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Elucidating social networking apps decisions

Performance expectancy, effort expectancy and social influence

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Abstract

Purpose – The purpose of this paper is to investigate the determinants of behavioural intention and use behaviour towards social networking apps. Exogenous latent constructs, namely, performance expectancy, effort expectancy and social influence are the key antecedents proposed based on the unified theory of acceptance and use of technology to predict the usage intention and behaviour of social networking apps (i.e. endogenous latent constructs). Experience as a moderator is the extended construct to explain social networking apps user's behavioural intention.

Design/methodology/approach – To target young generation (Millennial), a cross-sectional data collection approach was conducted to collect data from the social networking apps users (i.e. Facebook, WhatsApp, WeChat, Twitter, Instagram, YouTube, Snapchat and others) whereby a total of 384 valid questionnaires were obtained from six universities in Malaysia. Statistical analysis using partial least squares path modelling approach and a variance-based structural equation modelling (VB-SEM) techniques is performed to analyse the measurement and structural relationship.

Findings – The findings indicate that performance expectancy, effort expectancy and social influence determine behavioural intention, and behavioural intention impacts social networking apps use behaviour. Moreover, the moderation analysis reveals that the relationship between effort expectancy and behavioural intention is moderated by experience, whereas the relationship between social influence and behavioural intention is not moderated by experience.

Originality/value – While the surge of social networking apps has gained tremendous popularity among Millennial as an attractive market segment, previous studies mainly have focussed on intention and behaviour of online users in general. Despite apps and related technologies which have opened a new era of effective communications in marketing, social networking apps usage intention and behaviour focussing on Millennial is not well understood in the current literature. This study contributes and sheds lights on the current issue of social networking apps usage intention and behaviour and looks into a key rising market segment, the Millennial users.

Keywords Effort expectancy, Social influence, Apps, Behavioural intention, Performance expectancy, Social networking apps

Paper type Research paper

Nankai Business Review International
Vol. 9 No. 2, 2018
pp. 118-142

2040-8749
DOI 10.1108/NBRI-01-2017-0003

1. Introduction

Social networking apps are getting more vital in consumer's daily life which has led to the emergence of significant opportunities for development of the social media and mobile apps market. In addition, there is a huge potential for the future growth of mobile industry worldwide. Wong *et al.* (2015a) mentioned that understanding the predictor of consumer usage intention in the mobile industry is important. Likewise, the surge of social networking apps has gained tremendous popularity among Millennial as an attractive market segment. Despite apps and related technologies having opened a new era of communications, social networking apps usage intention and behaviour is not well understood in the current literature (Hew *et al.*, 2015; Rivera *et al.*, 2015; Brown *et al.*, 2016), and it highlighted that behavioural intention is the dominant indicator of mobile technology usage. For instance, researchers have testified users' behavioural intention to adopt mobile technologies in m-learning (Yang, 2013b), m-banking (Yu, 2012) and mobile advertising (Wong *et al.*, 2015b) and retailing (Rezaei *et al.*, 2016b). However, a study that focuses on the behavioural intention of individual towards social networking apps is still lacking (Kang, 2016); thus, this study attempts in understanding the social networking apps usage decisions.

In the modern area, mobile devices have become a necessary gadget resulting in exponential growth of mobile applications (apps) since the first iPhone was released into the market in 2007 (Carter and Yeo, 2016). Wireless mobile technologies offer a wealth of mobile apps which is currently expanding at a breakneck pace (Rezaei *et al.*, 2016b, Amin *et al.*, 2014). Social networking apps are also considered as one of the mobile commerce applications. Social networking apps are normally used by people to send instant messages; share information, photos, videos and news; and build a good interpersonal relationship with people within their social circles (Lin and Lu, 2015). Examples such as Facebook, Messenger, WhatsApp and WeChat have almost become the must-have application among young adults in their daily life (Hew *et al.*, 2015). Mobile apps are programs or software that user can download, access and perform certain activities on mobile devices (Kang, 2016). In addition, mobile apps are carried by a variety of mobile devices, for instances, smartphone, tablets and personal digital assistant and available mainly on Apple IOS or Android platform. The trend of using mobile devices and mobile apps has hit the nail on the head. Therefore, this trend makes the study of mobile apps usage intention important (June, 2016). Bomhold (2016) suggested that people use mobile apps mainly for social and communication purpose (e.g. social networking apps), followed by search engines (e.g. Google) and entertainment (e.g. gaming and music).

Malaysia is one of the developing countries in Asia, where internet technological infrastructures are relatively advanced (Chong *et al.*, 2012; Valaei *et al.*, 2016). According to a recent report by Malaysia Digital Association (MDA, 2016), internet users account for 67.7 per cent of the country population. Mobile phone penetration rate is 144.8 per cent, meaning there are 144 mobile phones per 100 Malaysians. A survey conducted by Nielson indicates that Malaysia ranks right after Hong Kong and Singapore, in terms of smartphone ownership. When mobile users are asked what they do on the phones, the top reason is to stay connected on social media, followed by entertainment and games. Social network penetration rate reached 67.7 per cent in 2015, as reported by The Departments of Statistics in Malaysia. A large percentage of the social networking apps users come from the younger generation including teenagers, university students and young professionals who are technology savvy (Rezaei, 2018). Young adult between 18 and 24 years of age consists of 74 per cent of the total use for social networking apps (Beneke *et al.*, 2016). Bowen and Pistilli (2016) have also discovered that the younger generations heavily rely on mobile devices and frequently browse through social networking apps like Facebook, Twitter and Instagram. Mobile phones have become an important part in the social life of people. Marketing researchers (Leong *et al.*, 2013; Rezaei, 2018) have concluded that social influence has a vital role in determining the behavioural intention to use mobile entertainment apps based on data collected via questionnaires collected from mobile entertainment apps users in

Malaysia. However, GlobalWebIndex (2015) revealed that social media penetration in Malaysia is 55 per cent of the total population which is around 17 million of users. Furthermore, mobile content downloaded in Malaysia is lower than the regional average. According to Malaysian Communications and Multimedia Commission, MCMC (2014), the downloading rate of social networking apps in Malaysia has declined 15.4 per cent from 2013 to 2014 because people tend to remain using same social networking apps without acquiring new social networking apps. Therefore, the focus of this study is to examine behavioural intention of young consumers in Malaysia who act as major social networking apps users.

