A FRAMEWORK FOR DEVELOPING SELF-DIRECTED TECHNOLOGY USE FOR LANGUAGE LEARNING

Chun Lai, The University of Hong Kong

Critical to maximizing the potential of technology for learning is enhancing language learners' self-directed use of technology for learning purposes. This study aimed to enhance our understanding of the determinants of self-directed technology use through the construction of a structural equation modelling (SEM) framework of factors and interactions that determine students' self-directed use of technology for language learning. A survey was conducted among second language learners at one university in Hong Kong to provide the basis for a model that describes how various psychological and sociocultural factors interact to influence language learners' use of technology for learning outside school. Attitudinal factors—such as *language learning motivation, perceived usefulness of technology for learning*, and *perceived compatibility between technology use and learning expectancies*—played a dominant role in shaping technology use. Perceived support from teachers and peers, self-regulation skills, and confidence in the selection and use of technology effectively impacted technology use mainly through strengthening perceived compatibility and usefulness. The findings suggest that attitudinal factors deserve much greater attention than currently given in promoting language learners' self-directed use of technology.

Keywords: Student Use of Technology, Out-of-Class Technology Use, Structural Equation Modelling

APA Citation: Lai, C. (2013). A framework for developing self-directed technology use for language learning. *Language Learning & Technology, 17*(2), 100–122. Retrieved from http://llt.msu.edu/issues/june2013/lai.pdf

Received: July 27, 2012; **Accepted:** November 16, 2012; **Published:** June 1, 2013

INTRODUCTION

In the ecology of learning, technology constitutes an important space (Benson, 2006; Greenhow, Robelia, & Hughes, 2009). Technology is expected both to enhance language instruction inside the classroom and to extend language education beyond the classroom (Chapelle, 2010; Zhao & Lai, 2007). Thus, encouraging and supporting the self-directed use of technology outside language classrooms is essential to maximizing the potential of technology for language learning. Self-directed learning has been defined as the "process in which individuals take the initiative, with or without the help from others, in diagnosing their learning needs, formulating goals, identifying human and material resources, choosing and implementing appropriate learning strategies, and evaluating learning outcomes" (Knowles, 1975, p. 18). So, are language learners engaging in self-directed learning with technologies outside their language classes? More specifically, do language learners engage in self-initiated use of technologies to regulate various cognitive, metacognitive, socio-affective, and behavioral processes and conditions that affect language learning and how? Understanding the nature of language learners' self-directed use of technology outside language classrooms is the first and foremost step towards supporting and enhancing self-directed use of technology for language learning.

Research has found that language learners do incorporate technology into their out-of-class learning repertoire (Inozu, Sahinkarakas, & Yumru, 2010; Murray, 2008). However, the types of technologies they use for language learning are limited and rather conventional (Winke & Goetler, 2008; Zhang, 2010).

More importantly, there are great variations in the frequency and type of technologies used and in the nature of technology use for self-regulated language learning (Lai & Gu, 2011). Because of these uncertainties, an essential question emerges as to which factors influence whether and how university students use technologies for learning outside language classrooms. The answer to this question may help identify possible areas of support that language educators can provide to enhance students' technology use for language learning.

The current literature lists factors that affect students' adoption of technology for learning in general. This includes awareness of the educational potentials of technological resources, perceived alignment between the use of technology and the demands of the study situations, and perceived availability of resources in the environment (Goodyear & Ellis, 2008; Lai, Lei, & Wang, 2012; McLoughlin & Lee, 2010). The literature on students' use of technology for language learning also identifies some domain-specific factors, such as learners' language learning beliefs and motivation, language profiles of the immediate living environments, and requirements of the language study situation (Hyland, 2004; Lai & Gu, 2011; Zhang, 2010). What is missing is a conceptualization of different motivating factors and potential interactions of these factors when predicting language learners' self-directed use of technology for learning. This study aimed to construct a framework to unravel the intricate relationships of predictive factors that impact university students' self-directed use of technology for language learning.

In this study, a theoretical model was constructed to capture the various factors and their relationships that might influence students' technology use for language learning. A survey was administered to university undergraduate language learners to collect information on their self-directed use of technology and related factors. The theoretical model then was evaluated and modified against the research data using structural equation modeling (SEM) so as to unravel how the various factors interact with each other to influence students' technology use.

