Research Project Report

Resistance to Online Learning Technology: Theoretical and Empirical Perspectives

By

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Abstract

The increasing popularity of online learning applications (OLAs) among institutions and individuals is an ongoing trend in information technology. This research investigates motivations behind the adoption of OLAs offering insights on inhibitors rather than enablers. The main focus is on dispositional resistance to change (RTC) and its role in OLA adoption. To this goal, an integrated research model was formulated to investigate the influence of RTC on key adoption predictors using a sample of 217 university students. A combination of cognitive dissonance and self-verification theories was used to shed the light on the mechanism of this influence. Findings indicate that RTC has a significant negative impact on effort expectancy and usage intention, but not on attitude and performance expectancy. This study contributes by theoretically underpinning and empirically validating the impact of RTC on OLA adoption decisions. Furthermore, it illustrates the importance of incorporating RTC into technology adoption studies in general and OLA studies in particular. The current research provides the foundation for future work in this severely underexplored area.

Keywords: resistance to change, technology acceptance, online learning, cognitive dissonance, self-verification, quantitative, survey.

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Igor Alexander Ambalov

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CHAPTER 1

Introduction

1.1 Research Topic Background

Information technology (IT) has brought about significant changes to various aspects of peoples' lives, impacting the way they communicate, seek entertainment, and acquire new knowledge. In recent years, a specific type of technology, known as online learning applications (OLA) has gained popularity among diverse user groups, including the general public, working professionals, and university students (Camilleri & Camilleri, 2019; Kross et al., 2021; Zydney & Warner, 2016).

The recent data suggests that learning applications (apps) are becoming more popular alongside traditional classrooms, indicating an ongoing trend. In 2022, the educational application industry reached $7 billion, a 7.2% increase from the previous year. The pandemic significantly contributed to this growth, as 1.6 billion students turned to these apps for learning. Leading learning apps now have millions of users, and the education app market is expected to grow by nearly 9% annually from 2023 to 2030 (Statista 2023; Wylie, 2023) as illustrated in Figure 1.1.

Figure 1.1 Leading language learning apps worldwide in September 2023, by downloads (*source*: Statista, 2003)

These apps have become popular because they allow convenient on-demand access to learning materials, allow easy customization, and can be used on various devices, whether stationary or mobile. Additionally, the interactive and multimedia-rich nature of these applications makes learning enjoyable, particularly for younger generations who have grown up in the digital age (Camilleri & Camilleri, 2019; Manchanda, 2022; Sydow, 2022). As a result, not only individuals but also institutions like schools and universities adopted this technology in order to enhance student education and deliver instruction to remote learners via the internet (Reports and Data, 2022; Wylie, 2023).

Given the widespread popularity of online learning applications, educational institutions may benefit significantly by understanding the motivations behind users' acceptance of this technology. Such knowledge can help organizations, including schools and universities, better align their offerings with learners' preferences. This, in turn, has the potential to enhance the quality of these offerings from an educational standpoint, and can also strengthen an institution's capacity to attract a larger number of learners, thereby expanding its customer base from a business perspective.

Much of previous information technology (IT) acceptance and continuance research is focused on the positive motivators (enabling perceptions) that influence individuals' decisions to accept and use technology. For example, the well-established models of technology acceptance and usage such as the Technology Acceptance Model (TAM) (Davis et al., 1989), Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001) focus on "enabling factors" (utilitarian and hedonic motivators) in explaining users' behavior. As a result, these factors have been extensively studied and are fairly well-understood. However, previous research has given limited attention to the inhibitors of technology acceptance, resulting in a significant gap in the understanding of their impact on technology adoption decisions. This gap is particularly evident in factors related to individual psychological traits, such as dispositional resistance to change (RTC) (Oreg, 2003).

Individuals often exhibit resistance when faced with technological innovations, which is commonly referred to as resistance to innovation (Oreg & Goldenberg, 2015). According to different theoretical perspectives, this resistance can originate from various sources: (a) situational antecedents, including both functional and psychological barriers to adoption (Ram and Sheth, 1989); (b) relative influence of both “reasons for” and “reasons against” adoption (Westaby, 2005); and (c) an individual's inherent disposition toward change, which represents a psychological trait (Oreg, 2003; Oreg & Goldenberg, 2015). Understanding these inhibiting factors and their influence on individuals' intention to use IT is important for developing effective measures that can circumvent or mitigate resistance and encourage technology adoption in both personal and organizational settings.

It is noted that previous studies that analyzed the impact of one’s resistance to adopt technology, used the definition of *resistance to change* to denote constructs unsimilar to individual disposition to avoid change, as defined by Oreg (2003) and also used in this study. Some of these studies used the term to actually refer to disinclination or unwillingness to adopt innovation, known in the literature as *resistance to innovation* (Oreg & Goldberg, 2015). A more comprehensive description of this concept is provided later in the literature review section.

While previous research has investigated IT adoption barriers from a reasoned action perspective to a reasonable extent, there has been limited attention given to the psychological nature of resistance to innovation. This study aims to bridge this gap by examining the influence of dispositional resistance to change on salient motivators of technology acceptance as suggested in the literature and specified in TAM. It contributes to the resistance of innovation literature by being the first attempt (as far as can be determined) to theoretically explain and empirically examine the inhibiting effect of individual disposition to resist change on key motivators of technology acceptance including intention, attitude, and expectations regarding performance and effort.

1.2 Problem Statement and the Research Questions

In light of the above exposition, this study seeks to answer the following research questions: (1) Does dispositional resistance to change (RTC) have a negative influence on technology acceptance predictors, as specified in TAM, in the context of OLA? If so, (2) What is the extend of this influence on each of the TAM constructs?

In order to provide answers to this questions, the following specific research questions are addressed:

1. Is RTC an important negative influence on users' intentions to adopt the OLA?
2. Is RTC an important negative influence on users' attitudes towards the to adopt the OLA?
3. Is RTC an important negative influence on users' effort expectancy regarding the OLA?
4. Is RTC an important negative influence on users' performance expectancy regarding the OLA?
5. What are the magnitudes of the effects of RTC on each of the above constructs?

1.3 Research Objectives

The objectives of this research study are: (1) to confirm that RTC is an important inhibitor of technology adoption in the context of OLA usage; (2) to theoretically justify and validate the mechanisms of influence that RTC exerts on users' decision to use OLA; and (3) to test the predictive ability of the RTC extended TAM in the context of OLA usage.

1.4 Research Hypotheses

The nine hypotheses presented in Table 1.1 are associated with the causal effect paths in the theoretical research model displayed in Figure 4.1.

Table 1.1 Research hypotheses associated with the theoretical research model

No.	Hypotheses
H1	Dispositional resistance to change has a direct negative influence on attitude toward using OLA.

Table 1.1 Research hypotheses associated with the theoretical research model (Cont.)

No.	Hypotheses
H2	Dispositional resistance to change has direct negative influence on intention to use OLA.
H3	Dispositional resistance to change has a direct negative influence on OLA performance expectancy.
H4	Dispositional resistance to change has a direct negative influence on OLA effort expectancy.
H5	Attitude has a direct positive influence on intention to use OLA.
H6	Performance expectancy has a direct positive effect on attitude toward OLA.
H7	Performance expectancy has a direct positive effect on intention to use OLA
H8	Effort expectancy has a direct positive effect on attitude toward using OLA.
H9	OLA effort expectancy has a direct positive effect on performance expectancy.

Note: All of the hypothesis in this table represents direct causal effects.

1.5 Scope and Delimitations

This study is quantitative, cross-sectional in time, adopts a field study approach, and examines adoption of an OLA among university students in Thailand.

Using a student sample in this context is justified because students are the primary end-users of OLAs. Their opinions are important for a better understanding of the factors that shape this technology adoption decisions. In addition, students are accustomed to using technology including online applications. The actual size of this population at the time of the study is unknown; however, according to Statista.com (2022), this number in 2022 was approximately 1.4 million.

The study is exclusively focused on dispositional resistance to change as one key inhibitor of technology adoption. Hence, dispositional resistance to change is integrated into TAM and modeled as a predictor of all of the TAM constructs. It is noted that, there are other inhibitors of adoption and use in the literature, but they are outside the scope of this study.

It is noted that the respondents in this survey provided opinions about one particular OLA (Voxy.com). This is as a delimitation of this research as the study is concerned with perceptions of individual OLA users based on their experience with any one of the available OLAs. However, it is important to note that participants' opinions may also be reflective of their experiences with other OLAs as well.

Another delimitation is the composition of the sample. Studying university students may be advantageous because these individuals represent a fairly homogeneous group in terms of socio-demographic characteristics. Given that identifying violations in the theory (if it is false) is more likely within a more homogeneous sample of participants than in a heterogeneous one, studying student populations can be seen as an advantage in such studies.

1.6 Definition of the Main Terms Used in the Study

The definitions used in this study are adopted from the related literature and slightly modified to fit the context of OLA.

Use Intention is defined as an individual's decision to use the OLA. The definition originates from Davis et al. (1989) seminal paper on IT acceptance paper and has been widely adopted by a multitude of studies in IT research.

Attitude is defined as users' general positive or negative feeling toward using the OLA. (Davis et al., 1989).

Performance Expectancy is defined as an individual's perception of the expected benefits of IT use (Venkatesh et al., 2003). In the context of OLA usage, it is interpreted as the extent to which users of OLA believe that using the technology will enhance their learning performance.

Effort Expectancy is defined as users' perception of the congruence between expectation of OSM use and its actual performance (Bhattacherjee, 2001).

Resistance to Change is defined as a stable personality trait that manifests as a negative disposition toward a particular change (Oreg, 2003).

