-hailing apps prevalent in Thailand, because e-hailing apps in different countries may have different functionalities and user interface design. Thus, when deciding adoption of e-hailing apps in Thailand, Chinese tourists would face certain level of uncer-tainty, which would cause them to consult the opinion of important others. According to Hofstede (2001), Chinese culture has high score in collectivism, people from highly collectivism culture usually have tighter relationships tie with others and may prone to follow opinion of others, which means they would have higher social pressure when making decision. We believe that when con-sidering whether to adopt e-hailing apps in Thailand, Chinese tourists would consult the opinion of their important others. Faqih and Jaradat (2021) also claimed that the effect of social influence on usage intention is particularly stronger for developing countries cultures. Another rationale for the relationship between social influence and usage intention is that people would like to build up their relationships with their important people through following those people's views on certain behav-iors (Hernandez et al., 2011; Ifinedo, 2016). Venkatesh et al. (2003) mentioned that the effect would be more salient for women, more salient in mandatory setting, and would decrease with us-er's experience with the technology. Most extant researches support a positive relationship be-tween Social Influence and Usage Intention. For example, Zhou et al. (2010) found positive effect in the context of mobile banking technology. Surya et al. (2021) found positive effect in the con-text of e-hailing apps for usage purpose of buying food. Therefore, the following hypothesis is pre-sented:

Hypothesis H7: Social Influence has positive effect on Usage Intention of e-hailing apps among Chinese tourists in Thailand.

Conceptual Framework

The conceptual model is shown in Figure 1 below.

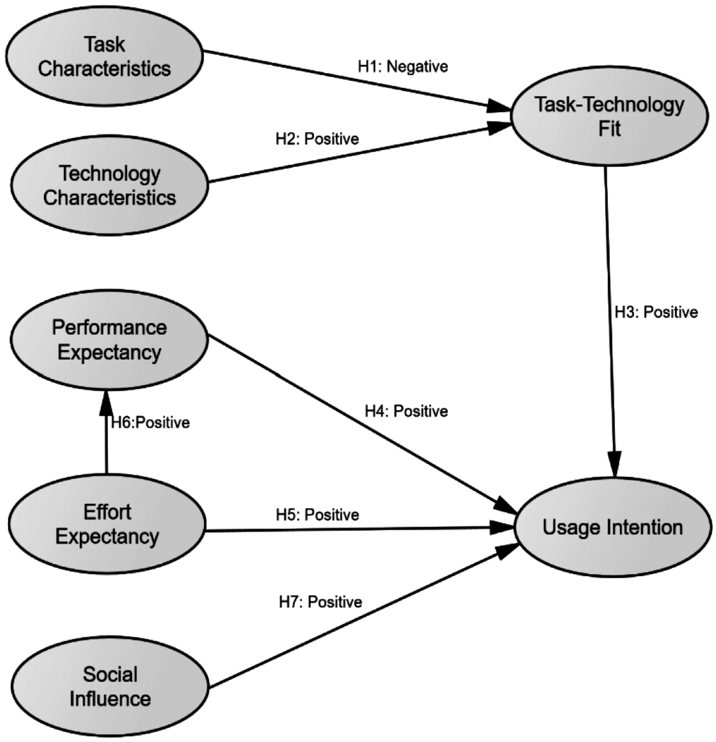

Figure 1: Conceptual model.

Methodology

Sample and data collection process

Participants of this research are Generation-Y and Generation-Z Chinese people who have visited Thailand as independent tourists before the outbreak of Covid-19 pandemic or plan to do so after the end of the pandemic. Survey questionnaires were collected by using the paid sampling services provided by WJX.CN website, which is the largest survey website in China and claim to use random sampling methods for paid sampling services to collect data from their various data-base of respondents. The survey collection process of the paid sampling service of WJX.CN fol-lowed ethical standard, and required respondents to agree on the platform's informed consent be-fore participating in the survey. The author also asked the respondents a question at the very be-ginning of the questionnaire to verify whether or not the respondents have visited Thailand as in-dependent tourists before the outbreak of Covid-19 pandemic or plan to do so after the end of the pandemic as an initial screening question, to double check to screen out un-targeted respondents by sampling error. In order to facilitate the Chinese respondents to understand the questionnaire, all questions were translated to Chinese language before presenting to respondents, and some screen-shot photos of the user interface of E-hailing apps in Thailand were presented to respondents in the beginning. After the end of the data collection period, there were a total of 396 usable question-naires obtained.