This study provides social networking apps marketers a better understanding in improving social networking apps usage intention and behaviour in adopting effective marketing strategies to meet consumers' needs. Young adults have become a potential market in social networking apps industry as statistic shows that 74 per cent of the users were Millennial between 18 and 24 years of age (GlobalWebIndex, 2015). From a theoretical standpoint, the study enhances our understanding of apps adoption behaviour and enriches the current literature. Unlike previous studies, most of the researchers presented mobile literature using technology acceptance model (TAM) such as and mobile learning (Huang *et al.*, 2016) and telecommunication services (Rezaei *et al.*, 2016a). A unified theory of acceptance and use of technology (UTAUT) model has been used to examine consumer behavioural intention in social networking apps. According to Venkatesh *et al.* (2012), UTAUT theory can explain 70 per cent of the variance of behavioural intention, whereas TAM model only shows the acceptance of 30 per cent. Therefore, drawn upon UTAUT model, this study provides valuable insight in understanding the usage intention of social networking apps.

The objectives of this study are as follows: to predict the behavioural intention and use behaviour of social networking apps using UTAUT as the theoretical foundation; and to investigate the moderating effect of experience on the relationship between effort expectancy, social influence and behavioural intention in using social networking apps among Malaysian Millennial. Accordingly, this study is structured in several sections. The first section provides a general introduction to the research background and brief overview of the study. Section 2 highlighted a comprehensive review of the literature. This section starts with grounded theories that are associated with new technology adoption and acceptance. Section 3 discusses the methodology of research methods which refers to methodology and approach used to conduct the research. In Section 4, the data collected are analysed and discussed. Finally, Section 5 summarises the study and provides implication and recommendation.

2. Theoretical background and hypotheses development

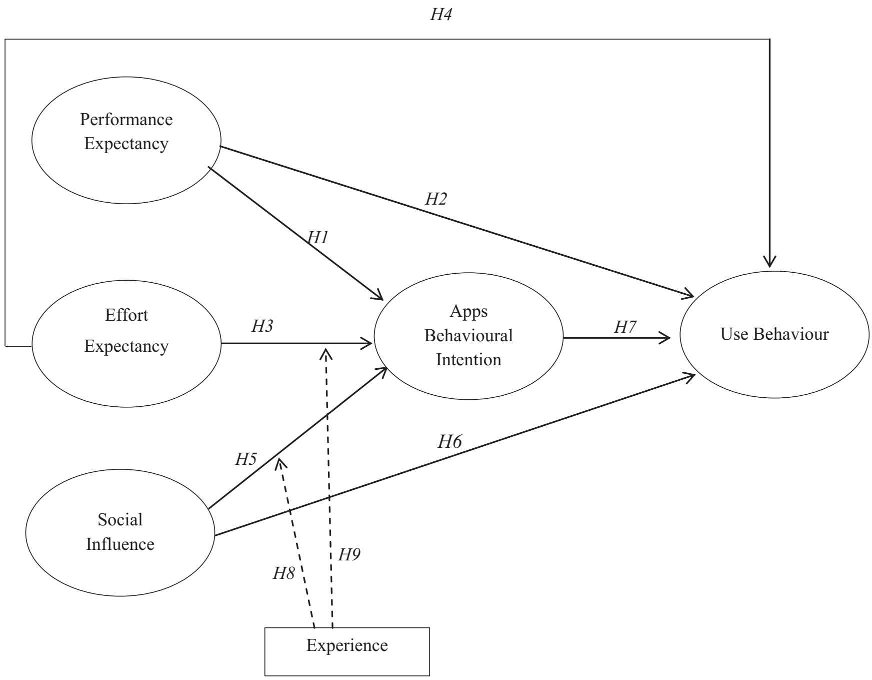
Previous studies have posited various theoretical models that focus on adoption or usage of new innovation such as diffusion of innovation (DOI), theory of planned behaviour (TPB), theory of reasoned action (TRA) (Ajzen and Fishbein, 1980), social cognitive theory (SCT) and TAM (Taylor and Todd, 1995). DOI is used to predict acceptance of technology which determined by five attributes including compatibility, complexity, observability, relative advantage and trialability (Rogers, 1995). Though, Crabbe *et al.* (2009) criticised that IDT is less appropriate for predicting individual adoption of technology but more preferred in measuring diffusion across national boundaries. TRA was developed by Ajzen and Fishbein (1980) indicating that a person's action would be affected by his or her behavioural intention to perform the action, and the determinant of behavioural intention is attitude and subjective norms. Similarly, TPB extended TRA by including perceived behavioural control into the model (Ajzen, 1991), and previous researchers study consumers' behavioural intention. Yang (2013a) used TPB and TAM to investigate consumers' acceptance of mobile apps among college students in Southeast America. IDT was applied in past study conducted by Taylor *et al.* (2011) to understand the young adult mobile apps usage.

UTAUT is a theory on technology adoption drawn from the compounding factors of DOI, SCT, the TPB and the TAM that hypothesises on four key constructs influencing behavioural intention and use behaviour which are effort expectancy, performance expectancy, facilitating conditions and social influence. Table AI depicts the definitions of constructs of this study. The UTAUT incorporates the construct of self-efficacy, social influence and attitude from the TPB and SCT, compatibility from DOI and perceived ease of use from the TAM. The UTAUT extends the TAM by integrating multiple contributing factors of behavioural intention that can best explain the adoption process (Kang, 2016). The UTAUT theory is primarily used in organisational contexts (Venkatesh *et al.*, 2012). However, studies that use UTAUT to identify mobile apps usage intention beyond the workplace are currently scarce. Hew *et al.* (2015) presented factors influencing consumers' behavioural intention to adopt mobile apps by using UTAUT theory. However, facilitating conditions are not included in this proposed model because many of the researchers claimed that facilitating conditions is not a significant driver of behavioural intention when performance expectancy and effort expectancy are present (Almatari *et al.*, 2012; Williams *et al.*, 2015). The young generations nowadays are able to use mobile gadgets without referring heavily to the user manual. Therefore, the variable facilitating condition is not tested in this study (Figure 1).

2.1 Performance expectancy

According to Brown *et al* (2016), performance expectancy is the extent to which using a technology will provide benefit to consumers and lead to performance gains. Results (Al-Gahtani *et al.*, 2007) proved that performance expectancy plays a significant role in affecting teachers' behavioural intention to use digital learning apps, as it facilitates teachers' job task and maximises educational effect. Chong (2013) proved that performance expectancy is the strongest determinant of behavioural intention to use mobile apps. Thus, if consumers find values and innovations from the social networking apps, they are more willing to purchase and pursue the social networking apps use. Consumers will evaluate performance expectancy of social networking apps with the respect to information exchange and communicative messages before he or she uses the apps. A research conducted by Bogart and Wichadee (2015) revealed that performance expectancy directly affects behavioural intention among LINE users in Thailand. However, the research did not consider the Malaysian market and other social networking apps such as Facebook, WhatsApp and Twitter. It may affect the accuracy of the constructs, as people in different countries have different cultural values and behaviour (Chong *et al.*, 2012; Valaei *et al.*, 2016).

