JISIB
Journal of Intelligence Studies in Business
Vol. 12 No. 1 (2022) pp. 65–82
Open Access: Freely available at: https://ojs.hh.se/

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1911-2004

# Mobile Applications Adoption and Use in Strategic Competitive Intelligence: A Structural Equation Modelling Approach

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*Received 9 August 2022 Accepted 17 November 2022*

**ABSTRACT** This article examined the key determinants of mobile applications' adoption and use in strategic competitive intelligence. A quantitative research based on a survey of 150 participants drawn from strategic competitive intelligence practitioners and analysts was used to examine and validate the extended UTAUT2 Model to identify the key determinants of mobile applications` adoption and use in SCI. PLS-SEM algorithm was used to analyse data. Findings show that PE, SI, HT, SE, and BI had significant influence over UB while EE, HM, PV, SN, and PR had an insignificant influence. Adoption and use of mobile applications was considered a planned behaviour. Perhaps the most important findings for SCIPs relate to the importance-performance map analysis that showed the greater absolute importance of self-efficacy on use behaviour. Previous empirical studies have largely ignored the influence of cognitive psychological perceptive which this study addressed by examining key determinants of behaviour intention and user behaviour.

**KEYWORDS:** Strategic Competitive Intelligence; UTAUT; UTAUT2; Adoption; Mobile Applications; Use behaviour; Unified Theory of Acceptance and Use of Technology

## 1. INTRODUCTION

Competitive intelligence has become a global phenomenon in today`s environment that is characterised by global competition. Big data analytics, AI, IoT, 5G/6G, cybersecurity, as well as the adoption and use of mobile applications such as WhatsApp, Facebook, Instagram, Twitter, and Telegram have enabled high-speed availability, transfer, and analysis of large amounts of data collected and accumulated by individuals and organisations over the years (Maune, 2021). In the last decades, companies have invested resources dramatically in Competitive Intelligence (CI) systems, which enabled business users to discover their rich, reliable, and relevant data.

CI is providing companies with the tools to make informed decisions. It is enabling companies to keep ahead of the competition and industry trends. The past decade has seen a tremendous growth in mobile applications usage the world over. By the end of 2020, reports estimated that there were about 3.5 billion

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smartphone users worldwide (Maune, 2021). According to statista.com website, an estimated 1.4 billion smartphones were sold in 2020 alone. This has increased the demand and use of mobile applications by companies. What is not known, however, are the major key determinants for the adoption and use of mobile applications in SCI. The influence these determinants have on behaviour intentions and use behaviour of mobile applications in SCI is still mystery.

Thus far, CI research has focused primarily on the same phenomenon, how to gather information to make better decisions (Solberg, 2019 cited by Maune, 2021). Research is now starting to address CI from a business intelligence perspective, big data analytics, and Artificial Intelligence this time around using algorithms as a predictive tool. Previously, CI research was more concerned with web and desktop applications but there is a rapid shift towards mobile applications due to information available anytime, anywhere from everyone who has a phone. This sudden shift has also been influenced by an increase in the number of mobile application and the number of active users per day (Maune, 2021). Mobile intelligence has now combined BI, transactions, and multimedia. Mobile applications have become the biggest data mining fields ever found before. Those companies that are ignoring mobile applications for intelligence are doing so at their own peril. What is currently unknown is how deep these data mining fields are and for how long they can be relied on by intelligentsia?

What business leaders often fail to understand are the key determinants for the adoption and use of mobile applications in SCI? This usually serves as a differentiator among CI practitioners and analysts. With the development of a number of mobile applications and the increase in mobile penetration globally, it is critical for SCI practitioners and analysts to appreciate the key determinants for the adoption and use of mobile applications in SCI. Mobile applications have become the focal area for new ideas and big data analysis with more and more organisations turning to these platforms to map their strategies. In this dynamic world, business leaders need to know what their competitors are up to. Additionally, they need to gather the trends, patterns, and relationships they see emerging across mobile platforms. The question that should be asked is, 'how do we capitalise on this intelligence?' Mobile applications platforms have become new areas to look for business opportunities. CI is very important in this regard and should be prioritised to identify these opportunities.

The aim of this study was to empirically examine and validate the proposed path analysis model (Maune, 2021). The model was an extension of the UTAUT2. We analysed the data to find key determinants for the adoption and use of mobile applications in SCI. Behaviour intention and use behaviour from a cognitive psychological perspective was used. More specifically, the major objectives of this research were; (i) to establish the key determinants for the adoption and use of mobile applications in SCI, (ii) to examine the influence of behaviour intention on use behaviour in the adoption and use of mobile applications in SCI, and (iii) to develop a path analysis model suitable for the adoption and use of mobile applications in SCI.

To achieve this, the authors adopted a positivism research philosophy. The authors used a deductive research approach to gather data through an online survey sent to CI practitioners and analysts as well as those involved in decision making in various organisations. An explanatory research design assisted the researcher in examining the relationship between variables as well as assisting in identifying significant paths within the path analysis model. One hundred and fifty online questionnaires were sent through different online platforms with 98 responses received. The findings have both managerial and practical implications; their contribution is scientific, practical, societal, political, and educational.

The remainder of the article will be as follows, first a literature review that elucidates the proposed path analysis model and the hypotheses will be followed by the research method used. This will address the research respondents and procedure, measurement, approach to SEM, analysis, model adopted, and the structural model analysis. Thereafter, discussion of results will follow. The study`s implications for research and practice as well as its limitations. The study conclusions will be given and the article will end with a reference list.

## 2. LITERATURE REVIEW

In this section, the study presents an overview of the extended unified theory of acceptance and use of technology (Venkatesh, Thong, and Xu, 2012) and explains the basic modifications made to the extended unified theory of acceptance and use of technology (UTAUT2) model to fit the study context. The section also discusses the new constructs that were added to the UTAUT2 (that is, perceived risk, trust, subjective norm, and self-efficacy) as discussed by Maune (2021).

## 2.1 Theoretical framework

### 2.1.1 Unified Theory of Acceptance and Use of Technology (UTAUT2)

Based on a review of the extant literature, Venkatesh, Morris, Davis, and Davis (2003) developed UTAUT as a comprehensive synthesis of prior technology acceptance research. UTAUT has four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) that influence behavioural intention to use a technology and/or technology use. We adapt these constructs and definitions from UTAUT to the consumer technology acceptance and use context. Here, *performance expectancy* is defined as the degree to which using a technology will provide benefits to consumers in performing certain activities; *effort expectancy* is the degree of ease associated with consumers' use of technology; *social influence* is the extent to which consumers perceive that important others (for example, family and friends) believe they should use a particular technology; and *facilitating conditions* refer to consumers' perceptions of the resources and support available to perform a behaviour (Venkatesh et al., 2003; Brown and Venkatesh, 2005). According to the UTAUT, performance expectancy, effort expectancy, and social influence are theorised to influence behavioral intention to use a technology, while behavioral intention and facilitating conditions determine technology use. Also, individual difference variables, namely age, gender, and experience are theorised to moderate various UTAUT relationships (Venkatesh et al., 2012). The lighter lines in Figure 1 show the original UTAUT along with the one modification noted above that was necessary to make the theory applicable to this context.

*Hedonic motivation* is defined as the fun or pleasure derived from using a technology, and it has shown to play an important role in determining technology acceptance and use (Brown and Venkatesh, 2005). In IS research, such hedonic motivation (conceptualised as perceived enjoyment) has been found to influence technology acceptance and use directly (van der Heijden, 2004; Thong, Hong, and Tam, 2006). In the consumer context, hedonic motivation has also been found to be an important determinant of technology acceptance and use (Childers, Carr, Peck, and Carson, 2001; Brown and Venkatesh, 2005). Thus, we add hedonic motivation as a predictor of consumers' behavioural intention to use a technology (Venkatesh et al., 2012).

An important difference between a consumer use setting and the organisational use setting, where UTAUT was developed from, is that, consumers usually bear the monetary cost of such use while employees do not. The cost and pricing structure may have a significant impact on consumers' technology use. For instance, there is evidence that the popularity of short messaging services (SMS) in China is due to the low pricing of SMS relative to other types of Mobile Internet Applications (Chan, Gong, Xu, and Thong, 2008). In marketing research, the monetary cost/price is usually conceptualised together with the quality of products or services to determine the perceived value of products or services (Zeithaml, 1988). We follow these ideas and define *price value* as consumers' cognitive tradeoff between the perceived benefits of the application and the monetary cost for using it (Dodds, Monroe, and Grewal, 1991). The price value is positive when the benefits of using a technology are perceived to be greater than the monetary cost and such price value has a positive impact on intention (Venkatesh et al., 2012). Thus, price value was added as a predictor of behavioral intention to use a technology (Venkatesh et al., 2012).