As shown in Table 1, among the respondents, 210 respondents are female (53.0%) and 186 respondents are male (47.0%). For age groups, 4 respondents are below 20 years old (1.0%), 82 respondents are 21-25 years old (20.7%), 137 respondents are 26-30 years old (34.6%), 107 re-spondents are 31-35 years old (27.0%), and 66 respondents are 36-40 years old (16.7%). About marital status, 97 respondents are unmarried (24.5%), 297 respondents are married (75.0%), and 2 respondents claim to be divorced (0.5%). Regarding educational level, 24 respondents are below Bachelor's level (6.1%), 329 respondents are at Bachelor's level (83.1%), 43 respondents are at Master's level (10.9%), and no respondent achieved Doctor's level. For monthly salary level, 25 respondents earn below 4,000 CNY (6.3%), 62 respondents earn between 4,001-6,000 CNY (15.7%), 99 respondents earn between 6,001-8,000 CNY (25.0%), 116 respondents earn between 8,001 - 10,000 CNY (29.3%), and 94 respondents earn higher than 10,000 (23.7%).

Table 1: Demographic characteristics for the participants (n=396).

	Options	Frequency	Percent
Gender	Female	210	53.0%
	Male	186	47.0%
Age Group	Below 20 years old	4	1.0%
	21 - 25 years old	82	20.7%
	26 - 30 years old	137	34.6%
	31 - 35 years old	107	27.0%
	36 - 40 years old	66	16.7%
Marital Status	Unmarried	97	24.5%
	Married	297	75.0%
	Divorced	2	0.5%
Education Level	Below Bachelor's	24	6.1%
	Bachelor's	329	83.1%
	Master's	43	10.9%
	Doctor's	0	0.0%
Monthly Salary Level	Below 4,000 CNY	25	6.3%
	4,001-6,000 CNY	62	15.7%
	6,001-8,000 CNY	99	25.0%
	8,001-10,000 CNY	116	29.3%
	Over 10,000 CNY	94	23.7%

Data analysis methods

This research used covariance based structural equation modelling approach (CB-SEM), performed with Amos 26 software, for examining our measurement model and the structural mod-el. For measurement model, this research verified the measurement model by examining reliability (internal consistency), convergent validity, and discriminant validity of measurements. Reliability of measurements was examined by using Composite Reliability and Cronbach's Alpha. Convergent validity of measurements was examined by using average variance extracted (AVE). Discriminant validity of measurements was examined by using the square root of AVE values, which were sup-posed to exceed other inter-construct correlations involving that construct. The assessment of reli-ability (internal consistency), as shown in Table 2, was justified by Composite Reliability and Cronbach's alpha, all of which exceeded the minimum threshold of 0.7 (Nunnally, 1978). The as-sessment of convergent validity was performed by using average variance extracted (AVE) in Ta-ble 3. Convergent validity was justified because all of the AVE values exceeded the minimum threshold of 0.7 (Hair et al., 2011). Assessment of discriminant validity was performed by compar-ing the square root of AVE values to other inter-construct correlations, the result in Table 3 shows that all the square root of AVE values (in bold) exceeded other inter-construct correlations involv-ing that construct, which justified discriminant validity of measurement model (Fornell & Larcker, 1981).

For the structural model, this research estimated path coefficients and the significance of those path coefficients by using bootstrap resampling method with 5,000 subsamples. We also have the R2 values which represent the amount of total variance explained in usage intention by independent variables in the integrated model.

Table 2: Reliability: CR(Composite Reliability)>0.7, Cronbach's alpha>0.7

	CR	Cronbach's Alpha
Task Technology Fit (TTF)	0.862	0.861
Task Characteristics (TAC)	0.809	0.809
Technology Characteristics (TEC)	0.812	0.806
Performance Expectancy (PE)	0.825	0.822
Effort Expectancy (EE)	0.832	0.825
Social Influence (SI)	0.881	0.867
Usage Intention (UI)	0.841	0.840

Table 3: AVE, square root of AVE, and inter-construct correlation.