Consumers also perceive usefulness differently towards different social networking apps (Lim *et al*, 2011), for instance, social networking apps must be able to provide a useful function to users in terms of information sharing, joining special interest group (Wong *et al.*, 2014) and connection building (Lewis, 2010). Based on various supports, we can conclude that if users find that social networking apps are useful, the adoption rate of social networking apps is higher. Researchers (Wong *et al*, 2015a; Al-Gahtani *et al.*, 2007) suggested that performance expectancy would significantly affect behavioural intention and use behaviour in technology adoption. Pynoo *et al.* (2011) used the UTAUT to identify factors influencing teachers' usage of digital learning apps. Groß (2015) also pointed out that performance a positive impact on consumer's usage intention and usage behaviour in a



Notes: ⟶ Direct effect; - - → Moderating effect

Figure 1.
Theoretical research framework

mobile shopping context. It is supported by Rivera *et al.* (2015) who highlighted that consumers' decisions on whether to use mobile apps depend on whether it is useful in making a task easier to complete. Based on various supports, this study hypothesises as follows:

H1. There is a positive relationship between performance expectancy and behavioural intention in using social networking apps.

H2. There is a positive relationship between performance expectancy and use behaviour of social networking apps.

2.2 Effort expectancy

Effort expectancy is defined as the level of ease associated with the use of a technology (Venkatesh *et al.*, 2012), and it is repeatedly recognised as a critical predictor of user's behavioural intention (Wong *et al.*, 2015a). Park and Ohm (2014) have shown that the user-friendliness of mobile apps exerts positive significant influence over the adoption of mobile apps because the lesser effort is required to use the apps. Prior studies suggested that effort expectancy plays a crucial role in determining behavioural intention to use and actual use of technology. Wu *et al.* (2008), however, claimed that effort expectancy poses a less significant impact on the behavioural intention of 3G mobile telecommunication user in Taiwan, as it is not adequate to attract consumers only with factors of effort expectancy alone. Zhou *et al.* (2010) have also pointed out the direct relationship between effort expectancy and behavioural intention by using UTAUT constructs. If a new technology requires less effort to learn and understand the way of using it, users' adoption intention of the technology would be higher. For example, simplicity and self-efficacy of an advertising medium would determine whether an advertising firm adopts social media for advertisement (Curtis *et al.*, 2010).

Research conducted by Im *et al.* (2008) shows that a simplicity-driven system with maximised efficiency is more favoured by consumers compared with technology that is complicated to use. However, the consumer may perceive differently towards effort expectancy in using social networking apps compared with m-shopping apps. However, previous researchers (Taylor and Strutton, 2010; Choi *et al.*, 2011) argued that effort expectancy is not as critical as performance expectancy in serving as a determinant of behavioural intention, as it has a more significant effect on post-adoption usage. Empirical studies have also suggested that consumers intend to use e-learning apps if the application is easy to use (Chiu and Wang, 2008). Yang (2015) conducted a study to investigate young consumers' behavioural intention in acquiring mobile shopping apps based on survey questionnaire collected from university students in the USA. The findings demonstrated that effort expectancy was a positive predictor of the adoption of mobile shopping apps. As the complexity of technology reduces, the intention of the individual to use the technology is likely to increase (Wong *et al.*, 2015a). For example, Groß (2015) claims that mobile shopping apps are effortless to use if the consumer can easily obtain product information, make payment and check delivery status. However, the measuring criteria of effort expectancy in using social networking apps are different which includes the ease of reaching people and interacting with them (Lim *et al.*, 2011). In fact, most of the empirical studies proved that ease of using social networking apps support higher intention to use. Wu *et al.* (2012) also revealed that use behaviour of I Pass in Taiwan MRT is positively affected by effort expectancy. Therefore, this research hypothesises as follows:

H3. There is a positive relationship between effort expectancy and behavioural intention in using social networking apps.

H4. There is a positive relationship between effort expectancy and use behaviour of social networking apps.

2.3 Social influence

Consumers are likely to download the same apps with reference group such as friends, family and a colleague to communicate and exchange information with them. Social influence refers to the degree to which individuals perceive that significant others, such as family and friends, believe they should use a technology (Martin and Herrero, 2012). They tend to influence the behaviour of the person to adopt or use a new system. Chong (2013) proposed that social influence plays an important role in determining users' behavioural intention in the study of mobile-commerce. This is further supported by Chong *et al.* (2012) who observed that social influence critically influences apps to use intention of consumers in Malaysia especially Chinese consumers. Venkatesh *et al.* (2012) also described social influence as the extent to which an individual concerns about opinion and perception of others who are important to the person. Individuals who desire social acceptance likely comply with others' expectations, and it may contribute to individual's behavioural intention to use the system (Gruzd *et al.*, 2012). Sulieman *et al.* (2015) also validated social influence to be the stimulator of usage behaviour of electronic library services.

According to Wei *et al.* (2009), social influence can be classified into two categories, namely, mass media influence and interpersonal influence. A previous study (Martin and Herrero, 2012) has pointed out that individual tends to follow what reference group said and behave if those referent others have power and authority to award the desired behaviour, as well as punishing non-behaviour. For example, individual's behaviour intention in using a technology can be affected by advertisement appeared in television, newspapers, radio and internet. These advertising mediums are categorised as mass media influence. Furthermore, Taylor *et al.* (2011) also testified that young adult's intention to use mobile apps is significantly affected by peers rather than family members based one survey conducted in the US Midwest universities. As for interpersonal influence, it usually results from reference group that influence individual's opinion, attitude and behaviour, for instance, family, friends, co-workers and much more. Moreover, social influence strongly influences consumers' behavioural intention especially in social networking apps compared with other mobile apps (Kucukemiroglu and Kara, 2015). The young generation in Malaysia likes to use Facebook compared to many other social networking apps because their friends and family are also using it and people around think he or she should use it as well. Therefore, the following hypotheses are proposed:

H5. There is a positive relationship between social influence and behavioural intention in using social networking apps.

H6. There is a positive relationship between social influence and use behaviour of social networking apps.