Prior research on technology use has introduced two related yet distinct constructs, namely *experience* and *habit*. Experience, as conceptualised in prior research (Venkatesh et al., 2003; Kim and Malhotra, 2005), reflects an opportunity to use a target technology and is typically operationalised as the passage of time from the initial use of a technology by an individual. For instance, Kim, Malhotra, and Narasimhan (2005)`s measure has five categories with different periods of experience**.** Venkatesh et al. (2003) operationalised experience as three levels based on passage of time: post-training was when the system was initially available for use; 1 month later; and 3 months later. Habit has been defined as the extent to which people tend to perform behaviours automatically because of learning (Limayem, Hirt, and Cheung, 2007), while Kim et al. (2005) equate habit with automaticity. Venkatesh et al. (2012) argue that although conceptualised rather similarly, habit has been operationalised in two distinct ways:

first, habit is viewed as prior behavior (see Kim and Malhotra, 2005); and second, habit is measured as the extent to which an individual believes the behavior to be automatic (Limayem et al., 2007). Consequently, there are at least two key distinctions between experience and habit. One distinction is that experience is a necessary but not sufficient condition for the formation of habit. A second distinction is that the passage of chronological time (experience) can result in the formation of differing levels of habit depending on the extent of interaction and familiarity that is developed with a target technology (Venkatesh et al., 2012). For instance, in a specific period of time, say 3 months, different individuals can form various levels of habit depending on their use of a target technology (Venkatesh et al., 2012). This is perhaps what prompted Limayem et al. (2007) to include prior use as a predictor of habit; and likewise, Kim and Malhotra (2005) controlled for experience with the target technology in their attempt to understand the impact of habit on technology use. Ajzen and Fishbein (2005) also noted that feedback from previous experiences will influence various beliefs and, consequently, future behavioral performance. In this context, habit is a perceptual construct that reflects the results of prior experiences (Venkatesh et al., 2012).

Venkatesh et al. (2012) argue that the empirical findings about the role of habit in technology use have delineated different underlying processes by which habit influences technology use. Related to the operationalisation of habit as prior use, Kim and Malhotra (2005) found that prior use was a strong predictor of future technology use. Given that there are detractors to the operationalisation of habit as prior use (see Ajzen, 2002), some work, such as that of Limayem et al. (2007), has embraced a survey and perception-based approach to the measurement of habit. Such an operationalisation of habit has been shown to directly affect technology use over and above the effect of intention and moderate the effect of intention on technology use such that intention becomes less important with increasing habit (Limayem et al., 2007). Similar findings in the context of other behaviors have been reported in psychology research (see Ouellette and Wood, 1998).

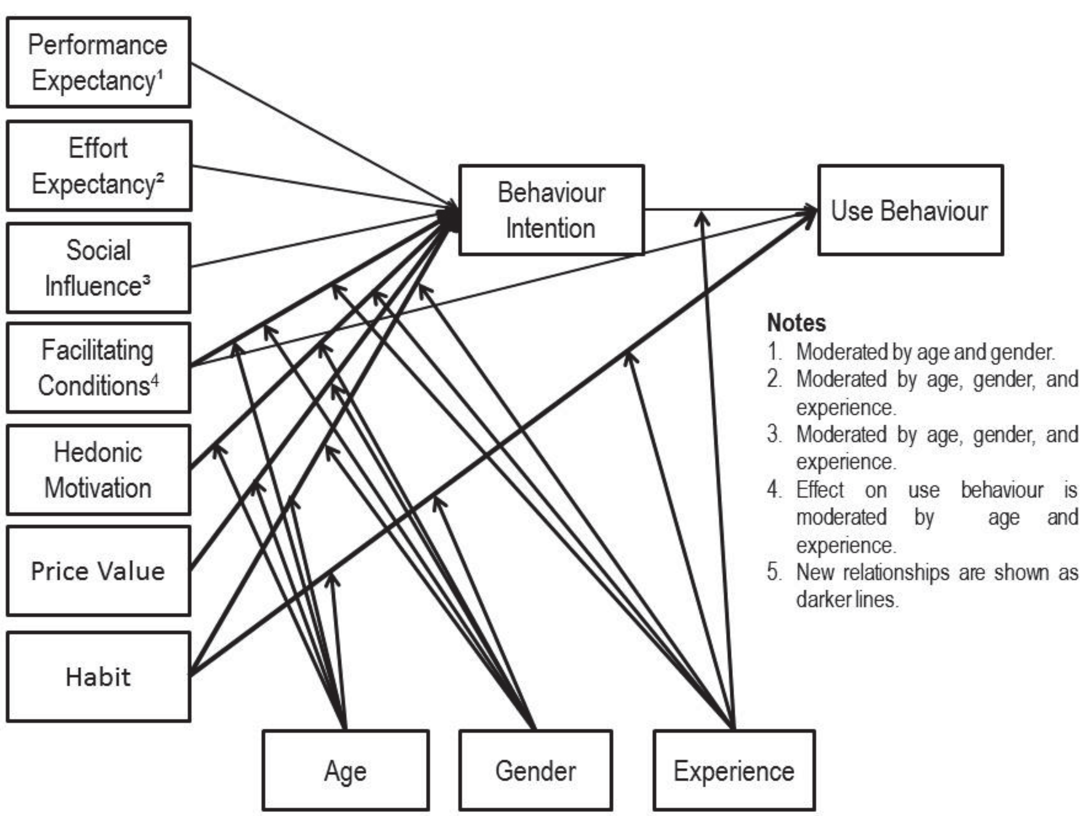


*Figure 1* UTAUT2 Model.

*Source: Adapted from Venkatesh et al. (2012).*

## 2.2 Conceptual framework

### 2.2.1 Identifying constructs to incorporate into UTAUT2

This section presents an overview of the four constructs that were added to UTAUT2 and discusses them in detail (see Maune, 2021). The constructs are perceived risk, trust, subjective norms, and self-efficacy. This approach complements the UTAUT2 constructs as given by Venkatesh et al. (2003) and Venkatesh et al. (2012). The constructs were identified through a literature review carried out by Maune (2021). The conceptual framework developed in the previous study (Maune, 2021) formed the basis of the current study. In technology acceptance and use, perceived risk and trust have proven to be strong predictors of behavioural intention (see Maune, 2021). Risk has been considered a strong driver of behavioural intention and use behaviour of mobile applications. Recent developments in the operations of big technology companies have caused risk and trust to be amongst the strongest predictors of behavioural intention and use behaviour of mobile applications in gathering SCI data. The use of mobile applications in SCI gathering has become popular recently. Technology developers are coming up with useful tools to gather SCI data from mobile application platforms. The platforms include Facebook, Whatsapp, and Instagram among others. These platforms are proving to be rich mines for SCI.

Subjective norm and self-efficacy were borrowed from the Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1980) and the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Fundamental to the TPB and other reasoned action models is the idea that behaviour is guided by intentions (Ajzen, 2012). Subjective norms are the individual's beliefs about whether significant others think he or she should engage in the behaviour and are assumed to capture the extent of perceived social pressures exerted on individuals to engage in certain behaviour. O'connor and Armitage (2003) argue that subjective norms are a function of normative beliefs. To them, normative beliefs represent pressures that are generated from specific others, such as parents and friends with respect to the behaviour in question. Normative beliefs and the personal motivation to comply with such beliefs and significant others determine subjective norms (O'connor and Armitage, 2003). With respect to the operational definition of subjective norms, Ajzen and Fishbein (1980) claim that subjective norms represent actors' perceptions about pressures generated from important significant others with respect to the behaviour (Chatzisarantis and Biddle, 1998).

Measures of subjective norms also respect a personal tendency to comply with pressures generated from significant others. According to the self-determination theory, psychological events that include compliance and pressure, represent control, and therefore, it is argued that subjective norms cover only the controlling dimension of personal experience. The subjective norm is also based on salient beliefs, called normative beliefs, about whether particular referents think the respondent should or should not do the action in question (East, 1993). East (1993) further argues that like expected values, these referent influences are covered by two measures: *(n)*, the likelihood that the referent holds the normative belief, and *(m),* the motivation to comply with the views of the referent. Thus $\sum n_i m_i$ is the determinant of the subjective norm.