	AVE	MSV	TTF	TAC	TEC	PE	EE	SI	UI
TTF	0.609	0.558	0.781						
TAC	0.515	0.311	0.558	0.718					
TEC	0.592	0.530	0.728	0.556	0.769				
PE	0.611	0.573	0.697	0.527	0.589	0.782			
EE	0.558	0.489	0.699	0.426	0.584	0.566	0.747		
SI	0.717	0.471	0.575	0.399	0.548	0.542	0.440	0.847	
UI	0.638	0.573	0.747	0.480	0.647	0.757	0.696	0.686	0.799

AVE for Average Variance Extracted, column 4-10 show square root of AVE values (in bold) and inter-construct correlations.

Results

Most of the model fit indices shown in Table 4 indicate that our proposed model appeared to fit well. Except for Adjusted Goodness of Fit Index (AGFI), Goodness of Fit Index (GFI), Tuck-er-Lewis Index (TLI) and Comparative Fit Index (CFI) all exceeded the acceptable minimum threshold of 0.9 (Byrne, 2010; Schumacker & Lomax, 2016). Root mean-square error of approxi-mation (RMSEA) also meet the acceptable requirement of less than 0.08 (Browne & Cudeck, 1992).

Table 4: Model fit indices

Fit index	GFI	AGFI	TLI	CFI	RMSEA
Recommended value	>0.90	>0.90	>0.90	>0.90	<0.08
Actual value	0.918	0.893	0.957	0.964	0.045

The path coefficients, the test of their bootstrap significance with 5,000 subsamples, and hypotheses results are presented in Table 5 and Figure 2. Hypothesis 1 proposes a negative effect of task characteristic on task-technology fit. However, the result indicates that task characteristic and task-technology fit are positively associated (β=0.302; p<0.01); the result is also statistically significant. Thus, the results reject Hypothesis 1. Hypothesis 2 proposes a positive effect of tech-nology characteristic on task-technology fit. The result indicates that technology characteristic and task-technology fit are positively associated (β=0.646; p<0.001); the result is also statistically sig-nificant. Thus, the result supports Hypothesis 2. Hypothesis 3 proposes a positive effect of task-technology fit on usage intention. The result indicates that task-technology fit and usage intention are positively associated (β=0.281; p<0.01); the result is also statistically significant. Thus, the re-sult supports Hypothesis 3. Hypothesis 4 proposes a positive effect of performance expectancy on usage intention. The result indicates that performance expectancy and usage intention are positively associated (β=0.388; p<0.001); the result is also statistically significant. Thus, the result sup-ports Hypothesis 4. Hypothesis 5 proposes a positive effect of effort expectancy on usage inten-tion. The result indicates that effort expectancy and usage intention are positively associated (β=0.309; p<0.01); the result is also statistically significant. Thus, the result supports Hypothesis 5. Hypothesis 6 proposes a positive effect of effort expectancy on performance expectancy. The result indicates that effort expectancy and performance expectancy are positively associated (β=0.560; p<0.001); the result is also statistically significant. Thus, the result supports Hypothesis 6. Hypothesis 7 proposes a positive effect of social influence on usage intention. The result indi-cates that social influence and usage intention are positively associated (β=0.400; p<0.001); the result is also statistically significant. Thus, the result supports Hypothesis 7.

Table 5: Standardized path coefficient, bootstrap significance, and hypotheses results

Hypothesis	Path	Standardized Path coefficient	Lower	Upper	P	Supported
H1	TAC → TTF	.302	.162	.434	.001	Not
H2	TEC → TTF	.646	.529	.739	.000	Yes
H3	TTF → UI	.281	.109	.459	.002	Yes
H4	PE → UI	.388	.238	.540	.000	Yes
H5	EE → UI	.309	.151	.447	.001	Yes
H6	EE → PE	.560	.462	.643	.000	Yes
H7	SI → UI	.400	.276	.528	.000	Yes