2.4 Apps behavioural intention and use behaviour

The behavioural intention has been repeatedly adopted as an endogenous variable (Leong *et al.*, 2013; Brown *et al.*, 2016; Rivera *et al.*, 2015). According to Yi *et al.* (2016), behavioural intention is the subjective probability of performing a behaviour which leads to usage intention. Hence, motivational factors that create the intention indicate the level of willingness of people to take the effort to engage in the behaviour. Behaviour intention is defined as the willingness and intention of an individual to perform certain behaviour (Keong *et al.*, 2012). Use behaviour can be defined as the intensity of users in using a technology (Venkatesh *et al.*, 2003; Awwad and Al-Majali, 2015). Use behaviour was commonly measured by the actual frequencies of technology use. Venkatesh *et al.* (2012) have conducted several studies regarding the use of technology using the construct "use behaviour". Ajzen and Fishbein (1980) explained behavioural intention as an evaluation about the motivation of people to act upon or complete a particular behaviour. According to Venkatesh *et al.* (2003), behavioural intention can be used to predict desired behaviour or actual use of a technology. Thus, to determine whether consumers would download the social networking apps, the behavioural intention of the consumer has to first be identified. Behavioural intention is an extremely significant element of the use behaviour (Awwad and Al-Majali, 2015). Review of literature by Williams *et al.* (2015) has shown that numerous technology adoption models are developed to explain the use behaviour of technology. It is because use behaviour can best identify consumers' actual usage of a particular technology.

Previous studies (Yang, 2013b; Yu, 2012; Wong *et al.*, 2015b; Rezaei, 2018) related to mobile technologies have proved the direct association between behavioural intention and usage behaviour. In addition, behavioural intention is validated to be a strong indicator of actual consumer use behaviour of mobile banking service (Chen, 2013) and act as a proxy for measuring actual use behaviour in mobile internet services market (Awwad and Al-Majali, 2015). Hew *et al.* (2015) explained consumer's behavioural intention in term of mobile apps adoption as the intention of the consumer to use or download the mobile app. Kuo and Yen (2009) considered behavioural intention as the major determinant of actual use behaviour of 3G mobile value-added services. Research conducted by Jati and Laksito (2012) shows that behavioural intention has a direct effect on use behaviour of the consumer using e-learning system. A comprehensive analysis of the literature by Salim (2012) revealed that use behaviour of social media in Egypt positively affected by behavioural intention. Therefore, this study hypothesis as follows:

H7. There is a positive relationship between behavioural intention and use behaviour of using social networking apps.

2.5 Experience

Experience refers to an opportunity for an individual to use a particular technology with the passage of time from the initial use (June, 2016). Hence, the term "experience" in this research can be described as the period of usage experience of Malaysian Millennial towards social networking apps. The finding shows that users' experience significantly affects the relationship between acceptance of technology and its determinants. According to Bomhold (2016), the effects of effort expectancy on behavioural intention are moderated by experience. With increasing experience, users' behaviour in using a technology would be led by more associated cues. In this research, the experience would be operated based on years of usage ranging from one year of experience to five years of experience. Oppositely, consumers that have less experience in using social networking apps would concern more about whether the social networking apps are easy to operate. In a word, the effect of effort expectancy of a technology will reduce as experience increases. A literature review by Im *et al.* (2008) uses UTAUT to investigate the moderating effect of experience towards users' acceptance of the technology. According to Carter and Yeo (2016), the experience served as a moderator between effort expectancy and behavioural intention. Almatari *et al.* (2012) claimed that the relationship between effort expectancy and behavioural intention to use M-learning is moderated by experience. Such effect will be stronger for those who adopt M-learning at early stages of individual experience. The comprehensive analysis on the effect of experience done by Samuel (2014) indicates that users' experience exerts a considerable amount of influence towards the effect of effort expectancy and social influence on behavioural intention.

As a result, users would pay less attention in easiness of a technology to use. Furthermore, meta-analytic review by Taylor *et al.* (2011) highlighted that users' affiliation needs are higher and more likely to be influenced by the opinion of reference group when users are a lack of experience towards social networking apps. Experience has been conceptualised in numerous prior studies as a moderator. Kim and Malhotra (2016) separated individual's experience into five different periods. In addition, empirical evidence has demonstrated that effort expectancy construct tends to be more salient in the early stages of mobile apps adoption (Carter and Yeo, 2016). Wu *et al.* (2012) conducted a research on users' behavioural intention for I Pass in Taiwan. They explained user experience as individual's experience of using I Pass in the past time. Besides, prior research suggests that experience would moderate the effect of social influence on behavioural intention. Based on the observation of Varshney and Vetter (2012), social influence appears to be important only at the early stage of experience when the consumer initially uses the technology. With the passage of time, the role of social influence will weaken and change from significant to non-significant when the levels of user experience with the technology increases. Yang (2013b) found that social influence was less important with increasing experience. This is similar to the suggestion of Groß (2015) and Rezaei (2018) in the study of how the experience would affect the social influence in mobile shopping apps. The result indicates that the longer the usage experience of m-shopping apps, the less significant the social influence would affect behaviour intention to use. Experience reduces the effect of social influence on users' behavioural intention. Therefore, this study hypothesises as follows:

H8. The relationship between effort expectancy and behavioural intention is moderated by experience.

H9. The relationship between social influence and behavioural intention is moderated by experience.

3. Method

While qualitative research focuses on the subjective assessment of behaviour which concerns in generating measurable data (UWE Flick, 2011), a mono-quantitative research is used in this study, as the survey is conducted to analyse the relationship between performance expectancy, effort expectancy, social influence, behavioural intention and use behaviour. This study adopts quantitative method instead of qualitative because respondent's inner thought and opinions are not taken into account in this research (Saunders *et al.*, 2012). Numerical data are generated rather than subjective information and are analysed by using statistical techniques named structural equation modelling (SEM). As such, each construct (Figure 1) was measured with multiple items which adapted from previous empirical studies as shown in Table AII. A pilot test was conducted to determine potential problem and weaknesses in the questionnaires and survey approach related to questionnaire items.

3.1 Sampling plan and data collection

Probability sampling is used when the total population is identifiable, and non-probability sampling is used if the population is not known (Saunders *et al.*, 2012). In this research, non-probability sampling is adopted, as it is difficult to access information about the exact population of young smartphone users in Malaysia. According to Henry (1990), non-probability sampling is more suitable compared to probability sampling if the sample size is more than 50. As the respondents of the study were only Millennial born during the 1980s and 2000s, purposive sampling is advantageous to use, as it could generate findings with high consistency and accuracy. Therefore, we assume it as 1,000,000. Based on Krejcie and Morgan's (1970) table, the minimum sample size for infinite target population is 384, which is adequate to generate reliable results. Moreover, survey questionnaires were distributed to students from few different universities in Malaysia such as Sunway University, Help University, TAR University College, Segi University and Taylor's University. University students were selected because they are in the age range of Millennial and most are smartphone users. According to Yang (2015), university students are more open to adopting new ICTs. Online questionnaires were also spread to young adults in social-networking sites, as they are the potential users of social-networking apps. The online questionnaires were also administered in social networking sites as it helps to gain responses quickly. It is beneficial to use questionnaires because of convenience, cost saving and large coverage. Questionnaires were distributed to respondents within two weeks of time in different universities. 500 set of online and offline questionnaires were distributed among Generation Yers in universities. However, five questionnaires were not returned. A total of 384 valid questionnaires were obtained from six different universities in Malaysia. We performed *t*-test analysis and the results show insignificant differences between two groups of respondents (online and offline). Table I shows the summary of a demographic profile of respondents. Theretofore, cross-sectional data collection approach is conducted as data collected explains the situation at only one-point time.