According to the TPB model, subjective norms predict the intention, which in turn predicts use behaviour. Subjective norm is a strong indicator of individual use behaviour (Fishbein and Ajzen, 1975; Ha, 1998; Broadhead-Fearn and White, 2006; Yadav, Chauhan, and Pathak, 2015). According to Bandura (1997), self-efficacy refers to beliefs in one`s capabilities and knowledge to organise and execute the courses of action required to produce/perform certain behaviour/attainments. Studies by Bandura (1986), Zimmerman, Bandura, and Martinez-Pons (1992), Zhao, Seibert, and Hills (2005), and Bailey and Austin (2006) have identified self-efficacy as a much more consistent predictor of behaviour and behavioural change. Clearly, one way in which self-efficacy can influence the performance of difficult behaviours is by its effect on perseverance. The more people believe that they have the capacity to perform an intended behaviour, the more likely they are to persevere and, therefore to succeed (Ajzen, 2012). A considerable body of research attests to the powerful effects of self-efficacy beliefs on motivation and performance (see Bandura and Locke, 2003). Subjective norms are used to complement social influence while self-efficacy was used to complement performance expectancy and effort expectancy. Research by Roy (2017) shows that subjective norms and self-efficacy were strong predictors of behavioural intention and use behaviour in mobile applications.

Venkatesh et al. (2012) argue that UTAUT and related models hinge on intentionality as a key underlying theoretical mechanism that drives behaviour. Many, including detractors of this class of models, have argued that the inclusion of additional theoretical mechanisms is important (Venkatesh et al., 2012).

These constructs have become critical in the recent past in determining the adoption and use of mobile applications in SCI gathering. With SCI taking major strides in helping companies achieving sustainable competitive advantage, mobile applications have become the critical mining fields for SCI gathering.

Based on the study by Maune (2021) as well as the above explanations, perceived risk, trust, subjective norms, and self-efficacy were integrated into UTAUT2 as shown in figure 2.

### 2.2.2 Hypothesis development

This section presents the hypotheses that were developed to validate the proposed model in figure 2. These hypotheses were derived from the review of theoretical and empirical studies in the sections above. These hypotheses are to validate and test the proposed path analysis model by Maune (2021). Therefore, we hypothesised the following:

**H1.** The greater the individual`s performance expectancy regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H2.** The greater the individual`s effort expectancy regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H3.** The greater the individual`s social influence regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H4.** The greater the facilitating conditions are perceived as favourable to mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H5.** The greater the hedonic motivation is perceived as favourable to mobile apps use,

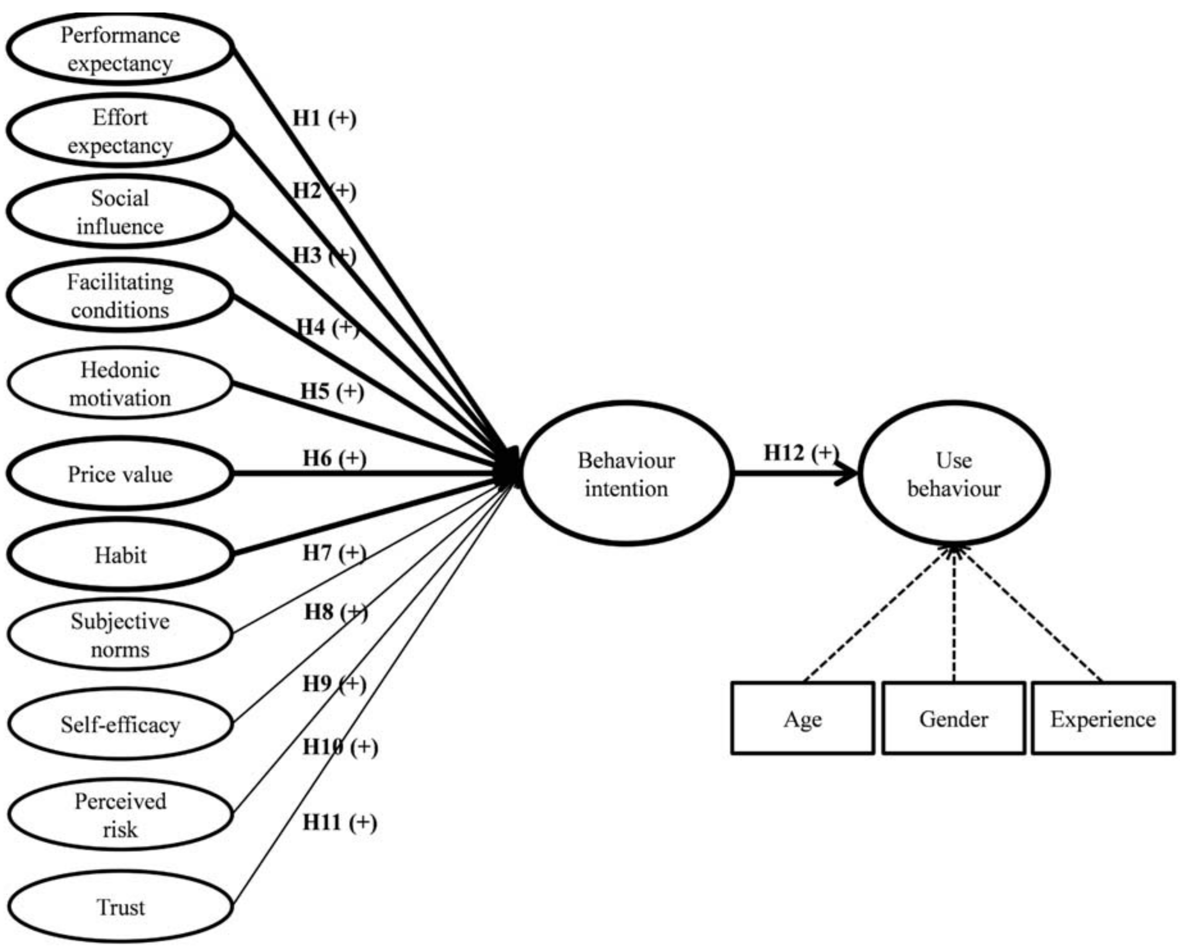


*Figure 2.* Research model.
*Source: Adapted from Maune (2021).*

the higher the level of behaviour intentions to use mobile apps in SCI.

**H6.** The greater the price value is perceived as favourable to mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H7.** The greater the individual`s habit regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H8.** The greater the subjective norms are perceived as favourable to mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H9.** The greater the individual`s self-efficacy regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H10.** The greater the perceived risk is seen as favourable to mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H11.** The greater the individual`s trust regarding mobile apps use, the higher the level of behaviour intentions to use mobile apps in SCI.

**H12.** The greater the individual`s behaviour intentions to use mobile apps, the greater the likelihood of the individual`s use behaviour of mobile apps in SCI.

## 3. METHOD

This article targeted SCIPs and analysts as well as those in decision making. This study was conducted in the context of mobile applications use in SCI. All applications that can be downloaded from application stores such as Play Store and App Store among others were evaluated within the scope of mobile applications. These applications have made it easy for individuals and organizations to access large amounts of data. Mobile applications have both increased and strengthened the role of SCI in decision making globally. They have become big data mines for gathering intelligent information for decision making in competitive environments.

### 3.1 Respondents and procedure

One hundred and fifty questionnaires were sent via email and WhatsApp platforms to SCI practitioners and analysts. The questionnaire was created on the Google Forms platform. The link generated was then sent to the respondents. The survey needed approximately 15 to 20 minutes to complete. Before this, a pilot questionnaire was sent to five people with and without CI knowledge to elicit salient features, ambiguous, negatively worded, and difficult questions. Such questions were deleted or rephrased in the main questionnaire. Completed questionnaires were returned, automatically through the Google forms platform to the corresponding author by 98 respondents (65.3%). After cleaning the data, that is, removing observations with missing data, and suspected unengaged respondents, 96 (64% response rate) were retained for analysis. The sample size used was guided by Marcoulides and Saunders (2006). In this study, unengaged respondents were defined as those who recorded the same response for all consecutive items (for example, a 7 throughout all the observed variables). Table 1 denotes the demographic descriptive statistics of the study.

*Table 1 Demographic Descriptive Statistics.*

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 74 | 77% |
| | Female | 22 | 23% |
| Age | <20 | - | - |
| | 21 – 30 | 12 | 12.5% |
| | 31 – 40 | 37 | 38.5% |
| | 41 – 50 | 11 | 11.5% |
| | >50 | 36 | 37.5% |
| Experience | Up to 1yr | 9 | 9.4% |
| | 1 to 2yrs | - | - |
| | 2 to 3yrs | 5 | 5.2% |
| | 3 to 4yrs | 4 | 4.2% |
| | 5yrs or more | 78 | 81.2% |
| Education | High School | - | - |
| | College | - | - |
| | Bachelor`s Degree | 1 | 1% |
| | Master`s Degree | 55 | 57.3% |
| | PhD | 40 | 41.7% |

*Source: Authors` compilation.*

### 3.2 Measurement

This article adapted the measurement scales from prior research (Table 2). The latent variables and the measurement items are as given in Table 2. The scales for the UTAUT2 constructs, that is, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention were adapted from

Venkatesh et al. (2012). The perceived risk scale was drawn from Abrahão et al. (2016), and the scale for trust was adapted Groß (2015), while the scales for subjective norms, self-efficacy, and use behaviour were adapted from Shneor and Munim (2019).