THEORETICAL FRAMEWORK

To better understand which factors affect students' self-directed use of technology for language learning and how these various factors interact with each other to shape their decisions on technology use, this study referred to the Theory of Planned Behavior (TPB; Ajzen, 1985), a theory acclaimed for explaining individual behavioral intentions. This study used the TPB as a theoretical structure and referred to the literature concerned with the adoption of technology and to self-regulated learning models to identify key constructs and interactions in determining self-directed technology use for language learning. These key theoretical constructs and the hypothesized inter-relationships between these constructs were placed into a preliminary theoretical framework—technically known as a *conceptual model*—to explain students' self-directed use of technology for language learning. This conceptual model was the basis for the Structural Equation Modeling (SEM). As is common in SEM studies, based on the findings from the preliminary conceptual model, a refined model was then suggested and analyzed.

The Theory of Planned Behavior

The TPB posits that human behavioral intentions are predicted by three key constructs: (a) an attitudinal component; (b) a perceived behavior control component; and (c) a social influence component. This theory has been widely used when studying the adoption of technology to explain variations in individual acceptance and use of technology (Davis, 1989; Venkatesh, Morris, Davis, & Davis, 2003). Lai et al. (2012) used the TPB to examine factors that affect undergraduate students' use of technology for learning across different disciplines and found that it is a useful framework to help identify key determinants of students' adoption of technology and the interactions thereof.

While the TPB provides useful constructs to explain an individual's acceptance of technology, the underlying structures of and psychological antecedents to the key constructs are nevertheless context and domain specific (Straub, 2009; Venkatesh, Davis, & Morris, 2007). Thus, I also referred to the domain of self-regulated language learning to further identify factors that are critical to self-directed learning and the relationships thereof. Mercer (2011) points out that self-directed language learning behavior is contingent on “a learner’s sense of agency involving their belief systems, and the control parameters of motivation, affect, metacognitive/self-regulatory skills, as well as actual abilities and the affordances, actual and perceived in specific settings” (p. 9). This conceptualization of self-directed behavior as a product of the interaction between individual psychological factors (such as learner beliefs, dispositions and styles, motivation, knowledge of study tactics and learning strategies, skills) and contextual characteristics (such as the context for learning, resources, time, and influences from teachers) is common to several models of self-regulated behaviors (Weinstein, Woodruff, & Awalt, 2007; Winnie & Hadwin, 1998). I referred to this body of literature to identify additional factors and relationships that may influence language learners’ use of technology.

Below are the key constructs and hypothesized inter-relationships, as suggested by the relevant literature, which may influence language learners’ self-directed technology use. These factors are the ones that have been placed into the SEM model.

Attitudinal Factors

Attitudinal factors are beliefs about the value of and affective feelings towards technology use for performance. Three attitudinal factors were included in the conceptual model as predictors of undergraduate students’ self-regulated use of technology for language learning: *perceived usefulness*, *attitude to technology use*, and *educational compatibility*. *Perceived usefulness* (belief in enhanced performance through the technological behavior) and *attitude to technology use* (affective appraisal of the technological behavior) have been shown to be robust predictors of individuals’ intention to use technology (Lee, Kozar, & Larsen, 2003; Yousafzai, Foxall, & Pallister, 2007). They have also been shown to have a significant impact on students’ intentions to adopt technological resources for learning (Clark, Logan, Lucklin, Mee, & Oliver, 2009; Lai, Lei, & Wang, 2012; Šumak, Polancic, & Hericko, 2010). *Educational compatibility*—the perceived compatibility between the technological behavior and learning preferences and values—is another belief variable that has significant direct and indirect effects on students’ adoption of technology for learning (Chen, 2011; Lai et al., 2012). When interviewing foreign language learners on their selective use of technology for learning outside language classrooms, Lai and Gu (2011) found that perceived usefulness of technology for language learning and perceived compatibility of technology use with one’s language learning beliefs and approaches predicted whether learners would use technology to self-regulate their language learning experience. Barrs (2010) also found that perceived compatibility affected student participation in self-directed language learning in self-access centers. Therefore, the following hypotheses were proposed for this current study:

> Hypothesis 1: *Perceived usefulness* (PU) influences students’ *technology use* directly and indirectly via *attitude to technology use*.
>
> Hypothesis 2: *Attitude to technology use* (ATU) directly influences students’ *technology use*.
>
> Hypothesis 3: *Educational compatibility* (EC) influences students’ *technology use* directly and indirectly via *perceived usefulness* and *attitude to technology use*.