Measure	Items	Frequency	(%)
Gender	Male	183	47.7
	Female	201	52.3
Age	18-21	316	82.3
	22-25	56	14.6
	26-29	7	1.8
	30-35	5	1.3
Education level	SPM	28	7.3
	Foundation	57	14.8
	Diploma	61	15.9
	Degree	227	59.1
	Master	4	1
	Others	7	1.8
University	Taylor's University	101	26.3
	Sunway University	56	14.6
	Monash University	58	15.1
	Inti University	64	16.7
	SEGI University	31	8.1
	TAR University College	21	5.5
	Others	53	13.8
Income level	< RM 1000	250	65.1
	RM 1,001-RM 2,000	76	19.8
	RM 2,001-RM 3,000	25	6.5
	RM 3,001-RM 4,000	20	5.2
	RM 4,001-RM 5,000	7	1.8
	> RM 5,000	6	1.6
Experience	Less than 1 year	34	8.9
	1-3 years	111	28.9
	4-6 years	102	26.6
	> 6 years	137	35.7
Daily usage	Less than 1 h	6	1.6
	1-3 h	123	32
	4-6 h	134	34.9
	7-9 h	69	18
	> 9 h	52	13.5
Social network apps	Facebook	146	38
	WhatsApp	142	37
	WeChat	20	5.2
	Twitter	11	2.9
	Instagram	13	3.4
	YouTube	28	7.3
	Snapchat	17	4.4
	Others	7	1.8

Table I. Summary of demographic profile of respondents

3.2 Structural equation modelling

Partial least squares (PLS) path modelling approach, a SEM techniques using SmartPLS, was used to analyse the data. The advancement of SEM techniques has gone far beyond traditional multivariate technique in terms of convenience and efficiency accuracy (Malhotra *et al.*, 2016), as this technique enables researchers to test or modify theories and models (Anderson and Gerbing, 1982). The SEM technique is an influential and robust second-generation multivariate analysis method for parameter assessment, confirmatory and hypotheses testing which integrates the first-generation procedure which includes factor analysis, regression or path analysisand discriminant analysis. This statistical modelling technique is getting popularity in social and behavioural science research (Richardson *et al.*, 2009; Igbaria *et al.*, 2007; Liang *et al.*, 2010). There are two well-known techniques in the modern generation multivariate analysis (SEM) which are Maximum Likelihood (ML) estimation approach (Jöreskog, 1970; Jöreskog, 1978) or covariance-based CB-SEM and PLS variance-based approach (VB-SEM). VB-SEM and CB-SEM starts with theory or a set of theories and concept (Reinartz *et al.*, 2009; Rezaei, 2015; Hair *et al.*, 2011; Hair *et al.*, 2012) which sharing the same roots and functions (Hair *et al.*, 2012) but the decision on choosing appropriate statistical analysis techniques is vital and critical for social science researchers because incorrect choice of statistical technique can cause erroneous conclusion and inaccurate results (Rezeda, 2016; Rezaei, 2015; Ramayah *et al.*, 2014).

PLS path modelling is a method for complex causal model, as it can simultaneously assess multiple cause-and-effect relationships among the constructs (Sarstedt, 2008) and does not need strong assumptions such as distributions, normality and sample size (Henseler *et al.*, 2009; Sarstedt, 2008; Henseler, 2010). It has been broadly adopted by various researchers (Levin *et al.*, 2012; Ringle *et al.*, 2014; Henseler, 2010; Valaei *et al.*, 2016), ML focuses on factor analysis which is often used for theory testing known as covariance-based SEM (CB-SEM). Oppositely, PLS approach is a best practice for component analysis which appropriates for explaining the complex relationship between variables but less suitable for confirmatory testing (Hair *et al.*, 2011; Rezaei, 2018). As such, as there are a number of interactions between variables in this research, PLS is used in this study because it is capable for testing complex path models with latent variables (Chin *et al.*, 2015). The two-step approach is used for SEM analysis to test behavioural intention and use behaviour of the consumer. The focus of measurement model assessment is to evaluate causal relations between indicators/items and validation of theoretical construct while structural model evaluates the causal relations between theoretical constructs (Anderson and Gerbing, 1982).

3.3 Common method bias

Common method bias or sometimes called common method variance (CMV) can occur in a number of different ways. For example, it may arise when a single survey method is used to collect data from target responses or when data were collected from a single source (MacKenzie and Podsakoff, 2012; Podsakoff *et al.*, 2003; Rezaei, 2015). As such, CMV affects item reliabilities and the covariation between latent constructs (MacKenzie and Podsakoff, 2012), which in turn, influences structural relationship (Kline *et al.*, 2000). CMV could be problematic in behaviour studies because it introduces systematic variance brought by the measurement method instead of the construct itself (Podsakoff *et al.*, 2003; Rezaei, 2015). According to Reio, there are two ways to reduce CMV in research, namely, procedural design and statistical control. This study addressed CMV with using guideline recommend by Podsakoff *et al.* (2003). We avoid common scale anchors in minimising common rate effects, acquiescence biases, item characteristic effects, common scale formats, item priming effects and scale length during designing the questionnaire followed by a previous study

(Rezaei, 2018). As for data analysis, three statistical techniques including Harman's one-factor test, the partial correlation procedures and the structural model marker-variable technique were performed and the results reveal that the CMV is not a concern in this study.