Online Learning Application is defined as a software agent that delivers learning content over the internet, allowing learners to use predefined classes and learning materials.

1.7 Contribution to Theory and Practice

This research appears to be the first to investigate the construct of dispositional resistance to change in an online learning context. This is important because it provides insights on psychological IT usage inhibitors that are missing from the extant technology adoption and use models. The results may be valuable to the stakeholders and practitioners of online services and applications.

Thus, this study contributes by deepening our understanding of the important predictors of IT/OLA adoption by (1) theoretically extending TAM with a key technology adoption inhibitor, the construct of RTC; (2) examining the mechanisms by which RTC influences OLA usage considerations; (3) offering practical implications that are of value to OLA stakeholders and practitioners; and (4) providing the basis for future research in this largely unexplored area.

CHAPTER 2

Research Design and Methodology

2.1 Study Sample

An individual university student of any age residing in Thailand and having several weeks of experience using an OLA constitutes the unit of analysis in this study. The data were collected from a sample of undergraduate students from a private university in Thailand with about two months of prior voluntary use of an online English learning application. The university provided free access to the application on both mobile and stationary devices.

Using a student sample in this context is justified because students are the primary end-users of OLAs. Their opinions are important for a better understanding of the factors that shape this technology adoption decisions. In addition, students are accustomed to using technology including online applications.

2.2 Questionnaire

The questionnaire was developed in both English and Thai. For the English version, all measurement items were adapted from previous research to ensure their validity and reliability, with minor adjustments made to TAM-related measures to better fit the OLA context. The items for the RTC dimensions were used without modification, as they are intended to reflect a specific personality trait.

The translation into Thai was carried out by an English-speaking university professor who is a native Thai speaker. Both versions were pilot-tested by a group of ten students from the same population who are proficient in both Thai and English. Based on their feedback, several minor adjustments were made to the Thai version used to collect responses. The measurement items for the questionnaire are shown in Appendix B and Appendix C, for English and Thai versions, respectively.

2.3 Data Collection

The data was collected using a self-administered online questionnaire comprising 36 items total, including gender, age, usage frequency, and experience with the OLA. The questionnaire was hosted online using a free web survey service and the link to it was distributed to students via an instant messenger application.

Because this study uses PLS-SEM as the analysis technique, no particular target for the sample size is set; PLS-SEM works well with small sample sizes (Hair et al., 2022). However, with regard to factor analysis (used in this study to establish construct validity), Hair et al. (2014) recommends a minimum of 5 observations per variable. Since there are 31 observed variables (measurement items) used in the analysis, a sample size of over 155 is considered to be appropriate.

In total, 250 responses were collected within one month period. Since the questionnaire was set to “required response”, there were no missing values in the data. Outliers and careless responses (Meade & Craig, 2012) were removed from the data using SPSS, which resulted in 217 usable cases. This sample size was adequate for the use of PLS-SEM in the analysis of the research model (Hair et al., 2021).

2.4 Data analysis methods

The following methods are used in this study to analyze the data and estimate the theoretical research model.

First, a factor analysis with Principal Component (PCA) using SPSS is run to initially determine the validity of the latent construct including convergent validity and discriminant validity. Next, the confirmatory factor analysis is performed using SmartPLS 4 to examine factor loadings and average variance extracted (AVE) for each construct.

Further, in order to access the discriminant validity, the average variance extracted method by Fornell and Larcker (1981) is used. Furthermore, reliabilities of the measures are examined by Cronbach alpha and composite reliability tests. Finally, in order to estimate model effects and variances explained in the endogenous variables, a structural model analysis is performed using PLS–SEM (structural equation modeling) technique.

The PLS–SEM approach is appropriate in the context of this study for several reasons: (1) the main purpose of this study is an evaluation of the hypothesized effects rather than testing the model fit to the data; (2) PLS–SEM is insensitive to non-normed data which is a common problem in survey research; (3) it works well with small samples which may be a case in the current context; and (4) it is a better choice than CB-SEM if a model employs multidimensional constructs; and (5) it has been used in previous research in the online technology adoption and use contexts.

CHAPTER 3

Related Literature and Theoretical Background

3.1 Technology Acceptance Model

This study employs TAM (see Figure 3.1) as a theoretical basis to explain online learning behavior. However, the objective of this study is not to test TAM itself but, rather, to utilize its framework to examine the influence of resistance to change on OLA adoption. TAM represents a well-established generalized model of technology acceptance. In TAM, technology usage is predicted by use intention, which in turn is predicted by attitude toward usage. Attitude is further determined by perceived usefulness and perceived ease of use. In addition, perceived usefulness directly influences use intention.

It is noted that in subsequent revisions of TAM, attitude was removed from the model due to the inconsistences observed in empirical tests (Venkatesh & Davis, 1996, 2000). Nevertheless, the present study employs the original version of TAM (Davis et al., 1989), as it focuses on the influence of resistance to change on key technology acceptance predictors, including attitude.

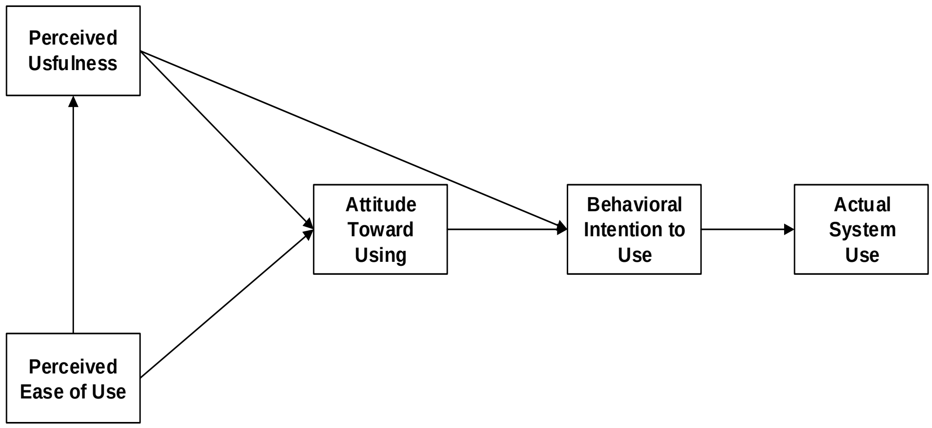


Figure 3.1 Technology Acceptance Model (TAM) (Davis, Bagozzi, and Warshaw, 1989)

In order to better capture the context of the OLA, a minor modification to the original TAM was made – the constructs of perceived usefulness and of perceived ease of use were replaced by their conceptually similar UTAUT counterparts: performance expectancy and effort expectancy, including their operational definitions and measuring scales.

3.2 Prior Research on Resistance to Change

Existing IS research on resistance to change as an individual characteristic or trait is scarce. For example, Bhattacherjee and Hikmet (2007), drawing upon dual-factor (enablers and inhibitors) perspective of technology adoption (Cenfetelli, 2004; Cenfetelli & Schwarz, 2011), examined resistance of healthcare information technology (HIT) usage among hospital physicians. They integrated resistance to change and IT acceptance literatures to incorporate the same-named construct into a TAM-based model. However, the construct that they used to measure resistance to change is conceptually similar to the construct of resistance to innovation, which denotes disinclination or unwillingness to accept innovation. This differs from one's general disposition to resist change, and the literature clearly distinguishes them as related but not similar, with the latter being a predictor of the former (Oreg, 2006; Oreg & Goldenberg, 2015). While the study's findings indicate that physicians' resistance to use HIT negatively affects both perceived usefulness and intention to adopt the technology, the conceptualization of the construct, as one's unwillingness to change established work-related behaviors, limits its contribution to the understanding of the influence of dispositional resistance to change on technology adoption.

Several prior studies (Gupta & Arora, 2016; Pillai & Sivathanu) applied behavior reasoning theory (BRT) (Westaby, 2005) to investigate the role of resistance to innovation in the context of mobile shopping technology. This theory posits that a better understanding of human decision-making should consider individuals' context-specific "reasons for" and "reasons against" a given behavior. In BRT, inhibiting influences are seen as reasons against a behavior, including situational and work-related factors (e.g., unenjoyable work, low pay, lack of opportunities) unrelated to personal traits. Although these studies found the inhibiting effect of self-efficacy and adoption barriers (traditional, image, and usage) on mobile shopping technology adoption, these findings do not explain the role of dispositional resistance to change in this process.

A different perspective of resistance to change was taken by Kaur et al. (2020a) who investigated the effect of resistance barriers on the adoption of mobile payment technology. This study adapted the innovation resistance theory from marketing and consumer research (IRT) (Ram & Sheth, 1989) to hypothesize that users' functional and psychological barriers to innovation influence adoption of the mobile payment system. The functional barriers specified by IRT include usage, value, and risk barriers, while psychological barriers encompass tradition, and image. The study found that the functional barriers had a significant effect on use intention, while the effect of the psychological barriers was not supported. In IRT, tradition and image barriers are viewed as psychological factors. However, these factors are conceptually unrelated to individual characteristics, and hence, the results of this study also do not provide additional insights on how resistance to change as a disposition influences the adoption decision process.

In a systematic review of quantitative empirical research spanning a 60-year period and totaling 79 studies, Oreg et al. (2011) examined individual responses to organizational change. This work resulted in a conceptual model of change recipient reactions to organizational change (CRRM) that outlines the complex relationships between: (a) change antecedents, including individual characteristics; (b) direct responses to change that include affective, cognitive, and behavioral components; and (c) the final outcomes of change in terms of work-related and personal consequences. In relation to change recipient characteristics, this model suggests that individual traits, including dispositional resistance to change, are linked to attitudes and intentions to resist change, which, in turn, result in behaviors aimed at resisting and avoiding change.