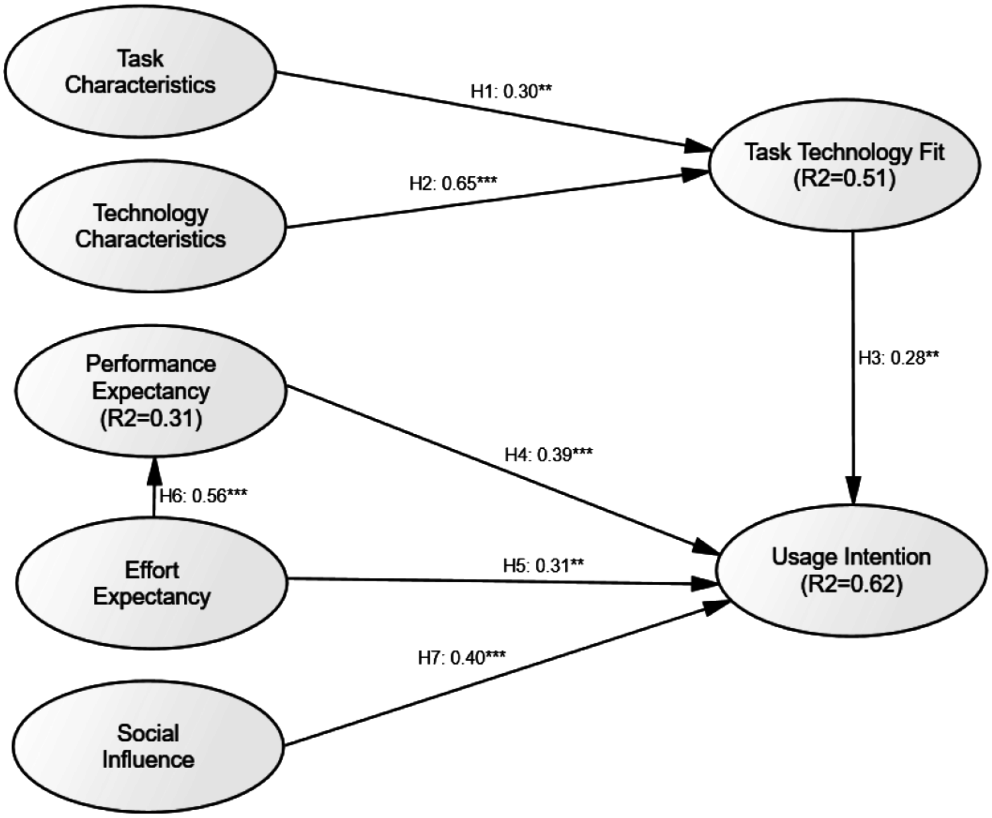

Figure 2: Results from hypothesis testing.

Conclusion and Discussion

Discussion of the results

This research was conducted to examine the antecedents of usage intention of e-hailing apps by integrating TTF and UTAUT model, by using the case of Gen Y and Gen Z Chinese inde-pendent tourist who has visited Thailand before the outbreak of COVID-19 pandemic or planned to visit Thailand after the end of pandemic. The integrated model explained 62% of the total variance in usage intention of e-hailing apps, a percentage which should be considered moderate (Hair et al., 2011).

The results show that both task characteristic and technology characteristic have positive effect on task-technology fit. The positive relationship between task characteristic and task-technology fit that we found here contradicts with the results from some prior research on other technologies such as mobile banking technology and healthcare wearable devices technology (H. Wang et al., 2020; Zhou et al., 2010). While there are also some other researches that supports a positive relationship between task characteristic and task-technology fit, but there is still lack of enough logical explanation for this positive relationship (Faqih & Jaradat, 2021; Hsieh & Lin, 2020; Khan et al., 2018). Our second hypothesis for the positive relationship between technology characteristics and task-technology fit confirmed with prior researches that the more advanced the technology, the easier for the technology to fit the task requirements (Goodhue & Thompson, 1995; Khan et al., 2018; Zhou et al., 2010). The result for hypothesis 3 also shows that task-technology fit positively affect usage intention of e-hailing apps, if independent tourists perceive better fit between their task requirement for using e-hailing during their trip and the functionalities provided by the app, they are more likely to use the app, and this result confirmed with prior re-searches that task-technology fit will make people to perceive a technology as more useful, more important, provide more relative advantages and net benefits, thus increase people's utilization of the technology (Davis, 1989; Dishaw & Strong, 1999; Goodhue & Thompson, 1995; Hartwick & Barki, 1994).