4. Results

4.1 Measurement model

The reliability and validity of measurement model (The first stage) are examined using the SmartPLS software (Ringle *et al.*, 2005) before conducting a test for structural models. The first step includes construct validity testing and discriminant validity testing for measurement model and the second step involves hypothesis testing for structural model. To examine the measurement model, a construct validity test was conducted including the assessment of outer loadings, average variance extracted (AVE), composite reliability (CR) and Cronbach's alpha (Levin *et al.*, 2012; Rezaei, 2015; Valaei *et al.*, 2016). Table II reported that outer loadings of all measurement items are well above the minimum threshold value of 0.7 except SI1 and SI5 whose outer loadings are 0.695 and 0.670, respectively. As for composite reliability, CR values for all construct exceeds 0.6. It indicates the high level of internal consistency reliability of construct. As depicted in Table II, AVE values are reported to be greater than 0.5 as recommended by Rezaei (2015) and Leong *et al.* (2011), thus demonstrating convergent validity. According to Hair *et al.* (2012) reflective indicators of Cronbach's alpha is 0.7 or greater. As the Cronbach's alpha values for all constructs are well above 0.7, it shows that the scales were reliable.

Construct	Items	Item loadings	AVE*	Composite reliability (CR)**	Cronbach's alpha
Performance expectancy (PE)	PE1	0.740	0.576	0.871	0.815
	PE2	0.765			
	PE3	0.817			
	PE4	0.747			
	PE5	0.721			
Effort expectancy (EE)	EE1	0.735	0.559	0.864	0.803
	EE2	0.747			
	EE3	0.747			
	EE4	0.729			
	EE5	0.781			
Social influence (SI)	SI1	0.695	0.534	0.851	0.781
	SI2	0.790			
	SI3	0.739			
	SI4	0.755			
	SI5	0.670			
Behavioural intention (BI)	BI1	0.731	0.594	0.854	0.772
	BI2	0.795			
	BI3	0.784			
	BI4	0.772			
Use behaviour (UB)	UB1	0.767	0.643	0.843	0.721
	UB2	0.848			
	UB3	0.788			

Notes: *Average variance extracted (AVE) = (summation of the square of the factor loadings)/{(summation of the square of the factor loadings) + (summation of the error variances)}; **Composite reliability (CR) = (square of the summation of the factor loadings)/{(square of the square of the factor loadings) + (summation of the error variances)}

Table II.
Construct validity

Discriminant validity was also tested by evaluating Fornell and Larcker's (1981) criterion and cross-loading criterion. Based on Table III, the off-diagonals values represent correlations between latent constructs. Squared correlation refers to shared values between constructs. The loadings and cross-loadings of exploratory factor analysis as reported in Table IV shows that the loadings between own construct are higher than cross-loadings. Therefore, discriminant validity is achieved.

4.2 Structural model

PLS-SEM algorithm was used to assess the significance of the structural model relationship, and PLS-SEM bootstrapping procedure (option) was used to assess the statistical significance among constructs. As shown in Table V, the path coefficients values represent

Research constructs	PE	EE	SI	BI	UB
PE	*0.576**				
EE	0.228	*0.559*			
SI	0.306	0.254	*0.534*		
BI	0.384	0.340	0.223	*0.594*	
UB	0.312	0.212	0.250	0.373	*0.643*

Notes: The off-diagonal values in the above matrix are the square correlations between the latent constructs and diagonal are AVEs; Performance expectancy (PE); Effort expectancy (EE); Social influence (SI); Behavioural intention (BI); Use behaviour (UB)

Table III.
Discriminant validity – Fornell–Larcker criterion

Items	PE	EE	SI	BI	UB
PE1	*0.740*	0.503	0.516	0.526	0.490
PE2	*0.765*	0.433	0.531	0.528	0.483
PE3	*0.817*	0.462	0.570	0.558	0.538
PE4	*0.747*	0.354	0.529	0.507	0.436
PE5	*0.721*	0.413	0.549	0.518	0.481
EE1	0.378	*0.735*	0.440	0.464	0.468
EE2	0.429	*0.747*	0.457	0.469	0.482
EE3	0.443	*0.747*	0.419	0.492	0.484
EE4	0.500	*0.729*	0.497	0.549	0.488
EE5	0.383	*0.781*	0.407	0.496	0.475
SI1	0.512	0.439	*0.695*	0.499	0.461
SI2	0.561	0.462	*0.790*	0.575	0.509
SI3	0.507	0.423	*0.739*	0.503	0.502
SI4	0.546	0.468	*0.755*	0.542	0.531
SI5	0.468	0.378	*0.670*	0.520	0.444
BI1	0.530	0.551	0.531	*0.731*	0.502
BI2	0.591	0.534	0.587	*0.795*	0.597
BI3	0.520	0.466	0.562	*0.784*	0.582
BI4	0.499	0.487	0.546	*0.772*	0.552
UB1	0.505	0.507	0.550	0.575	*0.767*
UB2	0.566	0.546	0.573	0.448	*0.848*
UB3	0.468	0.489	0.489	0.596	*0.788*

Notes: Bold values are loadings for each item that are above the recommended value of 0.5; and an item's loadings in its own variable are higher than all of its cross-loadings with other variable

Table IV.
Discriminant validity – loading and cross-loading criterion

the hypothesised relationship between the reflective constructs. The level and significance of the path coefficient were obtained through bootstrapping 1,000 resample and the findings of hypothesis testing are reported accordingly. Based on Table V, the standardised path coefficients, *t*-values and R^2 values, are presented to assess the predictability of behavioural intention and use behaviour. The results reveal that 64.2 per cent of the total variation in behavioural intention to use social networking apps can be explained by using variation in performance expectancy, effort expectancy and social influence. On the other hand, there are 63.4 per cent of variation accounted for use behaviour of social networking apps which explained by performance expectancy, effort expectancy, social influence and behavioural intention. Consequently, in line with a previous study (Hew *et al.*, 2015), it proved that the UTAUT model is applicable in determining user's usage intention and use behaviour of social networking apps.

When the behavioural intention of social networking apps was predicted, it was found that performance expectancy (Beta = 0.279, $p < 0.01$), effort expectancy (Beta = 0.295, $p < 0.01$) and social influence (Beta = 0.349, $p < 0.01$) were significant predictors. Use behaviour was also significantly affected by performance expectancy (Beta = 0.116, $p < 0.05$), effort expectancy (Beta = 0.193, $p < 0.01$), social influence (Beta = 0.162, $p < 0.01$) and behavioural intention (Beta = 0.432, $p < 0.01$). Among all the exogenous latent constructs, social influence appears to be the strongest determinant of behavioural intention; the behavioural intention is the most influential factor of use behaviour because of greater beta values. All the direct structural relationships are statistically significant to predict behavioural intention and use behaviour (Table V). Hence, *H1*, *H2*, *H3*, *H4*, *H5*, *H6* and *H7* are supported.