All items were measured using a seven-point Likert–type scale, with the anchors being "completely disagree" and "completely agree." Gender was coded using 1 or 2 dummy variables where 1 represented men and 2, women. Age was measured in years, while experience was also measured in years. Use behaviour was measured using both scale and frequency of mobile applications use. The researcher created an online questionnaire using Google forms in English and was reviewed by university staff, SCIPs and university students for content validity, completion time, and simplicity. The online questionnaire was pilot tested among five selected individuals from the researcher`s WhatsApp professional groups who were not part of the main survey. Preliminary evidence showed that the scales were reliable and valid.

*Table 2. Survey Variables, Measurement Items, Factor Loadings, and Sources.*

| Latent variable | Measurement items | Factor loadings | Source |
|---|---|---|---|
| PE (*performance expectancy)* | PE1. I find mobile Apps useful in my daily life. | 0.995 | PE1-4 adapted and modified from "performance expectancy" in and Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| | PE2. Using mobile Apps increases my chances of achieving things that are important to me. | *Removed* | |
| | PE3. Using mobile Apps helps me accomplish things more quickly. | 0.824 | |
| | PE4. Using mobile Apps increases my productivity. | *Removed* | |
| EE (*effort expectancy)* | EE1. Learning how to use mobile Apps is easy for me. | 0.819 | EE1-4 adapted and modified from "effort expectancy" in and Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| | EE2. My interaction with mobile Apps is clear and understandable. | 0.848 | |
| | EE3. I find mobile Apps easy to use. | 0.798 | |
| | EE4. It is easy for me to become skillful at using mobile Apps. | *Removed* | |
| SI (*social influence)* | SI1. People who are important to me think that I should use mobile Apps. | 0.710 | SI1-3 adapted and modified from "social influence" in Venkatesh et al. (2012) and Venkatesh et al. (2003) for SI1-2. |
| | SI2. People who influence my behaviour think that I should use mobile Apps. | 0.999 | |
| | SI3. People whose opinions I value prefer that I use mobile Apps. | *Removed* | |
| FC (*facilitating conditions)* | FC1. I have the resources necessary to use mobile Apps. | *Removed* | FC1-4 adapted and modified from "facilitating conditions" in Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| | FC2. I have the knowledge necessary to use mobile Apps. | *Removed* | |
| | FC3. Mobile Apps are compatible with other technologies I use. | *Removed* | |
| | FC4. I can get help from others when I have difficulties using mobile Apps. | *Removed* | |
| HM (*hedonic motivation)* | HM1. Using mobile Apps is fun. | 0.914 | HM1-3 adapted and modified from "hedonic motivation" in Venkatesh et al. (2012). |
| | HM2. Using mobile Apps is enjoyable. | 0.959 | |
| | HM3. Using mobile Apps is very entertaining. | *Removed* | |
| PV (*price value)* | PV1. Mobile Apps is reasonably priced. | 1.000 | PV1-3 adapted and modified from "price value" in Venkatesh et al. (2012). |
| | PV2. Mobile Apps is a good value for the money. | *Removed* | |
| | PV3. At the current price, mobile Apps provide good value. | *Removed* | |
| HT (*habit*) | HT1. The use of mobile apps has become a habit for me. | 1.000 | HT1-4 adapted and modified from "habit" in Venkatesh et al. (2012). |
| | HT2. I am addicted to using mobile Apps. | *Removed* | |
| | HT3. I must use mobile Apps. | *Removed* | |
| | HT4. Using mobile Apps has become natural to me. | *Removed* | |

| | | | |
|---|---|---|---|
| PR (*perceived risk*) | PR1. I would not feel completely safe to provide personal information through mobile apps. | 0.782 | PR1-4 adapted and modified from “risk” in Abrahão et al. (2016). |
| | PR2. I am worried about the future use of mobile apps platforms because other people might be able to access my data. | 0.945 | |
| | PR3. I do not feel protected when sending confidential information via mobile apps platforms. | *Removed* | |
| | PR4. The likelihood that something wrong will happen with the mobile apps platforms is high. | 0.819 | |
| TT *(trust)* | TT1. I think they are honest. | *Removed* | TT1-5 adapted and modified from “trust” in Groß (2015). |
| | TT2. I think they are trustworthy. | *Removed* | |
| | TT3. I think they provide good services to users. | *Removed* | |
| | TT4. I think they care about their users and take their concerns seriously. | *Removed* | |
| | TT5. I think they keep users’ security and privacy in mind. | *Removed* | |
| SN *(subjective norms)* | SN1. People who are important to me think that I should use mobile apps in SCI. | 0.827 | SN1-4 adapted and modified from “subjective norms” in Shneor and Munim (2019). |
| | SN2. People who influence my behavior encourage me to use mobile apps in SCI. | 0.864 | |
| | SN3. My colleagues think that I should use mobile apps in SCI. | 0.917 | |
| | SN4. My friends think that I should use mobile apps in SCI. | *Removed* | |
| SE (self-efficacy) | SE1. I have confidence in my ability to use mobile apps platforms in SCI. | *Removed* | SE1-4 adapted and modified from “subjective norms” in Shneor and Munim (2019). |
| | SE2. I have the expertise needed to use mobile apps. | 0.627 | |
| | SE3. I am confident in my ability to navigate and use mobile apps in SCI. | 0.906 | |
| | SE4. I am confident in my ability to use mobile apps platforms in SCI. | 0.922 | |
| BI (*behavioural intention)* | BI1. I intend to continue using mobile apps in SCI in the future. | 1.000 | BI1-3 adapted and modified from “behavioural intention” in and Venkatesh et al. (2003) and Venkatesh et al. (2012). |
| | BI2. I will always try to use mobile apps in SCI. | *Removed* | |
| | BI3. I plan to continue to use mobile apps in SCI frequently. | *Removed* | |
| UB (use *behaviour)* | UB1. I frequently use mobile apps in SCI. | 0.890 | UB1-2 adapted and modified from “subjective norms” in Shneor and Munim (2019). |
| | UB2. I spend much effort in using mobile apps in SCI. | 0.887 | |
| | **FREQUENCY:** Roughly estimating please indicate how many times have you used mobile apps platforms in SCI in the past year? (Please indicate the number of times). | 1.000 | |

### 3.3 Approach to structural equation modelling

There are several distinct approaches to SEM This study adopted the approach by Maune, Matanda, and Mundonde (2021) the Partial Least Squares (PLS) using SmartPLS 3 software to analyse data. The PLS-SEM was used because of the small sample size and its predictive accuracy. Despite its limitations, PLS-SEM is useful in applied research projects and has been deployed in fields such as behavioural sciences, marketing, organisation, management information system, and business strategy (Maune et al., 2021). The data set was first cleaned before imported into SmartPLS 3.

### 3.4 Analysis

The PLS path modeling estimation for this study is shown in Fig. 3. The following observations came out of the path analysis model:

### 3.4.1 Reflective measurement model

The study adopted a reflective measurement model. Each reflective indicator is related to a specific construct or latent variable by a simple regression (Maune et al., 2021).

As part of the measurement model evaluation, some items (see table 2) were omitted from the analysis due to high cross-loading and low factor loadings (<0.600) (Gefen and Straub, 2005). To test the reliability of the constructs, the study used Cronbach`s alpha and composite reliability (CR) (Table 3). All the CRs were higher than the recommended value of 0.700 (Hair et al., 2017). Cronbach`s alpha of each construct exceeded the 0.700 thresholds. Convergent validity was acceptable because the Average Variance Extracted (AVE) were all above 0.500 (Bagozzi and Yi, 1988). The results for reliability and validity, along with the factor loadings for the items are as shown in Table 3. Discriminant validity was assessed by the Fornell-Larcker criterion. Table 4 shows

*Table 3* Loadings, Collinearity, Reliability, and Validity.

| | Loadings | VIF | Cronbach`s Alpha | Composite Reliability | AVE |
|---|---|---|---|---|---|
| PE1 | 0.995 | 2.400 | 0.866 | 0.909 | 0.834 |
| PE3 | 0.824 | 2.400 | | | |
| EE1 | 0.819 | 1.459 | 0.760 | 0.862 | 0.676 |
| EE2 | 0.848 | 1.683 | | | |
| EE3 | 0.798 | 1.538 | | | |
| SI1 | 0.710 | 1.856 | 0.809 | 0.855 | 0.751 |
| SI2 | 0.999 | 1.856 | | | |
| HM1 | 0.914 | 2.380 | 0.865 | 0.935 | 0.877 |
| HM2 | 0.959 | 2.380 | | | |
| PV2 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| HT1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| SN1 | 0.827 | 1.599 | 0.841 | 0.903 | 0.757 |
| SN2 | 0.864 | 2.550 | | | |
| SN3 | 0.917 | 2.637 | | | |
| SE2 | 0.627 | 1.349 | 0.785 | 0.866 | 0.689 |
| SE3 | 0.906 | 2.203 | | | |
| SE4 | 0.922 | 2.075 | | | |
| PR1 | 0.782 | 2.980 | 0.833 | 0.887 | 0.725 |
| PR2 | 0.945 | 3.546 | | | |
| PR4 | 0.819 | 1.528 | | | |
| BI1 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| UB1 | 0.890 | 1.506 | 0.734 | 0.883 | 0.790 |
| UB2 | 0.887 | 1.506 | | | |