Among a few empirical works that examined the role of resistance to change as a disposition in technology adoption are two studies of Nov and Ye (2008, 2009) that investigated the effect of this construct on effort expectancy in the context of a digital library system (see Figures 3.2 and 3.3). They found a significant negative relationship between these constructs indicating that individuals inclined to resist change tend to believe that digital libraries are more difficult to use. Their findings also indicated that resistance to change exerts indirect effects on both performance expectancy, and adoption intention via effort expectancy, in support of their assumption that resistance to change may have an indirect impact on users' intentions to adopt technology.

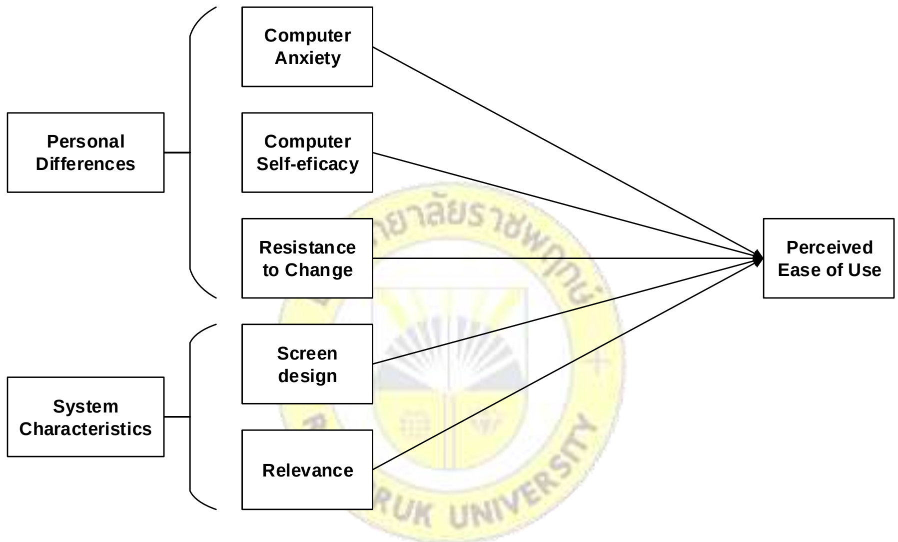


Figure 3.2 Resistance to change model (Nov and Ye, 2008)

While the above studies examined the role of resistance to change in various technology contexts, nearly all of them focused on a conceptually different the same-named construct. This study however specifically focuses on the dispositional resistance to change, as defined by Oreg (2003), distinguishing it from previous studies. Consistent with this aim, the upcoming section provides a more detailed description of dispositional resistance to change and describes the theories applied in this research.

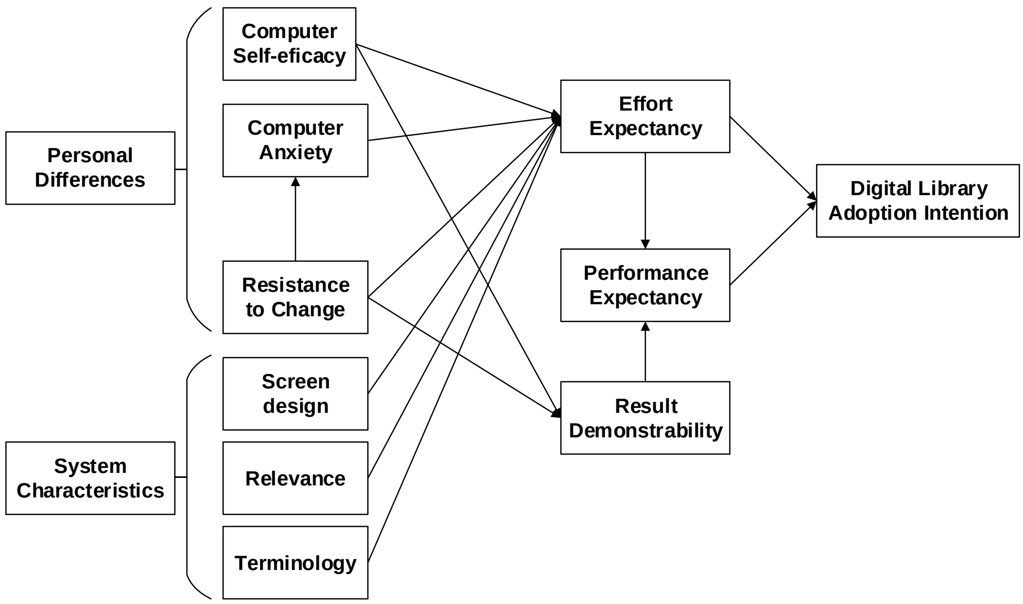


Figure 3.3 Resistance to change integrative model (Nov and Ye, 2009)

3.3 Resistance to Change Construct

Oreg (2003, 2006) conceptualized resistance to change as a stable personality trait that manifests as a negative disposition toward a particular change (henceforth, RTC is referred to the dispositional resistance to change) noting that this construct is distinct from attitude against change, which is conceptually similar to resistance to innovation (RTI). In the context of IT usage behavior, RTI is viewed as the disinclination to adopt new technology, and it is directly predicted by RTC (Oreg & Goldberg, 2015).

This study focuses on RTC; it adopts the Oreg's (2003) view of RTC as a reflective second-order factor comprised of four dimensions (first-order constructs) including routine seeking; emotional reaction; short-term thinking; and cognitive rigidity. This view aligns with Hardin et al.'s (2007) recommendations to use reflective multidimensional constructs when: (1) first-order factors are expected to correlate, and (2) these factors reflect the psychological and theoretical construct of interest. According to Oreg (2003), the four dimensions represent behavioral, affective, and cognitive aspects of one's disposition to change. Drawing from prior research, Oreg and Goldberg (2015) noted that "some people are disinclined toward change and innovation because they like their routines; they feel uneasy and sometimes even threatened by the notion of change. They focus on the short-term inconveniences of change, and they tend to hold on to their opinions and a priori decisions”. The following definitions are based on this notion. Hence, routine seeking refers to the preference for stability and familiar patterns of behavior. Short-term thinking is the tendency to resist changes, even if they could lead to long-term benefits. Emotional reaction refers the tendency to feel uneasy and even fearful at the notion of change. Cognitive rigidity is characterized by strongly held preexisting opinions and a priori decisions.

The indicators for the first-order constructs in the Oreg’s (2003) RTC scale are generalized and therefore can be used in different context, including technology adoption. The scale has been validated in previous research, including technology adoption studies (Nov & Ye, 2008, 2009).

CHAPTER 4
Theoretical Research Model

4.1 Research Model Theoretical Foundation

This research integrates Cognitive Dissonance Theory (CDT) (Cooper, 2012; Festinger, 1957) and Self-Verification Theory (SVT) (Swann, 2012; Talaifar & Swann, 2020) to examine the relationships between RTC and TAM. Both theories have been previously employed to explain various behaviors, including technology acceptance, making them appropriate for this study's context. In addition, CRRM framework depicted above provides empirical support for the hypothesized RTC relationships.

Behavioral psychologists contend that specific personal characteristics and traits can influence individuals' cognitions, feelings, and behaviors (Ajzen, 1987). The literature offers ample evidence to support this contention. For example, Rosen and Kluemper (2009) found that personality traits impact technology adoption considerations, including beliefs about technology utility, ease of use, and intentions; Barnet et al. (2015) found a direct link between personality and the intention to use online learning management systems; and according to McCrae & Costa, (1995) personal traits are causally associated with habits and attitudes. These findings highlight the role of personality in shaping adoption behaviors. Consequently, if positive personality traits can promote favorable IT-related behaviors, it is plausible that negative traits can have the opposite effect. Moreover, considering that dispositions are a subset of one's personality, they can potentially impede IT behaviors. The literature suggests that certain personal dispositions are associated with an individual's resistance to adopt innovation, whatever it may be (Oreg & Goldenberg, 2015). As noted by Oreg and Goldenberg (2015), "knowing one's dispositional orientation toward change can help predict the likelihood that innovations in general will be resisted".

It is reasonable that novelty-seeking individuals are more likely to accept change readily than their more traditional routine-seeking counterparts, as they are naturally more inclined to new experiences. In the context of technology usage, individuals predisposed to resist change are more likely to develop unfavorable attitudes and intentions toward technological innovation; leading to reluctance in adopting new technology. The literature provides theoretical basis for this assumption.

Self-Verification Theory (SVT) (Swann, 2012; Talaifar & Swann, 2020) posits that individuals have a fundamental psychological need to actively confirm and validate their self-concept, whether it is negative or positive. Self-concept – the overall perception of oneself – can encompass narrower self-conceptions related to specific contexts or individual characteristics, such as traits and dispositions. Hence, if dispositional resistance to change is part of a person's self-concept, he or she often identifies as a “traditionalist”, as defined by Rogers (2003). The literature describes these individuals as being inflexible in their behavior, maintaining the status quo due to strongly held predefined views and habits. They often resist change because of the added work it entails in the short term, and they are reluctant to learn and adjust due to the discomfort associated with novelty. This represents the common dispositional resistor to innovation, as described by Oreg and Goldenberg (2015) and as adopted in this study.

Cognitive Dissonance Theory (CDT) (Cooper, 2012; Festinger, 1957) proposes that individuals experience discomfort when their beliefs, attitudes, and behaviors are in conflict. To reduce this discomfort, they try to align their cognitions, attitudes, and behaviors. This need for consistency, influences decision-making and behavior.