Attitudinal Factor Antecedents

The literature on self-regulated learning suggests a few antecedents of these attitudinal factors. One significant antecedent might be *language learning motivation*. Interest and task value beliefs (i.e., interest in and beliefs about the importance of learning) are precursors to self-initiated efforts to learn (Weinstein, Woodruff, & Awalt, 2007; Winnie & Hadwin, 1998; Zimmerman, 2011) and have been found to affect foreign language learners’ autonomous learning behaviors and their self-regulated use of technology for learning (Ferede, 2010; Hyland, 2004; Lai & Gu, 2011). Therefore, learners’ interest and task value beliefs in learning a language may influence whether learners are willing to exert agency in managing their language learning experience and thus whether they are likely to perceive the use of technology as a worthwhile and value-added after-school endeavor to pursue. Based on the literature above, the following hypothesis was proposed:

> Hypothesis 4: *Language learning motivation* (LLM) influences students' *technology use* directly, and indirectly via *perceived usefulness*, *attitude to technology use*, and *self-regulated learning*.

Two other possible antecedents to the attitudinal factor are *language learning approaches* and *situated interpretation* of the learning context. These two variables may affect perceived educational compatibility between technology use and language learning. Language learners who believe in seeking language use opportunities beyond the classroom have been found to be more likely to take responsibilities for self-directing and self-managing their language learning and use technologies to regulate their language learning experience (Lai & Gu, 2011; Mercer, 2011). Such language learning approaches may also correlate positively with language learning motivation: on the one hand, belief in expanding language use and learning opportunities enhances learners' interest in the language; on the other, interest in learning the language and understanding the culture strengthens the belief in the importance of expanding language learning opportunities outside the classroom. Learners' situated interpretation of the learning context might be another antecedent of educational compatibility. What students set out to do in their studies is a situated interpretation of the study situation (Goodyear & Ellis, 2008), and teacher expectancies, the curriculum, course requirements, and assessment regimes have been found to be correlated with the frequency and nature of students' technology use (Selwyn, 2008). Thus, students' perceptions of the course expectations and approaches to achieving good assessment results may determine whether they perceive the use of technology as compatible with their learning needs and expectancies. The above reasoning led to the following hypotheses:

> Hypothesis 5: *Language learning approaches* (LLA) indirectly influence students' *technology use* via *educational compatibility*; *language learning approaches* positively correlate with *language learning motivation*.

> Hypothesis 6: *Situated interpretation* of technology use (SI) indirectly influences students' *technology use* via *educational compatibility*.

Perceived Behavioral Control

Perceived behavioral control refers to people's perceptions of their ability and the availability of the support necessary to achieve an expected behavior. This study used *computer self-efficacy*, *self-regulation*, and *facilitating conditions* to capture perceived behavioral control (Mercer, 2011; Weinstein et al., 2007).

Computer self-efficacy refers to users' perceptions of their capability to use computers to execute actions to achieve an intended outcome (Compeau & Higgins, 1995). It has been found to have a significant, positive influence on students' intention to use technology (Chang & Tung, 2008; Hsu, Wang, & Chiu, 2009), since efficacy beliefs are the foundation of human agency (Bandura, 2001). Rahimi and Katal (2012) found that English language learners' experience and familiarity with podcasts predicted whether they would use podcasting for English learning on their own. In the context of self-directed use of technology for learning, *computer self-efficacy* refers to confidence in one's ability to select appropriate technological solutions and utilize the chosen technologies effectively to meet learning needs (Ertmer & Ottenbreit-Leftwich, 2010; Lai et al., 2012). Lai and Gu (2011) found in their own interviews with foreign language learners that one major obstacle to self-regulated technology use for language learning was the lack of the knowledge and skills in selecting and using technologies appropriately and effectively for learning. Levy (2009) highlighted the importance of helping learners make informed choices on technology use so as not to be overwhelmed by the diversity of technologies available for learning. Closely related to computer self-efficacy are learners' self-regulation skills. *Self-regulation skills* have been found to be closely related to learner-initiated use of technology for learning in general (Bernacki, Aguilar, & Byrenes, 2011) and for self-initiated use of technology for language learning in particular (Lai & Gu, 2011). Thus, I hypothesize that *self-regulation skills* might not only affect student technology use for learning directly, but also indirectly through *computer self-efficacy*.