*Table 4* Fornell-Larcker Criterion.

| | BI | EE | HM | HT | PE | PR | PV | SE | SI | SN | UB |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BI | *1.000* | | | | | | | | | | |
| EE | 0.743 | *0.822* | | | | | | | | | |
| HM | 0.710 | 0.736 | *0.937* | | | | | | | | |
| HT | 0.518 | 0.298 | 0.514 | *1.000* | | | | | | | |
| PE | 0.471 | 0.548 | 0.554 | 0.010 | *0.913* | | | | | | |
| PR | 0.179 | 0.142 | -0.138 | -0.385 | 0.047 | *0.851* | | | | | |
| PV | 0.501 | 0.579 | 0.619 | 0.400 | 0.230 | 0.021 | *1.000* | | | | |
| SE | 0.810 | 0.720 | 0.603 | 0.499 | 0.105 | 0.056 | 0.443 | *0.830* | | | |
| SI | 0.453 | 0.449 | 0.382 | 0.566 | 0.397 | -0.102 | 0.404 | 0.458 | *0.867* | | |
| SN | 0.547 | 0.623 | 0.521 | 0.358 | 0.448 | -0.151 | 0.639 | 0.570 | 0.699 | *0.870* | |
| UB | 0.664 | 0.675 | 0.678 | 0.701 | 0.264 | 0.038 | 0.650 | 0.650 | 0.442 | 0.475 | *0.889* |

*Note: Values in Italic Represent Square-roots of AVE.*

*Table 5* Heterotrait-Monotrait Ratio (HTMT).

| | BI | EE | HM | HT | PE | PR | PV | SE | SI | SN | UB |
|---|---|---|---|---|---|---|---|---|---|---|---|
| BI | - | | | | | | | | | | |
| EE | 0.848 | | | | | | | | | | |
| HM | 0.742 | 0.890 | | | | | | | | | |
| HT | 0.518 | 0.404 | 0.557 | | | | | | | | |
| PE | 0.350 | 0.604 | 0.528 | 0.267 | | | | | | | |
| PR | 0.137 | 0.324 | 0.261 | 0.428 | 0.255 | | | | | | |
| PV | 0.501 | 0.674 | 0.641 | 0.400 | 0.227 | 0.200 | | | | | |
| SE | 0.825 | 0.886 | 0.623 | 0.562 | 0.373 | 0.232 | 0.510 | | | | |
| SI | 0.304 | 0.489 | 0.380 | 0.474 | 0.271 | 0.204 | 0.308 | 0.341 | | | |
| SN | 0.574 | 0.770 | 0.575 | 0.396 | 0.533 | 0.345 | 0.703 | 0.630 | 0.675 | | |
| UB | 0.775 | 0.893 | 0.829 | 0.818 | 0.312 | 0.194 | 0.759 | 0.810 | 0.428 | 0.636 | |

*Table 6* Mean, STDEV, T-Values, P-Values, Confidence Intervals, $R^2$, and $Q^2$.

| Hypothesis | Rel ationship | β | STDEV | T Statistics | P Values | 2.50% | 97.50% |
|---|---|---|---|---|---|---|---|
| $H_1$ | PE -> BI | 0.724 | 0.348 | 2.083 | 0.037 | 0.414 | 1.727 |
| $H_2$ | EE -> BI | -0.210 | 0.233 | 0.900 | 0.368 | -0.595 | 0.197 |
| $H_3$ | SI -> BI | -0.364 | 0.189 | 1.922 | 0.055 | -1.108 | -0.145 |
| $H_5$ | HM -> BI | -0.246 | 0.352 | 0.700 | 0.484 | -1.145 | 0.240 |
| $H_6$ | PV -> BI | 0.173 | 0.322 | 0.538 | 0.591 | -0.192 | 0.972 |
| $H_7$ | HT -> BI | 0.503 | 0.191 | 2.637 | 0.008 | 0.252 | 1.148 |
| $H_8$ | SN -> BI | -0.011 | 0.419 | 0.026 | 0.980 | 0.393 | 0.717 |
| $H_9$ | SE -> BI | 0.865 | 0.425 | 2.036 | 0.042 | 0.562 | 1.873 |
| $H_{10}$ | PR -> BI | 0.244 | 0.257 | 0.951 | 0.342 | -0.324 | 0.658 |
| $H_{12}$ | BI -> UB | 0.664 | 0.053 | 12.623 | 0.000 | 0.545 | 0.752 |
| | | **$R^2$** | **$R^2$ Adjusted** | **$Q^2$** | | | |
| | BI | 0.931 | 0.924 | 0.906 | | | |
| | UB | 0.441 | 0.435 | 0.344 | | | |

that the square root of AVE for the construct was greater than the inter-construct correlation (Fornell and Larcker, 1981). Discriminant validity was also assessed by the Heterotrait-Monotrait ratio of correlations (Henseler et al., 2015), with all values below the threshold of 0.900 implying the establishment of discriminant validity (see Table 5).

### 3.4.2 Structural model

After confirming the reliability and validity of the construct measures, the results of the structural model were evaluated. Maune et al. (2021) citing Tenenhaus et al. (2005) and Avkiran (2018) argue that the structural model analysis is done to provide supporting evidence to the theoretical model:

$$\xi_j = \beta_{jo} + \sum_i \beta_{ji}\,\xi_j + v_j$$

"Where: $\xi_j$ is the endogenous construct and $\xi_i$ represents the exogenous constructs, while $\beta_{jo}$ is the constant term in this (multiple) regression model, $\beta_{ij}$ are the regression coefficients, and $v_j$ is the error term; the predictor specification condition applies."

The structural model reflects the paths hypothesised in the research framework. The structural model was assessed based on the $R^2$, $Q^2$, and significance of paths. The goodness fit of the model is determined by the strength of each structural path determined by the $R^2$ value for the dependent variable, the value for $R^2$ should be equal to or over 0.1 (Falk and Miller, 1992). The results in table 6 show that all $R^2$ values are over 0.1. Hence, the predictive capability was established. Further, $Q^2$ establishes the predictive relevance of the endogenous constructs. Predictive relevance of the model is achieved when $Q^2$ is above zero (0). The results shows that there is significance in the prediction of the constructs (see table 6).

The structural model was also checked for collinearity issues by examining the VIF values