In line with CDT, for a resistor, adopting change or innovation can lead to a conflict between the behavior and the existing self-concept. This conflict can manifest as a mental tension and discomfort. To alleviate the uncomfortable feeling, resistors will adjust their attitudes and intentions to be more in line with their self-concepts, thereby reaffirming their natural disposition. In this capacity, the change in attitude and intention serves as a mechanism for self-verification aiding in the resolution of the conflict between self-concept and the new behavior.

4.2 Research Hypotheses

According to the CRRM model, a link exists between RTC and negative affectivity (emotional response) of change; and between RTC and the intention to resist change. This implies that RTC has a negative influence on attitude toward change and intention to adopt change. Oreg (2006) provides empirical support for these relationships finding them significant in an organizational context. In further support, a study of librarians and their willingness to use online applications finds that higher RTC scores are linked to lower willingness to adopt the technology (Aharony, 2009). Given all of the above reasoning, the first two hypotheses are:

H1: Dispositional resistance to change has a negative influence on attitude toward using OLA.

H2: Dispositional resistance to change has a negative influence on intention to use OLA.

A similar theoretical explanation can be used to justify the relationships between RTC and performance expectancy; and RTC and effort expectancy. As described earlier, one’s disposition to resist change is part of one’s self-perception, which needs to be actively maintained through verification. When such an individual encounters a new technology, the initial reaction is likely aversive, consequently leading to less favorable attitude toward adopting the technology. This is so because the negative reaction validates the way the person views oneself, and it aligns with the person's natural pattern of behavior. In order to justify this reaction and avoid mental discomfort, the person will often lower his or her expectations about the technology's performance and the effort required to use it. This pattern is empirically supported in the context of digital library adoption (Nov & He, 2008; 2009). In addition, Oreg and Goldenberg (2015) noted that individuals dispositionally resistant to change are more likely to a priori perceive innovation as too complex, and therefore more likely to evaluate it negatively. This leads to the next two hypotheses:

H3: Dispositional resistance to change has a negative influence on OLA performance expectancy.

H4: Dispositional resistance to change has a negative influence on OLA effort expectancy.

Since TAM is used in this study as a nomological framework, the following set of hypotheses reflects the application of TAM in the OLA context. Therefore, consistent with TAM, attitude has a positive effect on intention to use technology. Attitude is a general feeling (affect) toward the object of behavior. A favorable attitude toward OLA will positively influence one's decision to use the technology because individuals make decisions to perform a behavior toward which they have positive affect. Previous studies observed this effect in different settings, including e-learning (He et al., 2023; Lin, 2011; Park et al., 2012; Pillai & Sivathanu, 2018; Sumak et al., 2011). Therefore, the next hypothesis is:

H5: Attitude has a positive influence on intention to use OLA.

Performance expectancy is defined as the extent of one's belief that OLA will improve one's learning performance. The influence of performance expectancy on attitude and intention is, by definition, utilitarian. Thus, if one believes that the technology is useful in achieving a specific objective, one will likely have a positive attitude toward it. In addition, seeing the technology as a means to accomplish specific instrumental goals, even if one may not have a positive attitude toward it, may be sufficient in order to motivate one's usage intention. These effect paths were empirically confirmed in various IT context, including e-learning services (He et al., 2023; Lin, 2011; Sumak et al., 2011). Therefore, the following two hypotheses are proposed:

H6: Performance expectancy has a positive effect on attitude toward OLA.

H7: Performance expectancy has a positive effect on intention to use OLA.

Effort expectancy refers to the extent of one's beliefs that using OLA is easy and requires little effort. The underlying premise of TAM is that technology users are rational individuals. Therefore, it is reasonable to think that a user-friendly technology will generate positive feelings (affect) toward it. Conversely, a technology that is complicated and difficult to use may result in frustration and other negative reactions, particularly among early adopters.

This relationship is supported empirically; primarily in studies involving early adopters (He et al., 2023; Lin, 2011; Sumak et al., 2011). The influence tends to wane as the adopters gain more experience with the technology (Davis et al., 1989). This study examines OLA adoption among early users; therefore, the relationship is expected to bear out in the current context. Hence, the next hypothesis is:

H8: Effort expectancy has a positive effect on attitude toward using OLA.

As specified in TAM, effort expectancy has a positive influence on performance expectancy. The rationale behind it is that a technology that requires less effort to use is seen as more efficient – because one can save time and effort to focus on the immediate tasks – thus leading to improved performance. This relationship also has empirical support in the e-learning literature (He et al., 2023; Lin, 2011; Sumak et al., 2011). Therefore, the last hypothesis is:

H9: OLA effort expectancy has a positive effect on performance expectancy.

Based on the above hypothesized relationships, the complete theoretical research model is shown in Figure 4.1. Note, that Resistance to change modeled as a reflective second-order construct with four dimensions as specified above. Model variables, the labels used for indicators for latent variables, and reference to previous studies which were used as a source of an existing measuring instrument for the indicators are referenced in Appendix B.

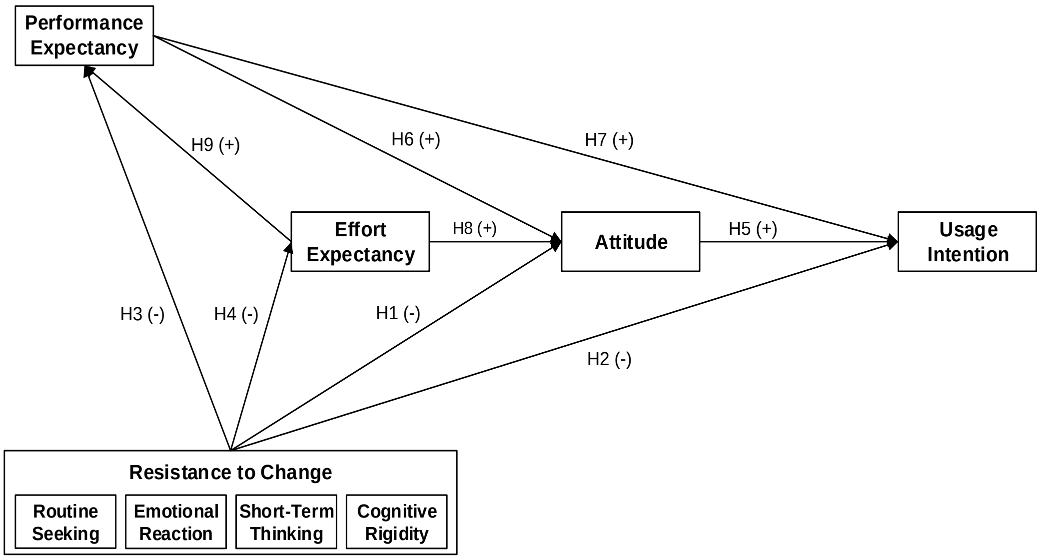


Figure 4.1 Theoretical research model

CHAPTER 5

Data Analysis and Results

5.1 Characteristics of the Respondents

Personal characteristics of the participants are presented in Table 5.1. These data correspond to the unit of analysis specification and it includes the respondent age, gender, use experience, and frequency of usage. As can be seen from the table, approximately one-third of the participants are male, while the remaining two-thirds are female. The majority fall within the age range of 18-22, and most have used the OLA for a period ranging between 1 and 2 months, with a frequency of 1 to 4 times per week.

Table 5.1 Demographic profiles

Category	Characteristic	Count	Percentage
Gender	Male	78	35.9
	Female	139	64.1
Age	18–22	140	64.5
M = 21.9; SD = 4.0	23–27	54	24.9
	28–32	21	9.7
	33–37	2	0.9
Experience (in months)	1	98	45.2
M = 1.6; SD = 0.6	2	101	46.5
	3	18	8.3
Frequency (times per	1–4	184	84.8
week)	5–9	22	10.1
M = 3.2; SD = 2.8	10–14	8	3.7
	15–21	3	1.4

Note: M: mean. SD: standard deviation.

5.2 Measurement model

Data analysis was performed using SmartPLS software – PLS-SEM is better suited for models with hierarchical (i.e., second-order) constructs than CB-SEM (e.g., AMOS) (Chin et al., 2003). However, in order to initially examine construct validity, the questionnaire items (indicators) were examined using principal component analysis (PCA) in SPSS. As expected, all indicators loaded significantly on their respective components, and no cross-loadings exceeded 0.36 (see Appendix A). This analysis confirmed that the constructs in the research mode had both convergent and discriminant validity (Kline, 2015; Straub et al., 2004).

The measurement model was evaluated next on the grounds of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity following the recommendations by Hair et. al. (2021). The indicator-level reliability of the measures was assessed by examining the indicator loadings on their respective constructs. All the loadings were above the minimum value of 0.70. The internal consistency reliability was established using Cronbach's alpha (CA) and composite reliability (CR) measures. As seen from Table 5.1, CAs and the CRs all exceed the recommended minimum of 0.70. These tests confirmed that the construct measures were reliable.

Convergent validity of the first-order latent constructs was established by examining factor loadings and average variance extracted (AVE) for each construct. The results confirmed the validity of the constructs: the observed variables' factor loadings were significant, exceeding the recommended minimum of 0.70, and explaining more than 50 percent of the variance of their respective indicators (see Table 5.2).