Facilitating conditions refer to the perceived availability of support in the environment that encourages and facilitates the adoption of technology. In the educational context, sources of support mainly come from teachers and peers. Research has found that teachers and peers play important roles in shaping students' technology use (Lai et al., 2012; Margaryan & Littlejohn, 2008). Instructors' feedback and guidance on possible technology-enhanced materials for learning have been found to be critical to enhance learners' self-directed use of technology for language learning (Castellano, Mynard, & Rubesch, 2011; Lai & Gu, 2011; Deepwell & Malik, 2008). Resources available in the peer networks that learners were in close contact with were also found to affect language learners' frequency of technology use for learning (Zhang, 2010). *Facilitating conditions* are found to be a robust predictor of technology adoption (Lee et al., 2003; Yousafzai et al., 2007), and they also moderate the influences of *computer self-efficacy* and *perceived usefulness* (Hsu et al., 2009; Lai et al., 2012). This suggests that there might also be a positive correlation between *facilitating conditions* and *situated interpretation*: perceived institutional expectations with respect to using technology for language learning may help attune students to the support available from peers and teachers, and support from peers and teachers may in turn reinforce perceptions of institutional expectations regarding technology use. Therefore, the following hypotheses were proposed:

> Hypothesis 7: *Computer self-efficacy* (CSE) directly influences students' *technology use*.
>
> Hypothesis 8: *Self-regulation* (SR) influences students' *technology use* directly, and indirectly via *computer self-efficacy*.
>
> Hypothesis 9: *Facilitating conditions* (FC) influence students' *technology use* directly, and indirectly via *computer self-efficacy* and *perceived usefulness*, and are positively correlated with *situated interpretation*.

Subjective Norm

Subjective norm refers to one's perception of whether or not significant others think a certain behavior should be performed. Research studies have found that significant others, such as teachers and peers, shape university students' use of technology (Margaryan & Littlejohn, 2008) and affect their decision to use technology and the frequency of their use of technology to support their language learning (Lai & Gu, 2011; Zhang, 2010). *Subjective norm* is hypothesized to have both a direct impact and an indirect impact on technology adoption (Venkatesh & Davis, 2000). Its direct predictive power may not be salient in voluntary settings (Chen, 2011; Venkatesh & Davis, 2000), but its indirect effect via perceived usefulness has been found (a) to stand regardless of whether the setting for the adoption of technology is voluntary or mandatory, and (b) to hold true in educational contexts (van Raaij & Schepers, 2008; Teo, 2010). This suggests that there might be a positive correlation between *subjective norm* and *situated interpretation* since peers and teachers are the major sources of social influence on university students' learning behavior; students' perceptions of peers' and teachers' expectations concerning the use of technology for language learning go hand in hand with their perceptions of the institutional expectations regarding this aspect. Thus, the following hypothesis was proposed:

> Hypothesis 10: *Subjective norm* (SN) indirectly influences students' *technology use* via *perceived usefulness* and is positively correlated with *situated interpretation*.

Thus, using the TPB as a frame of reference, I have synthesized the literature on the adoption of technology and the literature on self-regulated language learning and propose a conceptual model (see Figure 1) that depicts the interactive relationships that predict language learners' self-directed use of technology for learning. This preliminary conceptual model with hypothesized key predictors and inter-relationships was then tested against the research data to examine whether this conceptualized structure was reflected in the research data. Using the results from this preliminary model, a second corrected model was developed and analyzed.