Next, the moderating effect of experience towards effort expectancy–behavioural intention relationship and social influence–behavioural intention relationship was tested. The variance in behavioural intention explained by performance expectancy, effort expectancy and social influence increased from 64.2 per cent to 66 per cent after including the moderating effect, a beta value of effort expectancy*EXP and social influence*EXP are also evaluated to predict behavioural intention. The higher the proportion of explained variation in a model, the better the model fits the data; thus, the result in this study yields variance explained of over 60 per cent in behavioural intention. *H8*, which proposes that experience moderates the effect of effort expectancy on behavioural intention, was not supported. It is because the *p*-value is not less than 0.05 which indicates that the moderating

Hypothesis	Path	Path coefficient	SD	Standard error	*t*-statistics	Decision
H1	PE → BI	0.279	0.059	0.059	4.688**	Supported
H2	PE → UB	0.116	0.053	0.053	2.200*	Supported
H3	EE → BI	0.295	0.050	0.050	5.866**	Supported
H4	EE → UB	0.193	0.049	0.049	3.906**	Supported
H5	SI → BI	0.349	0.057	0.057	6.099**	Supported
H6	SI → UB	0.162	0.061	0.061	2.626**	Supported
H7	BI →UB	0.432	0.064	0.064	6.731**	Supported
H8	EE → EXP → BI	0.536	0.313	0.313	1.713	Not supported
H9	SI → EXP → BI	0.760	0.287	0.287	2.652**	Supported

Notes: t = 1.96; *$p < 0.05$; t = 2.58; **$p < 0.01$ (Hair *et al.*, 2011); Performance expectancy (PE); Effort expectancy (EE); Social influence (SI); Behavioural intention (BI); Use behaviour (UB)

Table V. Result of hypothesis testing and structural relationships effect of experience on effort expectancy–behavioural intention was not significant. Furthermore, *H9,* which predicted that experience moderate the effect of social influence on behavioural intention, is supported. It is because *p*-value is less than 0.01 and beta value shows that low level of experience enhances the effect of social influence on behavioural intention (Beta = 0.760; $p < 0.01$), which is corresponding to *H9*.

5. Discussion

In this study, UTAUT model was used as an underlying framework to assess the relationship between consumer's behavioural intention in using social networking apps and its key constructs including performance expectancy, effort expectancy and social influence to predict the actual use behaviour. Furthermore, the experience was incorporated in this study as a moderator to examine whether there is a moderating effect on the relationship between effort expectancy and behavioural intention and behavioural intention. Based on the results presented in the previous section, all relationships were testified to have a significant direct relationship with behavioural intention and use behaviour. Among all the three exogenous latent constructs, social influence was found to be the most important attributes of behavioural intention. The finding was inconsistent with of the past research studies (Wong *et al.*, 2015a, Salim, 2012; Sulieman *et al.*, 2015) which suggested that social influence had no significant effect on behavioural intention because what other people think is considered as an external factor that is less important compared to internal product factor of usefulness and user-friendliness. However, the significance of social influence on behavioural intention was similar to findings of Taylor *et al.* (2011) who also conducted research on young adult's mobile apps adoption. Chong *et al* (2012) also similarly suggest that social influence plays a significant role in m-commerce adoption. A possible explanation for this is that young adults rely more on the opinion of the reference group, especially the peers, to decide in adopting mobile apps, as both the studies focus on the Millennial. Age group of 16 to 26 is the most likely to be influenced stage in terms of buying behaviour compared other age group. It is because they have strong desire to adopt norms and behaviour of other who they aspire to associate with. In addition, Malaysia is considered to be a collectivist culture, where members of the society are more inter-dependent and relationship-oriented (Valaei *et al.*, 2016). This implies a strong tendency to conform to group norm or social influence (Hofstede and Hofstede, 1997). Therefore, the younger generation tends to consider the opinion of important others first when downloading an app rather than focussing on the complexity of use and usefulness of the app.

Effort expectancy was rated as the second important determinant of behavioural intention. It is supported by Tan *et al.* (2012) who claimed that effort expectancy has a strong impact on behavioural intention because apps that require significant efforts to use would discourage consumers from adopting it. Besides, performance expectancy was discovered as the least influencing factors that affect Millennial intention to use social networking apps. It is opposing to result of Almatari *et al.* (2012) who confirmed that performance expectancy has the strongest predictability towards behavioural intention compared to effort expectancy and social influence. Wong *et al.* (2015a) argued that consumer would not adopt a technology that is deemed not useful, no matter how user-friendliness the technology is and how strong it is recommended by others. On the other hand, the behavioural intention was rated as the dominant predictor driving consumers' use behaviour of social networking apps. It is closely aligned with most of the previous studies (Wu *et al.*, 2012; Williams *et al.*, 2015; Salim, 2012). For instances, empirical studies have concluded that behavioural intention of users acts as a definite indicator of actual usage for electronic tickets (Wu *et al.*, 2012), electronic library services and electronic learning platform (Samuel, 2014). Results also indicated that performance expectancy, effort expectancy and social influence exert a positive significant influence towards use behaviour of the young consumer for social networking apps.

Finally, the results suggest that consumers experience moderates the relationship between social influence and behavioural intention but app users experience do not moderate the relationship between effort expectancy and behavioural intention. Consumer's level of experience in using social networking apps exerts a moderating effect between social influence and behavioural intention. It is supported by Taylor *et al.* (2011) who obtained a similar result and proved that users who are a lack of experience in using apps tend to be influenced more by the opinion of others on the decision to acquire apps compared with experienced users. However, the moderating effect of experience on effort expectancy–behavioural intention relationship is consistent with past study of Venkatesh *et al.* (2012). The effect of effort expectancy on behavioural intention is not moderated by experience, such that the effect is supposed to be stronger for those with limited experience. It indicated that the more experienced the users are, the more attention they pay to the simplicity of use. While it has been argued that when consumers start using social networking apps, they are experienced and knowledgeable in evaluating the user-friendliness of apps and seek apps that are convenient to use, but the results of this study show that the adopted and experienced consumers are less influenced by ease of use. Therefore, Millennial experience is an important moderator that influence social factors and behavioural intention relationships.

5.1 Implications

From a theoretical standpoint, this study enriches the existing research gap of UTAUT model by extending behavioural intention to the use behaviour and integrating experience as a moderator to better explain user's adoption of social networking apps among Millennial. Overall, the outcome of the result was consistent with what is suggested in UTAUT model, as performance expectancy, effort expectancy and social influence is validated to have a significant relationship with behavioural intention and use. Consumer's use behaviour is also significantly affected by behavioural intention, performance expectancy, effort expectancy and social influence. Functional and contextual factors are incorporated in the UTAUT to improve the explanatory power in user's technology adoption. Thus, it is reasonable to assume UTAUT model to be superior compared with prior theoretical models in explaining technology acceptance and use (Martin and Herrero, 2012). Besides, Persaud and Azhar (2012) presented factors influencing behavioural intention of consumers to adopt mobile apps in Canada using TRA. Additionally, UTAUT is proposed by Venkatesh *et al.* (2003) describing intention to adopt a technology. Experience is confirmed to be a significant moderator, as it moderates the effect of social influence on behavioural intention. This could provide valuable insights towards current literature by serving as an extended construct of former UTAUT model. As there is a dearth of relevant research, this study set a foundation for future investigations. The new integrated model is believed to contribute to the knowledge bank and narrow down the research gap in investigating factors affecting social networking apps.