Table 5.2 Factor loadings and construct reliabilities

Factor	Item	Loading	Mean	SD	AVE	CR	CA
Usage Intention (UI)	UI1	0.81	3.92	0.67	0.67	0.89	0.83
	UI2	0.81	3.70	0.73			
	UI3	0.84	3.92	0.68			
	UI4	0.80	3.90	0.69			
Attitude (AT)	AT1	0.71	4.14	0.53	0.57	0.84	0.75
	AT2	0.77	4.17	0.58			
	AT3	0.76	4.08	0.59			
	AT4	0.77	3.87	0.62			
Performance Expectancy (PE)	PE1	0.75	4.33	0.58	0.65	0.88	0.82
	PE2	0.84	3.96	0.70			
	PE3	0.83	4.06	0.61			
	PE4	0.81	3.96	0.69			
Effort Expectancy (EE)	EE1	0.85	3.75	0.76	0.70	0.9	0.86
	EE2	0.82	3.78	0.71			
	EE3	0.84	3.71	0.72			
	EE4	0.84	3.82	0.70			
Routine Seeking (RS)	RS1	0.88	2.71	0.76	0.71	0.91	0.86
	RS3	0.81	2.32	0.67			
	RS3	0.87	2.65	0.79			
	RS4	0.81	2.39	0.78			
Emotional Reaction (ER)	ER1	0.85	2.47	0.77	0.72	0.88	0.80
	ER2	0.85	2.28	0.77			
	ER3	0.84	2.08	0.76			
Short-Term Thinking ST)	ST1	0.87	2.61	0.87	0.78	0.93	0.91
	ST2	0.88	2.53	0.91			
	ST3	0.90	2.76	0.98			
	ST4	0.89	2.77	0.90			

Table 5.2 Factor loadings and construct reliabilities (Cont.)

Factor	Item	Loading	Mean	SD	AVE	CR	CA
Cognitive Rigidity (CR)	CR1	0.83	2.33	0.78	0.73	0.91	0.88
	CR2	0.87	2.19	0.81			
	CR3	0.87	2.30	0.80			
	CR4	0.84	2.36	0.83			

Note: CA: Cronbach's alpha. CR: composite reliability (rho_c). SD: standard deviation. All factor loadings (shown standardized) are significant at $p < 0.001$ (2-tailed).

To establish discriminant validity of the construct measures, the correlations between each construct's square root of AVE and all other constructs in the model were examined (Fornell and Larcker, 1981). As seen from Table 5.3, the square roots of AVEs were greater than the corresponding inter-construct correlations, supporting the discriminant validity of the measures.

Table 5.3 Construct correlations

Construct	1	2	3	4	5	6	7	8	9
1. Use Intention	**0.82**								
2. Attitude	0.51	**0.75**							
3. Performance Expectancy	0.52	0.62	**0.81**						
4. Effort Expectancy	0.39	0.49	0.39	**0.84**					
5. Routine Seeking	-0.18	-0.12	-0.06	-0.21	**0.84**				
6. Emotional Reaction	-0.13	-0.04	-0.10	-0.10	0.36	**0.85**			
7. Short-Term Thinking	-0.21	-0.10	-0.03	-0.16	0.44	0.55	**0.88**		
8. Cognitive Rigidity	-0.07	-0.05	-0.07	-0.11	0.33	0.24	0.24	**0.85**	
9. RTC (second-order)	-0.21	-0.11	-0.08	-0.21	0.76	0.72	0.82	0.57	**0.62**

Note: The diagonal bolded elements are the square roots of AVE for that construct.

Of note, this criterion does not apply to the relationships between the second-order RTC and its dimensions, which are described further below. In addition, as recommended by Hair et al. (2021), the heterotrait-monotrait ratio (HTMT) value for every construct, including the second-order RTC, was below the recommended minimum of 0.90 thereby further affirming the discriminant validity of the model constructs.

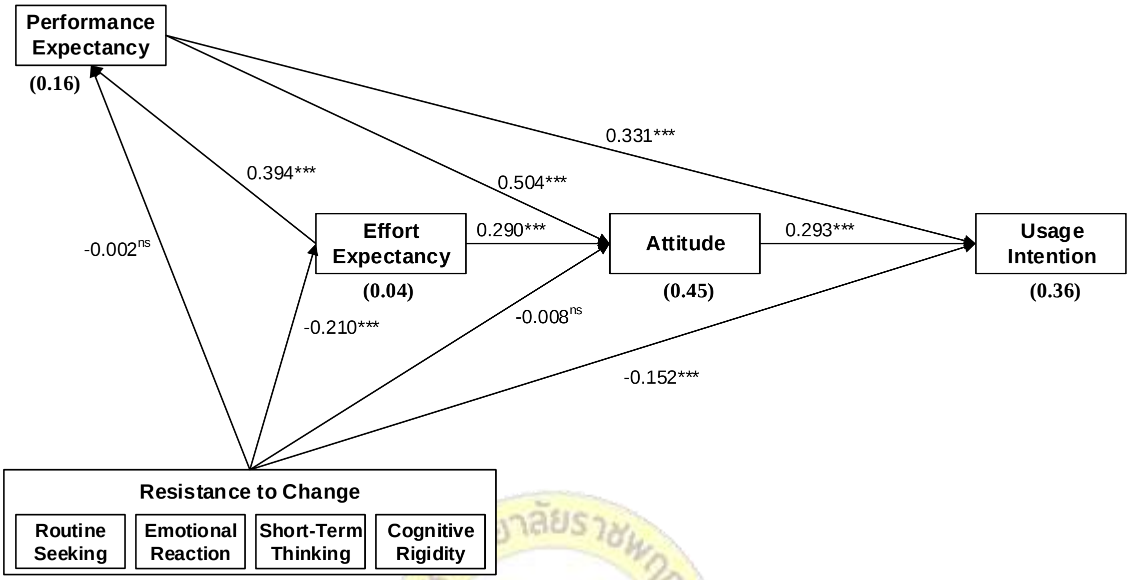
Convergent validity and discriminant validify of the second-order construct of RTC was assessed following the guidelines of Sarstedt et al. (2019) for high-order constructs in PLS-SEM. Except for AVE (0.39), all other values: the first-order construct intercorrelations (0.24 – 0.55***); factor loadings (0.57 – 0.82***); CA (0.88); CR (0.90); and HTMT (< 0.90) were within the recommended guidelines. In addition, the correlations with other model constructs (excluding RTC dimensions) were lower than the construct's square root of AVE (see Table 5.3). With respect to AVE, that it was below the suggested threshold of 0.50, indicated that the second-order construct explained less variance in its dimensions than expected. Nonetheless, considering that RTC is a pre-validated measure and that each of its first-order dimensions demonstrated adequate construct validity, the appropriateness of RTC as a second-order construct was largely supported.

The data was next examined for multicollinearity showing that the highest VIF value was 3.28, which is below the recommended minimum of 5.0, indicating that multicollinearity was not present in the data. In addition, the skewness and kurtosis were within the recommended range of -1/+1 (Hair et al., 2021), -0.58 and 0.96 respectively.

Lastly, common method bias was accessed by using both the Harman's single-factor test, which examines the amount of common variance in a single dimension (Podsakoff et al., 2003), and a full collinearity assessment method, which is based on VIFs generated via a complete collinearity test (Kock, 2015). Both methods indicated that the model is free from bias – in the former, the single factor did not explain the majority of the variance in the indicators (only 24%); and in the latter, all the VIFs were below the 3.3 threshold.

5.3 Structural model

As recommended by Hair et al. (2021), the analysis of the research model structure was performed using the bootstrapping procedure with 10,000 subsamples and the percentile method for confidence intervals. Figure 5.1 displays the results of the analysis. The notation *, **, or *** is used to indicate two-tailed statistical significance of the unstandardized path coefficients at a level of 0.05, 0.01, or 0.001, respectively.



Notes: Paths show standardized effects; R^2 is shown in parentheses; ns: not statistically significant; *** p < 0.001; ** p < 0.01; * p < 0.05

Figure 5.1 PLS-SEM analysis of the theoretical research model

As seen in Figure 5.1, the effect paths in the TAM portion of the research model were positive and statistically significant, thereby providing support for H5–H9. More specifically, attitude and performance expectancy directly predicted usage intention with the effect magnitudes of 0.29 and 0.33, respectively. Attitude and performance expectancy, in turn, were directly predicted by effort expectancy – the magnitudes of these effects were 0.29 and 0.39, respectively.

With respect to the RTC relationships in the model, two out of the four hypotheses were borne out, namely, H2 and H4, thereby confirming the negative influence of RTC on usage intention and effort expectancy; the respective magnitudes of these effects were 0.15 and 0.21. In addition, the predictors accounted for a significant proportion of the variance (R^2) in usage intention (0.36), nearly half of it in attitude (0.45), a small portion in effort expectancy (0.04), and a relatively modest amount in performance expectancy (0.16). Table 5.4 displays the summary of the structural model analysis results including standardized effects, *t*-values, and statistical significance of the effect paths. The effect paths correspond to the hypotheses associated with the theoretical research model which are depicted in Table 1.1.

Table 5.4 Structural model analysis results

No.	Effect Path	*t*-statistic	Size	Sig.
H1	RTC →Attitude	0.14	-0.01	ns
H2	RTC → Usage Intention.	2.70	-0.15	**
H3	RTC → Performance Expectancy	0.04	-0.00	ns
H4	RTC → Effort Expectancy	3.21	-0.21	***
H5	Attitude → Usage Intention	4.62	0.29	***
H6	Performance expectancy → Attitude	9.03	0.50	***
H7	Performance expectancy → Usage Intention	4.65	0.33	***
H8	Effort expectancy → Attitude	5.52	0.29	***
H9	Effort expectancy → Performance expectancy	6.12	0.39	***

Note: ns = not statistically significant. Shown standardized effects

Table 5.5 Total and indirect RTC effects

Indirect Effect	*t*-statistic	Effect	Sig.
RTC → Effort Expectancy → Attitude	2.73	-0.06	**
RTC → Performance Expectancy → Attitude	3.42	-0.00	ns
RTC → Effort Expectancy → Performance Expectancy	2.72	-0.08	**
RTC → Effort Expectancy → Performance Expectancy → Attitude	2.63	-0.04	**
Total effect			
RTC → Use Intention	3.26	-0.21	***

Note: ns = not statistically significant. Shown standardized effects.