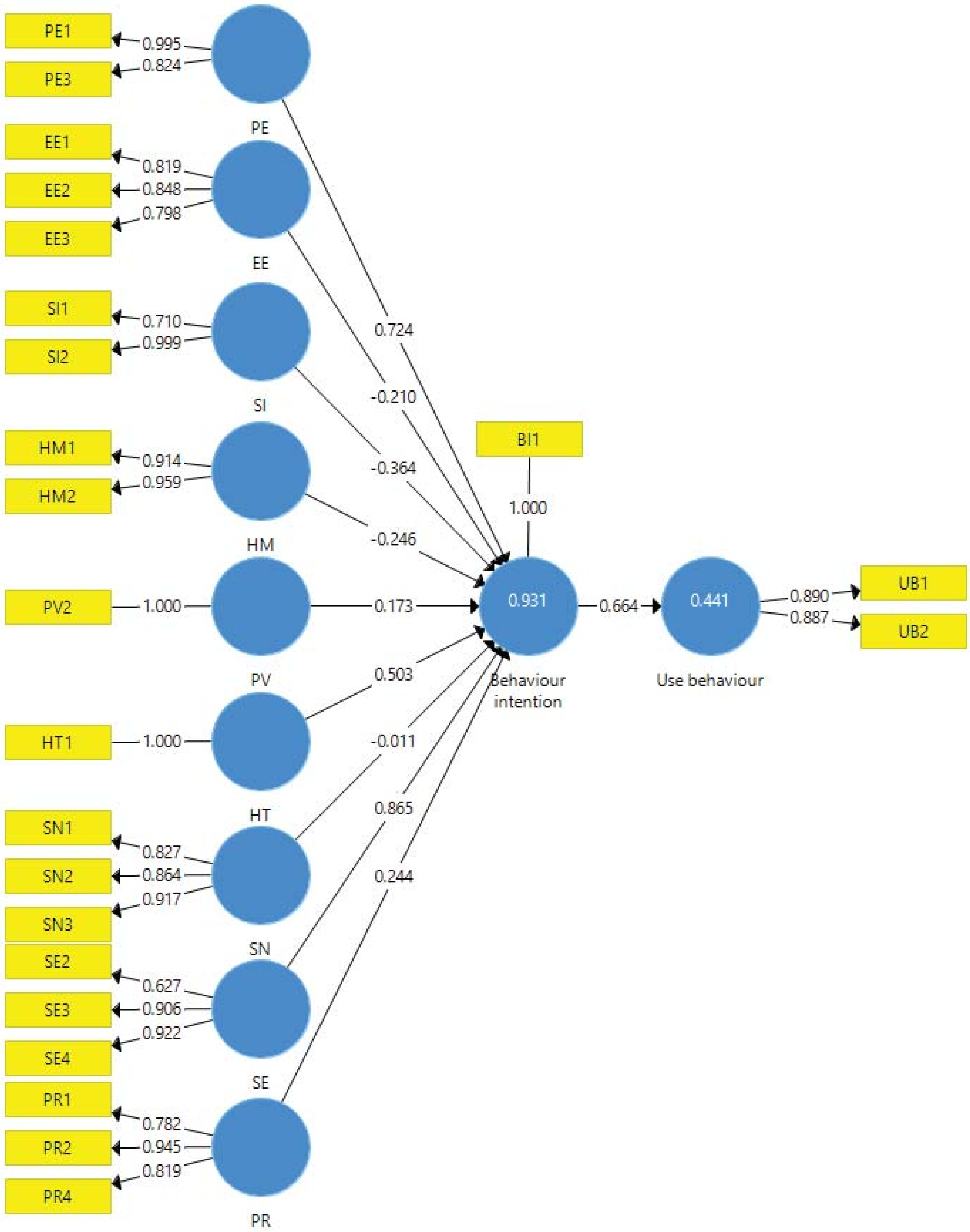


*Figure 3 SEM model and PLS-SEM results.*

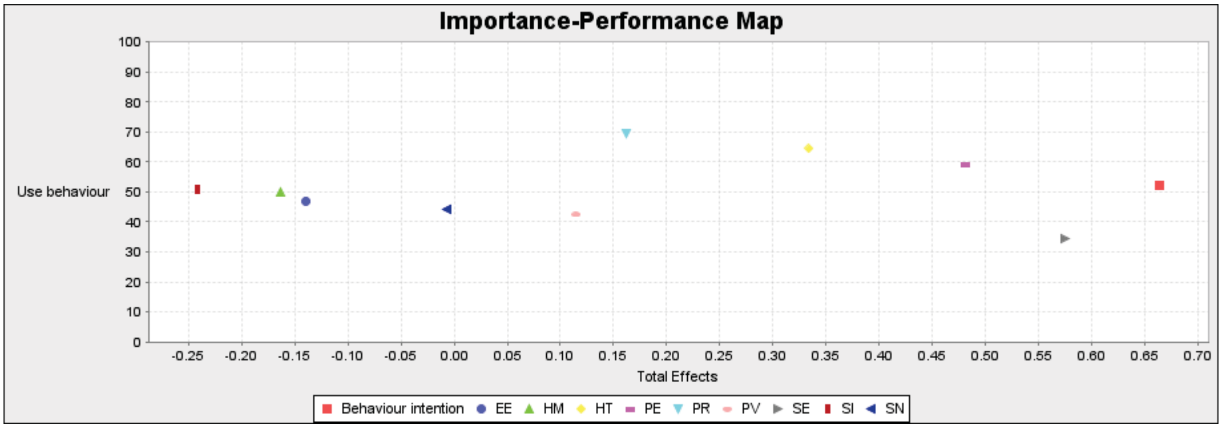


*Figure 4 Importance-Performance Map Analysis.*

of all sets of predictor constructs in the structural model. The results in Table 3 show the VIF values of all combinations of endogenous constructs and corresponding exogenous constructs. As can be seen in table 3, all VIF values are clearly below the threshold of 5. Therefore, collinearity among the predictor constructs is not a critical issue in the structural model. We therefore examined the results of the report. Further assessment of the goodness of fit and hypotheses testing were done to ascertain the significance of the relationships as shown in Table 6.

#### 3.4.3 Importance-Performance Map Analysis (IPMA)

The IPMA was computed to determine the relative importance of constructs in the PLS path analysis model. In this analysis, importance reflects the absolute total effect on the final endogenous variable in the path analysis diagram while performance reflects the size of latent variable scores. This analysis is particularly important in prioritising managerial actions. It is critical for managerial focus to be directed at improving the performance of those constructs that exhibit a large importance regarding their explanation of a certain target construct but, at the same time, have a relatively low performance.

In this case, a construct is more important if it has a higher absolute total effect on use behaviour (UB) as measured on the Y-axis. Here, SE (0.574) has somewhat greater absolute importance than any other constructs outside BI (0.664) (see Figure 4 and Table 7). Furthermore, a construct has greater performance if it has higher mean latent variable score, reflecting stronger measurement paths as measured on the X-axis. Here, PR (69.406) displays greater performance than any other constructs (see Figure 4 and Table 7).

## 4. DISCUSSION

The key determinants of mobile applications adoption and use in SCI using the modified UTAUT2 model were examined. More emphasis was placed on the cognitive psychological perspective of behavioural intention and use behaviour. Adoption and use of mobile applications were considered planned behaviour. A path analysis model developed in the previous study (Maune, 2021) was tested using PLS-SEM algorithm in SmartPLS software to ascertain critical paths and relationships. The results of the study are tabulated in Table 6. Of note, however, was the omission of latent variables FC and TT despite previous research findings which pointed out their significant effect on BI and UB (Venkatesh et al., 2003; Venkatesh et al., 2012; Groß, 2015). These latent variables were omitted because of high-cross loadings or low factor loadings (Gefen and Straub, 2005). The paths were, however, not supported by the data. In light of this, it is important for future studies to validate this using a bigger sample size. Futhermore, path HT->UB and FC->UB were removed despite the findings by Limayem et al. (2007), Venkatesh et al. (2012) and Venkatesh et al. (2003), respectively who found otherwise. These paths were, however, not supported by the data. The following latent variables show an insignificant relationship with BI as reflected by their p-values and t statistics (EE, HM, PV, SN, and PR). This was despite previous research pointing otherwise (see Appendix 2 in Maune, 2021) (Venkatesh et al., 2003; Venkatesh et al., 2012, Abrahão et al., 2016; Roy, 2017; Shneor and Munim, 2019). These findings confirm prior research findings (Liu and Tai, 2016; Barua et al., 2018; Chao, 2019; Tarhini et al., 2019; Khurana and Jain, 2019; Gharaibeh et al., 2020). Significant paths were identified and these included the following constructs, PE, SI, HT, SE, and BI. These had significant p-values and t-statistics. Consequently, the results were in line with various studies as shown in Appendix 2 by Maune (2021) that found significant paths/ relationships between the variables.

The structural model was assessed for goodness of fit using $R^2$, $Q^2$, and significance of paths, with the results shown in Table 6. The findings demonstrated predictive relevance of the constructs under study (Falk and Miller, 1992; Briones-Penalver et al., 2018).

Perhaps the most important finding for SCI practitioners and analysts relates to the IPMA that identifies areas where managerial action is likely to bring the greatest improvement of a selected target construct in the PLS path analysis model. In this study SE proves to be critical for managerial action because of its highest total effect (0.574) (see Table 7 and Figure 4). In terms of raising performance, it would be better for management to focus their efforts on SE, in the knowledge that it has a higher importance and its improvements is likely to lead to larger improvements in explaining UB. All else the same, a one unit rise in the performance of SE would bring about a 0.574 increase in the performance of UB (see Table 7 and Figure 4).

*Table 7* Importance-Performance Analysis.

| Construct | Performance | Total effect |
|---|---|---|
| BI | 52.083 | 0.664 |
| EE | 46.889 | -0.139 |
| HM | 49.791 | -0.164 |
| HT | 64.410 | 0.334 |
| PE | 58.950 | 0.481 |
| PR | 69.406 | 0.162 |
| PV | 42.448 | 0.115 |
| SE | 34.432 | 0.574 |
| SI | 50.923 | -0.242 |
| SN | 44.228 | -0.007 |
| UB | 46.303 | - |

### 4.1 Implications for research

This study addresses the call of the previous study (Maune, 2021) that emphasised the need to empirically examine and validate the proposed path analysis model/framework. This path analysis model was developed from literature as an extension of the UTAUT2 (see Figure 2). This path analysis model and its replication is critical for CI analysts and practitioners given the amount of data that is kept and passes through mobile applications. This data will go a long way in mapping sustainable competitive corporate strategies. Results from this study have implications for further future research.