Performance expectancy was found to have positive effect on usage intention in our result, which means that as independent tourists believe that using e-hailing app will help them to enjoy better tourism experience, they will have higher intention to use it, this finding confirm with prior researches on e-hailing apps (Ooi et al., 2020; Surya et al., 2021). Effort expectancy was found to have positive effect on usage intention, which means that as independent tourists perceive a e-hailing app as easy and effortless to use, they can overcome some unfamiliarity hurdles of using new technology and they are more likely to try it during their trip, which confirm with prior re-search findings on other technology such as driver state monitoring systems, online life insurance platform, and augmented reality technology (Faqih & Jaradat, 2021; Jiang et al., 2019; Smyth et al., 2021). Our research finding of the positive relationship between effort expectancy and perfor-mance expectancy confirmed with prior research findings that user's perceived ease to learn and use of a technology will positively influence their perception of usefulness and the performance from using it (Cimperman et al., 2016; Smyth et al., 2021; Zhou et al., 2010). Lastly, for Chinese tourists who are from highly collectivism culture, social influence also has positive effect on usage intention, which means that when Chinese tourists feel stronger social influence from their im-portant others, they are more likely to adopt e-hailing app during their trips, this finding confirmed with prior research that people tend to consult and interact with their social network when they are facing some uncertainty in a unfamiliar environment of adopting a new technology (Jiang et al., 2019; Tarhini et al., 2016).

Theoretical and practical contribution

Theoretical contribution

The results from this research add new knowledge that can contribute to existing lit-erature in the area of examine antecedents of usage intention of a technology. First, to the best of our knowledge, very few extant researches integrated TTF and UTAUT model to examine usage intention of technology. With 62% of explained total variance in usage intention, we confirmed that the integrated model appears to work well (H. Wang et al., 2020; Zhou et al., 2010). Second, for the effect of task characteristic on task-technology fit, where extant researches did not reach a consensus about whether the relationship should be positive or negative, we found a positive rela-tionship in the context of e-hailing app (Faqih & Jaradat, 2021; Goodhue & Thompson, 1995; Hsieh & Lin, 2020; Khan et al., 2018; Zhou et al., 2010). Third, this research is among the earliest ones that examine the usage intention of e-hailing apps from the perspective of foreign tourists ra-ther than from perspectives of local residents. As foreign tourists come from different cultural backgrounds and the transportation need of tourists may be different from the everyday transporta-tion need of local residents, it's worthwhile to examine the specific group of tourists, especially for Thailand where tourism is of great importance to economy.

Practical contribution

This research may help e-hailing companies in Thailand to improve their apps to better reach the market niche of foreign tourists, and may potentially help the Thailand Ministry of Tourism & Sport to design transportation related promotion policy to better attract Chinese tour-ists into Thailand after the end of COVID-19 pandemic. For example, since social influence has the highest path coefficient (0.40) as antecedent of usage intention in our results, the e-hailing compa-nies may consider promoting the usage of their apps by cooperating with some key opinion leaders (KOl) in Chinese social media (such as TikTok) to promote the use of the app during trips to Thai-land. Alternatively, the e-hailing companies may also team up with the Thailand Ministry of Tour-ism & Sport or the Immigration Office of Thailand to advertise and promote the usage of e-hailing through official channels.

Limitations and future research directions

There are research limitations that need to be clarified. The first issue is the scope of sam-ple coverage, which is limited to Gen-Y and Gen-Z Chinese independent tourists which have their specific cultural background. Further research may conduct comparison research on foreign tour-ists from other countries and cultural backgrounds. The second limitation is that we still found no theoretical explanation for the positive effect of task characteristic on task-technology fit in our results. To the best of our knowledge, even though some other researchers also found positive rela-tionship between task characteristic and task-technology fit, there seems lack of enough logical reasoning to explain the positive relationship (Faqih & Jaradat, 2021; Hsieh & Lin, 2020; Khan et al., 2018). To potentially solve this issue, further researches may consider integrate UTAUT model with other models (other than TTF model) to examine the antecedents of usage intention, to pro-vide more robust theoretical supports. The third limitation is that in the UTAUT part of the inte-grated model, this research didn't examine the potential moderating effect of gender, age, and us-age experience of respondents on adoption intention of technology (Venkatesh et al., 2003). Future researches may consider to examine those moderating effects. The fourth limitation is that user behaviour is constantly changing, therefore the cross-sectional data that we use may not reflect the changes later on.

Disclosure Statement

The authors report there are no competing interests to declare.

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