CHAPTER 6
Discussion

The focus of this research was to investigate the influence of RTC on users' intentions to adopt OLA. The RTC phenomenon has been scarcely researched in the context of IT and thus arguably requires more attention from IT researchers. As previously mentioned, much of prior RTC research was conducted in contexts other than IT, including marketing and organizational settings, and as a result, findings on the role of RTC in IT adoption and use are scant. Thus, the findings of this study should be viewed in terms of the contribution to theory and practice rather than the comparison of the results with previous findings.

6.1 Findings contributions and future research

This study makes several important contributions to research on IT adoption. First, it incorporates the RTC construct into the model of technology acceptance, expanding its explanatory capability beyond the scope of traditional IT adoption predictors, such as beliefs and affects. Second, it offers a theoretical explanation for the relationships between RTC and TAM constructs. Third, it provides a nomological validation of these relationships within the context of OLA acceptance, distinct from previous research. And finally, while not the primary focus of the study, the current findings affirm TAM's ability to explain OLA adoption.

By incorporating and testing the influence of RTC on the TAM constructs, the study sought to determine whether RTC plays an important role in influencing usage intention. The results revealed a negative impact of RTC on usage intention and effort expectancy, but not on attitude and performance expectancy – despite the proposed theoretical justification, RTC did not exhibit a significant influence on these constructs.

The nonsignificant effect of RTC on attitude and performance expectancy can be explained taking into account the moderating influence of rewards on cognitive dissonance occurrence. As mentioned earlier, sufficient rewards may hinder the dissonance arousal resulting in unchanged attitudes and cognitions. In other words, incentives perceived by individuals as adequate, can result in counter-attitudinal intentions and behaviors. Hence, if the student-participants in this study perceived the rewards and benefits (either extrinsic or intrinsic) of using the OLA as sufficient, it is plausible that they might not have experienced cognitive dissonance, or if they did, it could have been minor, resulting in no change in their attitudes and outcome expectations. If this is so, then a very weak and nonsignificant effect of RTC on attitude and performance expectancy would be the result.

While the effects of RTC on attitude and performance expectancy were not confirmed, the effects on effort expectancy and usage intention received support from the data. As predicted, the latter relationship was statistically and substantively significant (see Table 5.4). This suggests that those who are predisposed to resist change may have decreased intentions to use OLA regardless of their attitudes toward the technology and their expectations of positive outcomes. Noteworthy is that the total effect of RTC on usage intention is higher that its direct effect (see Table 5.5) indicating that, acting as mediators, TAM predictors slightly amplify RTC's influence on users' intentions to use the OLA. Future researchers should consider these patterns of indirect effects when predicting how RTC impacts IT behaviors.

With respect to effort expectancy, the support for this hypothesis shows that RTC is an important influence on effort expectancy in an OLA context. In practical terms this suggests that when individuals face a decision to adopt a new technology, the resistors evaluate the effort required to become proficient with the technology more carefully than others. This result is consistent with prior research that found a similar effect pattern in the context of digital library adoption (Nov & He, 2008, 2009).

Looking at the results, it is interesting that RTC did not have a significant influence on the considerations directly involved in the assessment of the potential rewards of the OLA use such as attitude and performance expectancy. Instead, it had a notable influence on the considerations about the behavior itself, specifically, effort expectancy and usage intention. Future research should investigate this effect pattern to see if it holds in other IT contexts.

Findings also show that RTC has an indirect negative effect on attitude and on performance expectancy via effort expectancy (see Table 5.5). That the direct effects of RTC on these constructs are near zero and nonsignificant indicates that the effects are fully mediated by effort expectancy. In more practical terms, if one considers the effort required to use a new technology, RTC is a negative influence on one's attitude and outcome expectations regarding that technology.

While RTC-related hypotheses received partial support from the data, the empirical evidence regarding the role RTC in IT usage remains limited. Future research should examine this construct in other IT-related contexts in order to gain a better understanding of its mechanisms of influence. Another thought is that while it is evident that RTC is an inhibitor, the construct of self-efficacy is an enabler of behavior. Nov and He (2008, 2009) used these constructs together in their research model to explain effort expectancy in an IT adoption context. However, the specific interaction between these constructs remains unexplored. This may be of interest for future research. Given that both of these constructs relate to the concept of oneself, exploring their relationship can yield valuable insights into a better understanding of the role of personal characteristics in IT usage.

In relation to TAM in this study, the research model based on TAM performed as expected. All the relationships within the model were supported. The magnitudes of the effects ranged from 0.29 to 0.50 (see Table 5.4). This provides additional support for the validity of TAM in the context of OLA adoption.

Considering the overall results, this research most significantly contributes by theoretically underpinning and empirically testing the influence of RTC on important predictors of technology adoption. This appears to be the first attempt to apply theory to explain RTC influences within a well-established theoretical model of IT acceptance. While not all of the hypotheses received support from the data, the ones that were borne out, confirm the validity of RTC in IT adoption decisions from a theoretical perspective.

6.2 Practical implications

As implied by the findings, understanding the mechanisms of RTC influence is important for designers and practitioners of online learning technologies to create systems that effectively align with the personal characteristics of potential adopters. For example, to encourage users who are resistant to change to adopt an OLA, it is essential for the new application to be seen as a “new old technology” with which the resistors are already familiar. This can be achieved by retaining many familiar features from the older versions of the same application or, in the case of a completely new application, making it intuitive and user-friendly. Initiatives such as online help, user training, and customer support, can further assist in alleviating the hesitations of resistors. These efforts will increase users’ awareness of the potential benefits of using the application and demonstrate how easily these benefits can be obtained.

It is important to note that due to the fairly small sample size the results of this study may not easily generalize to other populations. However, considering that RTC is a stable personal disposition and that individuals tend to display similar behaviors in technology adoption situations, these implications may also be relevant in other IT adoption settings.

6.3 Limitations

This study has several limitations that should also be addressed in future research. First, the sample size is not sufficient to represent the population under study. To address this concern, a larger sample size is needed. Another limitation is the sample respondents being university students. While studying university students in the context of OLA has many advantages, still these individuals represent a specific group in terms of socio-demographic characteristics distinct from general public and professionals. In addition, the participants in this study are mostly young persons (18-22), hence, findings cannot be generalized to older members of the population because age may be a significant moderator in OLA considerations.

Another limitation is the application of RTC in a specific context. Online learning may have different motivations than usage of productivity or entertainment applications. Examining RTC in other context may yield differing results.

Finally, this study focuses on examining intention rather than actual behavior. While IT researchers predominantly specify intention as a criterion variable, technology acceptance can only be objectively measured via the actual use of technology. The problem with studying actual usage however is how to measure it accurately. In most cases, obtaining objective data on actual behavior is a challenge.

CHAPTER 7
Conclusion

7.1 Research concluding statements

While much of the previous research investigated technology adoption enablers, the current study focuses on adoption inhibitors. To this end, this study integrates a salient behavior inhibitor – dispositional resistance to change – into the technology acceptance model in order to answer the questions – how does this individual characteristic impact users' considerations regarding the acceptance of technology in the context of e-learning such as OLAs; and is this construct an important negative influence on their adoption intentions?

Answering these questions is important for the planners and implementers of online learning systems along with education practitioners because this type of technology, while relatively new, is being actively integrated into schools and universities educational systems.

This study uses cognitive dissonance and self-verification theories to shed light on these research problems. The results show a significant negative impact of dispositional resistance to change on individuals' beliefs about the effort required for using a new OLA. They also demonstrate that dispositional resistance to change significantly and directly influences one's intention to use this technology. Although the study did not find the direct influence of dispositional resistance to change on users' beliefs about the utility of this technology and their attitudes toward its use, the results indicate significant yet indirect effects.

In summary, the study confirms that dispositional resistance to change is an important inhibitor of technology adoption in the context of OLA usage. Considering all of the above, this study offers an opportunity for future researchers to extend these findings to further investigate factors that hinder IT adoption and usage.

References

Aharony, N. (2009). Web 2.0 use by librarians. *Library & information science research*, *31*(1), 29-37.

Ajzen, I. (1987). Attitudes, traits, and actions: Dispositional prediction of behavior in personality and social psychology. In *Advances in experimental social psychology* (Vol. 20, pp. 1-63). Academic Press.

Barnett, T., Pearson, A. W., Pearson, R., & Kellermanns, F. W. (2015). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, *24*, 374-390.

Bhattacherjee, A., & Hikmet, N. (2007). Physicians' resistance toward healthcare information technology: a theoretical model and empirical test. *European Journal of Information Systems*, *16*(6), 725-737.

Camilleri, M. A., & Camilleri, A. C. (2019). The students' readiness to engage with mobile learning apps. *Interactive Technology and Smart Education*, 17(1), 28-38.

Cenfetelli, R. T. (2004). Inhibitors and enablers as dual factor concepts in technology usage. *Journal of the Association for Information Systems*, *5*(11), 16.

Cenfetelli, R. T., & Schwarz, A. (2011). Identifying and testing the inhibitors of technology usage intentions. *Information systems research*, *22*(4), 808-823.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information systems research*, *14*(2), 189-217.