Despite the popularity of the UTAUT2 in examining and testing relationships of constructs in the adoption and use of technology, this study followed a different approach by extending the UTAUT2 framework. This was done by adding four other constructs borrowed from other theories (Maune, 2021). The proposed framework was examined empirically to determine key antecedents to behavioural intention and use behaviour of mobile applications in CI. Through this approach, the study adhered to the cognitive psychological perspective of human behaviour in decision making. Building on this, the findings show insignificant paths for EE, HM, PV, SN, and PR while PE, SI, HT, and SE had significant paths in relation to BI and UB.

This study is the first to address the relationship between the modified UTAUT2, behaviour intention and use behaviour of mobile applications in SC,I empirically. This gap in knowledge was uncovered in the previous article (Maune, 2021) that used literature review to develop a conceptual framework of behaviour intention and use behaviour of mobile applications in SCI. An extended framework was developed to identify key antecedents to behavioural intention and use behaviour of mobile applications in SCI. Perspective antecedents in behavioural intention were given much attention in this study. The study validated these key antecedents to behavioural intention through PLS-SEM algorithm. Moreover, this study combined the UTAUT2 constructs with other four (perceived risk, subjective norm, self-efficacy, and trust) to examine their link with behaviour intention and use behaviour in SCI. Results from this study demonstrated that FC and TT were not supported and that the other findings were not far-off from previous studies as shown in Appendix 2 in Maune (2021). This study complements prior research that investigated relationships between UTAUT2, BI, and UB in various fields.

Furthermore, building on the UTAUT2, this study hypothesises that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, subjective norm, self-efficacy, trust, and perceived risk were determinants of behaviour intention and use behaviour in SCI. However, facilitating conditions and trust were not supported by the path analysis model. These findings confirm prior research (see Appendix 2 by Maune, 2021) and support the idea that use behaviour is a planned behaviour (Shneor and Munim, 2019). Moreover, findings are in agreement with the contention that EE, HM, PV, SN, and PR have insignificant influence on BI and UB (Liu and Tai, 2016; Barua et al., 2018; Chao, 2019; Tarhini et al., 2019; Khurana and Jain, 2019; Gharaibeh et al., 2020).

### 4.2 Implications for practice

The model explains and predicts PE, SI, HT, SE and BI, yet, performs poorly in explaining and predicting EE, HM, PV, SN, and PR. Hence, in deriving managerial implications, one is able to derive recommendations to drive BI and UB. The model has some key implications that are valid for SCI.

Perhaps, the most important finding for SCI practitioners and analysts relates to the fact that the path analysis model did not support FC and TT. Furthermore, research has shown how important is the IPMA to managerial decision making. The IPMA helps management determine important constructs in the PLS model. In this study the IPMA clearly shows important determinants critical in the adoption and use of mobile applications in SCI. It is particularly important in prioritising managerial actions. IPMA is helpful for managerial actions to be focused at improving the performance of those constructs that exhibit a large importance regarding their explanation of a certain target construct. In this case, constructs with a relatively higher importance but a relatively low performance are particularly interesting for improvements and must be the focus of management.

In fact, investing into the performance improvement of a construct that has a very small importance for the target construct would not be logical, since it would have little impact in changing (improving) the target construct. In this study, SE is particularly important for explaining the target construct, UB. In a ceteris paribus situation, a one-unit increase in the performance of SE increases the performance of UB by the value of the total effect, which is 0.574. At the same time, the performance of SE is relatively low, so there is substantial room for improvement. Consequently, in the PLS path model example, construct SE is the most relevant construct for managerial actions.

### 4.3 Limitations

This article examined the key determinants of mobile applications` adoption and use in SCI using an extended UTAUT2 model. Data collection and COVID-19 restrictions limited the scope and findings of this study. The impact of COVID-19 left the researcher using online questionnaires which proved to be a challenge due to the cost of using internet and stress of being locked at home. Initially, the researcher had targeted 150 respondents but due to a number of reasons such as the one mentioned above, 98 responses were received. After the data cleaning process, only 96 were found suitable for use for the purpose of this study. Participatory methods may be planned, to include various groups in the study. A bigger sample would be useful to validate findings.

A longitudinal study would also be useful in future studies that measure relationships between variables. In addition, future studies may extend the empirical analyses by considering advanced PLS-SEM techniques such as the FIMIXPLS, PLS multigroup, and PLS-POS methods to uncover unobserved heterogeneity and generate further differentiated findings and conclusions.

Researchers are encouraged to consider a lot of research ethics to overcome challenges associated with the Covid-19 pandemic. Despite all this, the researcher had to forge ahead with what works, because truth is a normative concept – truth is what works.

## 5. CONCLUSION

Finally, researchers are encouraged to test the relationships proposed in this study in other fields as well. Consequently, such an attempt would be of great significance from a theoretical perspective. Findings would extend academics` understanding of the key determinants of mobile applications adoption and use in SCI. The study placed more emphasis on the cognitive psychological perspective of behavioural intention and use behaviour. Furthermore, the study considered the adoption and use of mobile applications a planned behaviour.

To examine and validate the path analysis model developed by Maune (2021), the study followed a deductive approach with primary data collected through an online survey. The study applied the PLS-SEM algorithm to analyse relationships between latent and observed variables. Respondents were drawn from CI practitioners and analysts across the board. One hundred and fifty online questionnaires were sent via email and WhatsApp platforms. Completed questionnaires were returned automatically through the Google forms platform to the author by 98 respondents and after data cleaning process 96 responses were retained for analysis.

The study adopted a reflective measurement model. The study satisfied the validity and reliability tests such as Cronbach`s alpha, composite reliability, Average Variance Extracted, Fornell-Larcker criterion, and Heterotrait-Monotrait ratio. Once the construct measures were confirmed reliable and valid, the results of the structural model were then evaluated. The structural model was assessed for goodness of fit using $R^2$, $Q^2$, and significance of paths with the results shown in Table 6. The findings demonstrated predictive relevance of the constructs understudy (Falk and Miller, 1992; Briones-Penalver et al., 2018). Of importance, however, was the omission of FC and TT from the path analysis model because the two paths were not supported by the model. This was against prior research findings.

Perhaps the most important finding for SCI practitioners and analysts relates to the IPMA that identifies areas where managerial action is likely to bring the greatest improvement of a selected target construct in the PLS path analysis model. In this study SE proves to be critical for managerial action because of its highest total effect (0.574) (see Table 7 and Figure 4). The IPMA was run to determine the relative importance of constructs in the PLS model. The authors recommend management to prioritize the results of IPMA.

## REFERENCES


Abrahão, R. S., Moriguchi, S. N. and Andrade, D. F. *(*2016). "Intention of adoption of mobile payment: An analysis in the light of the Unified Theory of Acceptance and Use of Technology (UTAUT)," *RAI Revista de Administração e Inovação,*Vol. 13, pp. 221–230.

Ajzen, I. (1991). "The theory of planned behavior," *Organisational Behavior and Human Decision Process,* Vol. 50(2), pp. 179–211. https://doi.org/10.1080/08870446.2011.613995.

Ajzen, I. (2002). "Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives," *Personality & Social Psychology Review,* Vol. 6(2), pp. 107–122.

Ajzen, I. (2012). The theory of planned behaviour. In P. A.M. Lange, E. T. Higgins and A. W. Kruglanski (Eds.), *Handbook of theories of social psychology* (Vol. 1, pp. 438–459). London, UK: Sage.

Ajzen, I. and Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*, Englewood-Cliffs, NJ: Prentice-Hall.

Ajzen, I. and Fishbein, M. (2005). "The Influence of Attitudes on Behavior," in *The Handbook of Attitudes,* D. Albarracín, B. T. Johnson, and M. P. Zanna (eds.), Mahwah, NJ: Erlbaum, pp. 173–221.

Avkiran, N. K. (2018). Rise of the Partial Least Squares Structural Equation Modeling: An Application in Banking. In N. K. Avkiran, C. M. Ringle (Eds.), *Partial Least Squares Structural Equation Modeling* (pp. 1–29). International Series in Operations Research & Management Science 267. https://doi.org/10.1007/978-3-319-71691-6_1.

Bagozzi, R. P. and Yi, Y. (1988). "On the evaluation of structural equation models," *Journal of the Academy of Marketing Science*, Vol. 16(1), pp. 74–94.

Bailey, C. and Austin, M. (2006). "360 Degree Feedback and Developmental Outcomes: The Role of Feedback Characteristics, Self-Efficacy and Importance of Feedback Dimensions to Focal Managers' Current Role," *International Journal of Selection and Assessment,* Vol.14, pp. 51–66.

Bandura, A. (1986). *Social foundations of thought and action*, Englewood Cliffs, NJ Prentice-Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control,* New York: Freeman.