Practically, understanding young adult use behaviour of social networking apps in Malaysia and other emerging economy is essential. Malaysian government aspires to develop and further strengthen its digital economy. As documented by the Malaysian Communications and Multimedia Commission (MCMC, 2014), smartphone users in the country are dominated by young consumers, who heavily rely on social media to stay connected with their peers. The findings of the study help to inform industry manufacturers to further develop social networking apps to meet consumers' needs and strengthen their competitive positions in the industry. As the behavioural intention is the strongest determinant of consumer's use behaviour, app developers and app marketers should focus on improving elements that drive behaviour intention which includes performance expectancy, effort expectancy, and social influence to enhance the actual usage of social networking apps. Thus, marketing managers should be aware of elements that encourage a young adult to adopt social networking apps. Moreover, based on findings of the current study, social influence has been confirmed as the most significant driver among young Malaysians. Therefore, app developers should always consider the element of social needs or group norm and allocate greatest amount resources to improve the social influence of social networking apps. Marketing managers could create more social influence by advertising online and spread it to the social media to stimulate e-WOM (Rivera *et al.*, 2015). According to Gruzd *et al.* (2012), attractive words and meaningful messages delivered from advertisement would likely to encourage people to share it with their friends surrounding. As experience significantly moderates the effect of social influence on behavioural intention, apps developers and marketing managers are advised to increase social influence mainly on first time user. It is because they lack experience in using the apps and more likely to be influenced by words and suggestions of the reference group. For instances, developers can offer some benefits to existing users by giving extra points and marks when they invite their friends who have never used the apps to download it. Thus, it can help to attract more new users with limited experience when the apps are recommended by their friends.

In addition, effort expectancy was regarded as the second important direct predictor of behavioural intention in using social networking apps. Therefore, the effort expectancy aspect should be taken seriously to stimulate the growth of consumers' behavioural intention and use behaviour. Although young users are seen as relatively more competent in technology adoption, developers should continue to enhance the user-friendliness of social networking apps by providing simple guidelines for beginner to use when the apps are first download. Marketing managers and apps developers are also recommended to design a functional button of apps and place close to user's finger movement range to ensure convenience of user interface (Hew *et al.*, 2015). For example, developers can do an observation on consumers' daily use of apps to investigate what functions can be integrated to enable users to make specific responses based on a different situation such as aeroplane mode, silent mode, reject calls, voice record and much more. Finally, in terms of performance expectancy, managers should also put emphasis on increasing it, as result proved that performance expectancy would stimulate consumer's behavioural intention; thus, managers are suggested to create more apps features that are useful for consumers.

5.2 Limitations and future research direction

The chosen research methodology consists of several limitations. Because of time constraint and budget limitation, cross-sectional study was conducted instead of longitudinal study. However, the cross-sectional study failed to capture the change of consumers' behaviour across time and environment. Therefore, future research should consider longitudinal method; thus, changing behaviour would be considered because of technological change, trends and various factors. In addition, this research focussed on the Millennial segment which might be inadequate to generalise the whole population of social networking apps user in Malaysia. Future study is suggested to cover a wider group of respondent including different age group. Finally, the quantitative study might ignore the context of a phenomenon. Qualitative research provides detailed and rich information that covers subjective feelings; however, results generated from quantitative research can be generalised to the population. Thus, future research can be improved by including both quantitative and qualitative research approach, for instance, both survey and interview can be conducted to enhance validity and reliability of findings.

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Appendix

Elements	Type of variable	Definition of variable	Source
Performance expectancy (PE)	Exogenous latent construct	The degree to which using a technology will provide benefits to consumers in performing certain activities	Venkatesh *et al.* (2012)
		The extent to which an individual perceives that using a system will enhance his or her productivity, and thus lead to performance gains	Brown *et al.* (2016)
Effort expectancy (EE)	Exogenous latent construct	The degree of ease associated with consumers' use of technology	Venkatesh *et al.* (2012)
Social influence (SI)	Exogenous latent construct	The extent to which consumers perceive that important others (e.g. family and friends) believe they should use a particular technology	
Behavioural intention (BI)	Endogenous and exogenous latent construct	An individual subject probability of performing a behaviour	Yi *et al.* (2016)
		A user group willing to use information technologies for their tasks	Keong *et al.* (2012)
Use behaviour (UB)	Endogenous latent construct	The intensity of users in using a technology	Venkatesh *et al.* (2003)

Table AI. Definitions of the UTAUT constructs

Construct	Measurement items	Sources
Performance expectancy	*PE1*: I find social networking apps useful in my daily life *PE2*: Using social networking apps helps me accomplish things more quickly *PE3*: Using social networking apps increases my productivity *PE4*: Using social networking apps enhances my effectiveness on the task	(Al-Gahtani et al., 2007)
Effort expectancy	*EE1*: Learning how to use social networking apps is easy for me *EE2*: My interaction with social networking apps is clear and understandable *EE3*: I find social networking apps easy to use *EE4*: It is easy for me to become skilful at using social networking apps *EE5*: Using the social networking apps is simple to me	(Hew *et al.*, 2015)
Social influence	*SI1*: People who are important to me think that I should use social networking apps *SI2*: People who influence my behaviour think that I should use social networking apps *SI3*: People whose opinions that I value prefer that I use social networking apps *SI4*: People around me consider it is appropriate to use social networking apps	(Martin and Herrero, 2012)
Apps behavioural intention	*BI1*: I intend to continue using social networking apps in the future *BI2*: I will always try to use social networking apps in my daily life *BI3*: I plan to continue to use social networking apps frequently *BI4*: I will continue to use social networking apps on a regular basis	(Venkatesh *et al.*, 2012)
Apps usage behaviour	*UB1*: I have used social networking apps a lot in the past one month *UB2*: I have been using social networking apps regularly to communicate with people *UB3*: I have been using social networking apps in my daily life	(Awwad and Al-Majali, 2015)

Note: *All items are measured using 5-point Likert scale from "1 = Strongly disagree" to "5 = Strongly agree"

Table AII.
Measurement of exogenous and endogenous latent constructs