Cooper, J. (2012). Cognitive dissonance theory. *Handbook of theories of social psychology*, *1*, 377-397.

Festinger, L. (1957) *A Theory of Cognitive Dissonance*. Evanston, IL: Row, Peterson.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50.

Gupta, A., & Arora, N. (2017). Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory. *Journal of Retailing and Consumer Services*, *36*, 1-7.

Hardin, A. M., Chang, J. C. J., & Fuller, M. A. (2008). Formative vs. reflective measurement: Comment on Marakas, Johnson, and Clay (2007). *Journal of the Association for Information Systems*, 9(9), 3.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2014). *Multivariate Data Analysis* (7th ed.). Pearson Education.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. 3rd ed. Sage publications.

He, S., Jiang, S., Zhu, R., & Hu, X. (2023). The influence of educational and emotional support on e-learning acceptance: An integration of social support theory and TAM. *Education and Information Technologies*, 1-21.

Kaur, P., Dhir, A., Singh, N., Sahu, G., & Almotairi, M. (2020a). An innovation resistance theory perspective on mobile payment solutions. *Journal of Retailing and Consumer Services*, 55, 102059.

Kaur, P., Dhir, A., Ray, A., Bala, P. K., & Khalil, A. (2020b). Innovation resistance theory perspective on the use of food delivery applications. *Journal of Enterprise Information Management*, 34(6), 1746-1768.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. 4th ed. Guilford Press.

Kross, S., Hargittai, E., & Redmiles, E. M. (2021). Characterizing the online learning landscape: What and how people learn online. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1), 1-19.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, *11*(4), 1-10.

Lin, K. M. (2011). e-Learning continuance intention: Moderating effects of user e-learning experience. *Computers & Education*, 56 (2), 515-526.

Manchanda, A. (2022). *13 Must-Have Features of Successful Educational Apps*, Available at: https://www.netsolutions.com/insights/effective-features-of-best-educational-apps, Accessed: October 5.

McCrae, R. R., & Costa Jr, P. T. (1995). Trait explanations in personality psychology. *European Journal of Personality*, *9*(4), 231-252.

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological methods*, *17*(3), 437.

Nov, O., & Ye, C. (2008). Users' personality and perceived ease of use of digital libraries: The case for resistance to change. *Journal of the American Society for Information Science and Technology*, 59(5), 845-851.

Nov, O., & Ye, C. (2009). Resistance to change and the adoption of digital libraries: An integrative model. *Journal of the American Society for Information Science and Technology*, 60(8), 1702-1708.

Oreg, S. (2006). Personality, context, and resistance to organizational change. *European journal of work and organizational psychology*, 15 (1), 73-101.

Oreg, S., & Goldenberg, J. (2015). *Resistance to innovation: Its sources and manifestations*. University of Chicago Press.

Park, S. Y., Nam, M. W., & Cha, S. B. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British journal of educational technology*, 43(4), 592-605.

Pillai, R., & Sivathanu, B. (2018). An empirical study on the adoption of M-learning apps among IT/ITeS employees. *Interactive Technology and Smart Education*, 15(3), 182-204.

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), 879.

Ram, S., & Sheth, J. N. (1989). Consumer resistance to innovations: the marketing problem and its solutions. *Journal of consumer marketing*, 6(2), 5-14.

Reports and Data, 2022. Education Apps Market Report, Available at: https://www.reportsanddata.com/report-detail/education Rosen -apps-market, Accessed: October, 5.

Rogers, E. M. (2003). *Diffusion of innovations*. 5th ed. New York: Free Press.

Rosen, P. A., & Kluemper, D. H. (2008). The impact of the big five personality traits on the acceptance of social networking website. *AMCIS 2008 proceedings*, 274.

Sarstedt, M., Hair Jr, J. F., Cheah, J. H., Becker, J. M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian marketing journal*, *27*(3), 197-211.

Statista, 2022. *Number of higher education students in Thailand in 2022, by gender* Available at: https:// www.statista.com/statistics/1261687/thailand-number-enrolled-students-in-higher-education-by-gender, Accessed: October, 5.

Statista, 2023. *Leading language learning apps worldwide in February 2023, by downloads*. Available at: https://www.statista.com/statistics/1239522/top-language-learning-apps-downloads, Accessed: October, 5.

Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information systems*, *13*(1), 24.

Šumak, B., Heričko, M., & Pušnik, M. (2011). A meta-analysis of e-learning technology acceptance: The role of user types and e-learning technology types. *Computers in human behavior*, 27(6), 2067-2077.

Swann Jr, W. B. (2012). Self-verification theory. *Handbook of theories of social psychology, ed. P. Van Lang, A. Kruglanski & ET Higgins. Sage*, 23–42.

Swann Jr, W. B., Chang-Schneider, C., & Larsen McClarty, K. (2007). Do people's self-views matter? Self-concept and self-esteem in everyday life. *American psychologist*, *62*(2), 84.

Sydow, L. (2022). *Age and Gender Skew App Preferences. But by how much? It Depends on Region,* Available at: https://www.data.ai/en/insights/market-data/demographics-skew-app-preferences, Accessed: October, 5.

Talaifar, S., & Swann, W. B. (2020). Self-verification theory. *Encyclopedia of personality and individual differences*, 4813-4821.

Thibodeau, R., & Aronson, E. (1992). Taking a closer look: Reasserting the role of the self-concept in dissonance theory. *Personality and Social Psychology Bulletin*, *18*(5), 591-602.

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*, 27(3), 451-481.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management science, 46(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Westaby, J. D. (2005). Behavioral reasoning theory: Identifying new linkages underlying intentions and behavior. *Organizational behavior and human decision processes*, *98*(2), 97-120.

Wylie, L. (2023). *Education App Revenue and Usage Statistics*, Available at: https://www.businessofapps.com/data/education-app-market, Accessed: October, 5.

Zydney, J. M., & Warner, Z. (2016). Mobile apps for science learning: Review of research*. Computers & Education*, 94, 1-17.

Appendix A

PCA Analysis Results

Indicator	ST	CR	EE	RS	IU	PE	ER	AT
ST3	**0.85**	0.12	-0.08	0.18	-0.11	-0.04	0.19	-0.01
ST2	**0.81**	0.10	-0.03	0.20	-0.07	0.00	0.21	-0.02
ST1	**0.81**	0.01	0.03	0.17	-0.05	0.06	0.30	-0.01
ST4	**0.80**	0.09	-0.12	0.15	-0.07	0.04	0.28	-0.08
CR3	0.04	**0.86**	0.04	0.15	0.04	0.02	0.04	-0.09
CR2	0.06	**0.86**	-0.06	0.13	0.00	0.03	0.08	0.00
CR1	0.04	**0.83**	-0.05	0.10	0.02	-0.05	0.07	0.02
CR4	0.16	**0.79**	-0.05	0.11	-0.10	-0.06	0.13	0.02
EE1	-0.02	-0.02	**0.83**	0.02	0.04	0.15	-0.03	0.18
EE3	-0.03	-0.01	**0.80**	-0.10	0.16	0.12	-0.01	0.14
EE4	-0.14	-0.05	**0.79**	-0.10	0.11	0.13	0.01	0.16
EE2	-0.02	-0.06	**0.74**	-0.13	0.22	0.11	-0.10	0.14
RS1	0.12	0.16	-0.13	**0.84**	-0.13	-0.03	0.13	0.03
RS3	0.20	0.13	-0.04	**0.81**	-0.03	-0.01	0.17	0.01
RS2	0.13	0.04	-0.07	**0.78**	-0.06	0.08	0.19	-0.15
RS4	0.22	0.20	-0.04	**0.76**	0.02	-0.07	0.01	-0.01
IU2	-0.07	0.01	0.20	0.01	**0.81**	0.13	0.04	0.09
IU1	-0.09	0.01	0.08	-0.03	**0.76**	0.15	-0.05	0.23
IU3	-0.14	-0.05	0.12	-0.06	**0.75**	0.26	-0.02	0.16
IU4	-0.02	-0.02	0.12	-0.15	**0.69**	0.24	-0.12	0.18
PE2	-0.01	-0.01	0.16	0.00	0.16	**0.81**	0.04	0.18
PE4	0.02	-0.05	0.20	-0.05	0.19	**0.76**	-0.06	0.14
PE3	0.03	-0.05	0.18	-0.03	0.22	**0.67**	-0.06	0.32
PE1	0.02	0.02	-0.01	0.06	0.20	**0.67**	-0.09	0.30
ER2	0.21	0.02	0.01	0.06	-0.02	0.02	**0.85**	-0.07
ER3	0.20	0.19	0.00	0.09	0.04	-0.12	**0.80**	0.08

ER1	0.27	0.05	-0.07	0.23	-0.09	-0.02	**0.74**	0.01
AT3	-0.11	-0.07	0.26	-0.04	0.10	0.11	0.01	**0.75**
AT1	0.01	-0.04	0.01	0.03	0.17	0.28	0.00	**0.70**
AT2	-0.04	0.11	0.16	-0.03	0.14	0.36	-0.05	**0.63**
AT4	0.06	-0.03	0.33	-0.11	0.31	0.17	0.06	**0.56**

Notes: Extraction Method: Principal Component Analysis. Rotation Method: Equamax with Kaiser Normalization.

Appendix B
Measurement Items (English)

All items are measured with a 5-point Likert scale, with (1) for Strongly Disagree, and (5) for Strongly Agree.

Usage Intention (Lankton, 2012; Venkatesh et al., 2012)

UI1: I intend to use OLA for learning English.