Bandura, A. and Locke, E. A. (2003). "Negative self-efficacy and goal effects revisited," *Journal of Applied Psychology,* Vol. 88, pp. 87–99.

Barua, Z., Alam, M. Z., and Hu, W. (2018). "Using the UTAUT Model to Determine Factors Affecting Acceptance and Use of Mobile Health (mHealth) Services in

Bangladesh," *Journal of Studies in Social Sciences,* Vol. 17(2), pp. 137–172.

Briones-Penalver, A. J., Bernal-Conesa, J. A., and Nieves-Nieto, C. (2018). "Analysis of corporate social responsibility in Spanish agribusiness and its influence on innovation and performance," *Corporate Social Responsibility and Environmental Management,* Vol. 25(2), pp. 182–193.

Broadhead-Fearn, D. and White, K. M. (2006). "The role of self-efficacy in predicting rule-following behaviors in shelters for homeless youth: a test of the theory of planned behavior," *The Journal of Social Psychology,* Vol. 146(3), pp. 307–325.

Brown, S. A. and Venkatesh, V. (2005). "Model of Adoption of Technology in the Household: A Baseline Model Test and Extension Incorporating Household Life Cycle," *MIS Quarterly,* Vol. 29(4), pp. 399–426.

Chan, K. Y., Gong, M., Xu, Y., and Thong, J. Y. L. (2008, July 3–7). "Examining User Acceptance of SMS: An Empirical Study in China and Hong Kong." In *Proceedings of 12th Pacific Asia Conference on Information System*, Suzhou, China.

Chao, C. M. (2019). "Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model," *Front. Psychol.* 10:1652. Doi:10.3389/fpsyg.2019.01652.

Chatzisarantis, N. L. D. and Biddle, S. J. H. (1998). "Functional significance of psychological variables that are included in the Theory of Planned Behaviour: A Self-Determination Theory approach to the study of attitudes, subjective norms, perceptions of control and intentions," *European Journal of Social Psychology,* Vol. 28, pp. 303–322.

Childers, T. L., Carr, C. L., Peck, J., and Carson, S. (2001). "Hedonic and Utilitarian Motivations for Online Retail Shopping Behavior," *Journal of Retailing,* Vol. 7(4), pp. 511–535.

Dodds, W. B., Monroe, K. B., and Grewal, D. (1991). "Effects of Price, Brand, and Store Information on Buyers," *Journal of Marketing Research,* Vol. 28(3), pp. 307–319.

East, R. (1993). "Investment decisions and the theory of planned behaviour," *Journal of Economic Psychology,* Vol. 14, pp. 337–375.

Falk, R. F. and Miller, N. B. (1992). *A primer for soft modeling.* University of Akron Press.

Fishbein, M. and Ajzen, I. (1975). *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research,* Addison-Wesley, Reading, MA.

Fornell, C. G., and Larcker, D. F. (1981). "Structural equation models with unobservable variables and measurement error: Algebra and statistics," *Journal of Marketing Research*, Vol.18 (3), pp. 328–388.

Gefen, D. and Straub, D. (2005). "A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example," *Communications of the Association for Information Systems,* Vol. 16(1), pp. 91–109.

Gharaibeh, N., Gharaibeh, M. K., Gharaibeh, O. and Bdour, W. (2020). "Exploring intention to adopt mobile commerce: Integrating UTAUT2 with social media," *International Journal of Scientific and Technology Research*, Vol. 9 (3), pp. 3826–3833.

Groß, M. (2015). "Exploring the acceptance of technology for mobile shopping: An empirical investigation among Smartphone users," *The International Review of Retail, Distribution and Consumer Research*, Vol. 25(3), pp. 215–235.

Ha, C. L. (1998). "The theory of reasoned action applied to brand loyalty," *The Journal of Product and Brand Management,* Vol. 7(1), pp. 51–61.

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (2nd Ed.). Los Angeles: Sage.

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science,* Vol. 43, pp. 115–135.

Khurana, S. and Jain, D. (2019). "Applying and Extending UTAUT2 Model of Adoption of New Technology in the Context of M-Shopping Fashion Apps," *International Journal of Innovative Technology and Exploring Engineering (IJITEE)*, Vol. 8(9S), pp. 752–759. *DOI: 10.35940/ijitee.I1122.0789S19.*

Kim, S. S. and Malhotra, N. K. (2005). "A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Post-Adoption Phenomena," *Management Science,* Vol. 51(5), pp. 741–755.

Kim, S. S., Malhotra, N. K., and Narasimhan, S. (2005). "Two Competing Perspectives on Automatic Use: A Theoretical and Empirical Comparison," *Information Systems Research,* Vol. 16(4), pp. 418–432.

Limayem, M., Hirt, S. G., and Cheung, C. M. K. (2007). "How Habit Limits the Predictive Power of Intentions: The Case of IS

Continuance," *MIS Quarterly,* Vol. 31(4), pp. 705–737.

Liu, G-S. and Tai, P. T. (2016). "A Study of Factors Affecting the Intention to Use Mobile Payment Services in Vietnam," *Economics World,* Vol. 4(6), pp. 249–273. Doi: 10.17265/2328-7144/2016.06.001.

Marcoulides, G. A. and Saunders, C. (2006). "Editor's Comments – PLS: A Silver Bullet?" *MIS Quarterly*, Vol. 30(2), pp. iii–ix.

Maune, A. (2021). "Intention to use mobile applications in competitive intelligence: An extended conceptual framework," *Journal of Intelligence Studies in Business*, Vol. 11(2), pp. 6–29.

Maune, A., Matanda, E. and Mundonde, J. (2021). "Financial Inclusion as an Intentional Behaviour in Zimbabwe," *Acta Universitatis Danubius. OEconomica*, Vol. 17(4), pp. 177–211.

O'connor, R. C. and Armitage, C. J. (2003). "Theory of Planned Behaviour and Parasuicide: An Exploratory Study," *Current Psychology: Developmental, Learning, Personality, Social,* Vol. 22(3), pp. 196–205.

Ouellette, J. A. and Wood, W. (1998). "Habit and Intention in Everyday Life: The Multiple Processes by Which Past Behavior Predicts Future Behavior," *Psychological Bulletin,* Vol. 124(1), pp. 54–74.

Roy, S. (2017). "App adoption and switching behavior: applying the extended tam in smartphone app usage," *JISTEM–Journal of Information Systems and Technology Management,* Vol. 14(2), pp. 239–261. DOI: 10.4301/S1807-17752017000200006.

Shneor, R. and Munimb, Z. H. (2019). "Reward crowdfunding contribution as planned behaviour: An extended framework," *Journal of Business Research*, Vol. 103, pp. 56–70.

Solberg K. S. (2019). "The argument that 'there is nothing new in the competitive intelligence field,'" *Journal of Intelligence Studies in Business,* Vol. 9(3), p. 4–6.

Tarhini, A., Alalwan, A. A., Shammout, A. B., Al-Badi, A. (2019). "An analysis of the factors affecting mobile commerce adoption in developing countries: Towards an integrated model," *Review of International Business and Strategy,* Vol. 29(3), pp. 157–179.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y.-M., and Lauro, C. (2005). "PLS path modeling," *Computational Statistics and Data Analysis,* Vol. 48, pp. 159–205.

Thong J. Y. L., Hong, S. J., and Tam, K. Y. (2006). "The Effects of Post-Adoption Beliefs on the Expectation–Confirmation Model for Information Technology Continuance," *International Journal of Human-Computer Studies,* Vol. 64(9), pp. 799–810.

van der Heijden, H. (2004). "User Acceptance of Hedonic Information Systems," *MIS Quarterly,* Vol. 28(4), pp. 695–704.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly,* Vol. 27(3), pp. 425–478.

Venkatesh, V., Thong, J., and Xu, X. (2012). "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology," *MIS Quarterly*, Vol. 36(1), pp. 157–178.

Yadav, R., Chauhan, V. and Pathak, G. S. (2015). "Intention to adopt internet banking in an emerging economy: a perspective of Indian youth," *International Journal of Bank Marketing,* Vol. 33(4), pp. 530–544.

Zeithaml, V. A. (1988). "Consumer Perceptions of Price, Quality, and Value: A Means–End Model and Synthesis of Evidence," *Journal of Marketing,* Vol. 52(3), pp. 2–22.

Zhao, H., Seibert, S. E. and Hills, G. E. (2005). "The Mediating Role of Self-Efficacy in the Development of Entrepreneurial Intentions," *Journal of Applied Psychology,* Vol. 90, pp. 1265–1272.

Zimmerman, B. J., Bandura, A. and Martinez-Pons, M. (1992). "Self-motivation for academic attainment: The role of self-efficacy beliefs and personal goal setting," *American Educational Research Journal,* Vol. 29, pp. 663–676.