UI2: I determined to use OLA in the near future.

UI3: I will try to use OLA whenever I can.

UI4: I plan to use OLA to improve my English language skills

Attitude (Venkatesh et al., 2003)

AT1: Using OLA is a good idea.

AT 2: OLA makes learning English more interesting.

AT 3: Using OLA is fun.

AT 4: Overall, I like using OLA

Effort Expectancy (Venkatesh et al., 2003)

EE1. Learning to use OLA is easy for me.

EE2. My interaction with OLA is clear and understandable.

EE3. I believe it is easy to get the OLA to do what I want it to do.

EE4. I believe that using OLA is easy.

Performance Expectancy (Venkatesh et al., 2003; Premkumar & Bhattacherjee, 2005)

PE 1: I find OLA useful for learning English.

PE 2: Using OLA helps me to learn English more quickly.

PE 3: Using OLA can enhance my English skills.

PE 4: Using OLA can increase my chances of getting better grades.

Resistance to Change 4-dimensional scale (Oreg, 2003)

Routine Seeking

RS1: I generally consider changes to be a negative thing.

RS2: I'll take a routine day over a day full of unexpected events any time.

RS3: I like to do the same old things rather than try new and different ones.

RS4: Whenever my life forms a stable routine, I look for ways to change it.

Emotional Reaction

ER1: If I were to be informed that there's going to be a significant change regarding the way things are done at work or at the university, I would probably feel stressed.

ER2: When I am informed of a change of plans, I tense up a bit.

ER3: When things don't go according to plans, it stresses me out.

Short-Term Thinking

ST1: Changing plans seems like a real hassle to me.

ST2: Often, I feel a bit uncomfortable even about changes that may potentially improve my life.

ST3: When someone pressures me to change something, I tend to resist it even if I think the change may ultimately benefit me

ST4: I sometimes find myself avoiding changes that I know will be good for me.

Cognitive Rigidity

CR1: I often change my mind. *(reverse coded)*

CR2: Once I've come to a conclusion, I'm not likely to change my mind.

CR3: I don't change my mind easily.

CR4: My views are very consistent over time.

Appendix C
Measurement Items (Thai)

ความตั้งใจ

1. ฉันตั้งใจที่จะใช้ Voxy ในเวลาว่างเพื่อการเรียนรู้ภาษาอังกฤษ

2. ฉันมีความตั้งใจที่จะใช้ Voxy ในอนาคต

3. ฉันวางแผนที่จะใช้ Voxy เพื่อปรับปรุงทักษะภาษาอังกฤษของฉัน

4. ฉันจะพยายามใช้ Voxy เมื่อใดก็ตามที่ฉันสามารถทำได้

ทัศนคติ

1. การใช้ Voxy เป็นความคิดที่ดี (Q5)

2. Voxy ทำให้การเรียนภาษาอังกฤษน่าสนใจขึ้น

3. การใช้ Voxy เพื่อเรียนรู้เป็นสิ่งที่สนุก

4. โดยรวมแล้วฉันชอบการใช้ Voxy

ความง่ายในการใช้งาน

1. การเรียนรู้ในการใช้ Voxy ง่ายสำหรับฉัน

2. การโต้ตอบกับ Voxy ของฉันเป็นเรื่องที่ชัดเจนและเข้าใจง่าย

3. ฉันเชื่อว่ามันง่ายที่จะให้ Voxy ทำสิ่งที่ฉันต้องการ

4. ฉันเชื่อว่าการใช้ Voxy เป็นเรื่องง่าย

คาดหวังเรื่องประสิทธิภาพ

1: ฉันพบว่า Voxy เป็นประโยชน์ในการเรียนรู้ภาษาอังกฤษ

2: การใช้ Voxy ช่วยให้ฉันเรียนรู้ภาษาอังกฤษได้เร็วขึ้น

3: การใช้ Voxy จะสามารถพัฒนาทักษะภาษาอังกฤษของฉัน

3: การใช้ Voxy จะเพิ่มโอกาสให้ฉันได้เกรดที่ดีขึ้น

การมีนิสัยค้นหารูปแบบประจำตัว

1. ฉันมักพิจารณาการเปลี่ยนแปลงว่าเป็นสิ่งที่ไม่ดี

2. ฉันจะเลือกวันที่เป็นปกติมากกว่าวันที่เต็มไปด้วยเหตุการณ์ที่ไม่คาดคิดเสมอ

3. ฉันชอบที่จะทำสิ่งเดิมๆ มากกว่าพยายามสิ่งใหม่และสิ่งแตกต่าง

4. เมื่อชีวิตของฉันมีรูปแบบที่มั่นคง ฉันมักจะมองหาทางเปลี่ยนแปลง

ปฏิกิริยาทางอารมณ์

1.ถ้าฉันได้รับข้อมูลว่าจะมีการเปลี่ยนแปลงที่สำคัญเกี่ยวกับวิธีการดำเนินการที่ทำในที่ทำงานหรือมหาวิทยาลัย ฉันอาจจะรู้สึกเครียด

2. เมื่อฉันได้รับข้อมูลเกี่ยวกับการเปลี่ยนแปลงในแผน ฉันจะรู้สึกเกร็งเล็กน้อย

3. เมื่อสิ่งต่างๆ ไม่เป็นไปตามแผน ฉันรู้สึกเครียด

ความคิดในระยะสั้น

1. การเปลี่ยนแปลงแผนดูเหมือนจะเป็นงานยุ่งยากจริงๆ สำหรับฉัน

2. บ่อยครั้งฉันรู้สึกไม่ค่อยสบายใจบ้างเกี่ยวกับการเปลี่ยนแปลง แม้ว่ามันอาจมีความเป็นไปได้ที่การเปลี่ยนแปลงนั้นจะทำให้ชีวิตของฉันดีขึ้น

3. เมื่อมีคนกดดันให้ฉันเปลี่ยนบางสิ่งบางอย่าง ฉันมักจะต้านทาน แม้ว่าฉันจะคิดว่าการเปลี่ยนแปลงอาจเป็นประโยชน์สำหรับฉันในที่สุด

4. บางครั้งฉันพบว่าตัวเองกำลังหลีกเลี่ยงการเปลี่ยนแปลงที่ฉันรู้ว่าจะดีสำหรับฉัน

ความตึงเครียดทางการคิด

1. บ่อยครั้งฉันมีการเปลี่ยนใจ

2. เมื่อฉันตัดสินใจแล้ว ฉันไม่ค่อยที่จะเปลี่ยนใจ

3. ฉันไม่เปลี่ยนใจได้ง่าย

4. ความเชื่อของฉันเหมือนเดิมตลอดเวลา

Biography

Name	Dr. Igor Alexander Ambalov
Education	2019 Doctor of Philosophy (Ph.D.) Information Technology, Assumption University (ABAC), Vincent Mary School of Science and Technology. 2013 Master of Science (MSIT) Information Technology Assumption University (ABAC), Vincent Mary School of Science and Technology. 1983 Bachelor's degree in Economics, Moscow Mining University, Department of Economics and Management.
Academic and engineering skills	1. Quantitative research methods. 2. Software Engineering/Java development: Web and Android applications.
Current job	Full-time lecturer at Rajapruk University.
Research field	1. Information Technology usage behavior; factors that determine users' intention to accept and continue using IT (e.g., Social Technology), such as trust, affordance, and personality traits. Special focus on multidimensionality of constructs. 2. IS success based on DeLone and McLean model of IS success. Special focus on net benefits of IS usage.
Researcher information	ORCID: https://orcid.org/0000-0002-6481-3305 Researcher ID: 0000-0002-6481-3305

Research publications	1. Ambalov I. A. (2018). A meta-analysis of IT continuance: An evaluation of the expectation confirmation model, *Telematics & Informatics, Elsevier.* (Scopus, Q1), Volume 35, Issue 6, September 2018, Pages 1561-1571. https://doi.org/10.1016/j.tele.2018.03.016 2. Ambalov I. A. (2021). Decomposition of perceived usefulness: A theoretical perspective and empirical test, *Technology in Society, Elsevier* (Scopus, Q1), Volume 64, February 2021, 101520. https://doi.org/10.1016/j.techsoc.2020.101520, 3. Ambalov I. A. (2021). An investigation of technology trust and habit in IT use continuance: A study of a social network, *Journal of Systems and Information Technology, Emerald Publishing Limited* (Scopus, Q2), Volume 23 Issue 1, May 2021, Pages 53-81. https://doi.org/10.1108/JSIT-05-2019-0096 4. Ambalov, I. A. (2022). An Examination of the Influences of Habit, Compatibility, and Experience on the Continued Use of Short-Form Video-Sharing Services: *A Case of TikTok. International Journal of e-Collaboration (IJeC)* (Scopus, Q2), Volume 18 Issue 1, Pages 1-19. https://doi.org/ 10.4018/IJeC.304371 5. Ambalov, I. A. (2022). The Roles of Habit and Compatibility in the Continued Use of Short-Form Video Sharing Services: A Study of TikTok. In *Virtual Technologies and E-Collaboration for the Future of Global Business* (Pages 215-237). IGI Global. https://doi.org/10.4018/978-1-6684-5027-7.ch012
Current projects	"Muze Radio: Music & Talk Stations", Google Play Store audio streaming application. Available at: https://play.google.com/store/apps/details?id=com.cyberia.radio.AppRadio
Academic referee work	2020–Current; *The Electronic Journal of Information Systems in Developing Countries*; Wiley. 2018 – 2020; *Cyberpsychology, Behavior, and Social Networking*; Mary Ann Liebert.