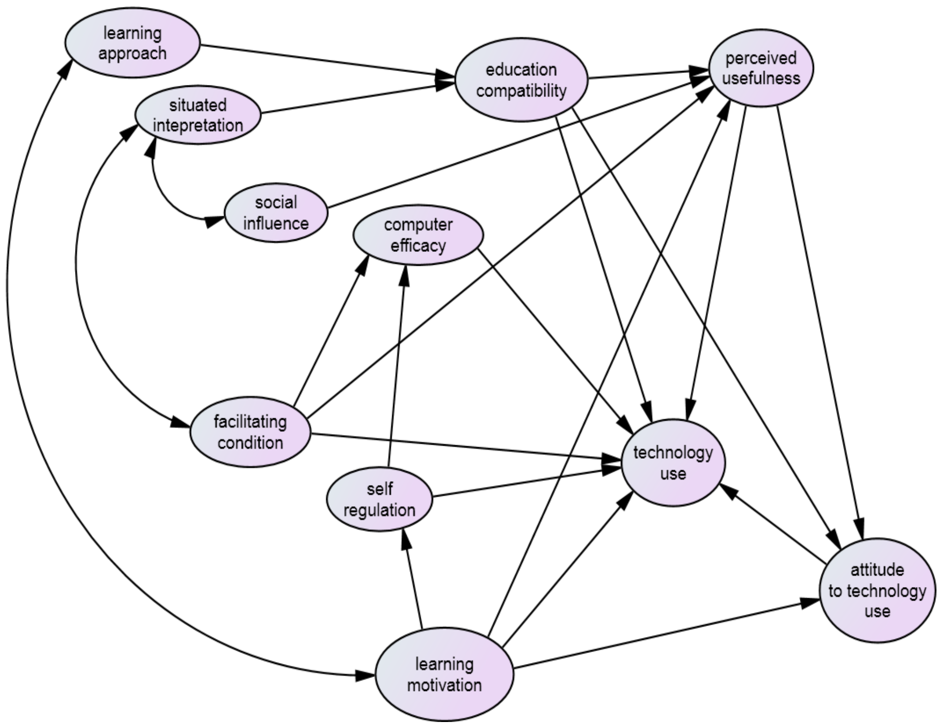

Figure 1. The conceptual model.

RESEARCH METHODOLOGY

Participants

The participants in this study were second language learners recruited from one university in Hong Kong. The study was announced through course coordinators of foreign language departments and through on-campus flyers posted in libraries and in instructional buildings for modern language courses. Participants could either complete an online or paper survey. 373 language learners completed the online survey and six participants filled out the paper survey. After discarding 40 incomplete questionnaires, a data set of 339 usable questionnaires remained, an adequate sample size for structural equation modeling since the general rule of thumb is that number of participants should be no less than 200, or 5–20 times the number of parameters (i.e., variables and hypothesized relationships) to be estimated (Kline, 2005).

Participants ranged from 18 to 31 years of age, with the average age being 21. Most participants were female (75%), and most were in the first two years of their studies (1st year: 41%; 2nd year: 30%; 3rd year and above: 29%). The participants were from diverse disciplinary backgrounds, though around 40% were studying in fields related to language or culture-studies. At the time of the study, the participants were studying a variety of languages, with 24% studying resource-rich languages that are abundant in their immediate environment (Chinese or English), and 76% studying resource-poor languages to which students had limited exposure in the immediate environment (e.g., French, German, Japanese, Korean, Spanish, etc.). A large proportion of the participants (62%) rated themselves at the beginner level, and only a small number (7%) rated themselves at the advanced proficiency level. The participants rated themselves as having relatively high levels of motivation: when asked whether they were highly motivated to understand the language and culture, 68% of the participants partly agreed or agreed, 16% strongly agreed, and only 16% disagreed; when asked whether they spent a lot of spare time learning the language, 62% of the participants partly agreed or agreed, 8% strongly agreed, and 30% disagreed.

Materials

A survey collected data on students' self-reported frequency of the use of technology for language learning outside language class and several predictor variables (See Appendix A for information on each construct and its indicating items). The dependent variable, *technology use*, assessed the frequency of technology use to support various needs in language learning. A 6-point Likert scale was used, with 1 indicating never, 2 indicating less than 1 hour a week, 3 indicating 1–3 hours, 4 indicating 4–7 hours, 5 indicating 7–14 hours, and 6 indicating more than 14 hours. To ensure this construct reflected self-directed use of technology for learning, we included at the beginning of this section an item that measured the frequency of technology use, required by a teacher, to finish language class assignments, and excluded this item when analyzing self-directed technology use. All the independent constructs were rated on a 6-point Likert-type scale, with 1 being strongly disagree and 6 being strongly agree. In addition, some demographic characteristics of the students (gender, age, major, years of language study, proficiency in the language being studied) were collected. The survey items were constructed referring to previous works on language learners' self-regulated use of technology for learning and were adapted from existent instruments in technology adoption literature to fit the specific context of language learning (Lai & Gu, 2011; Lai et al., 2012, Chen, 2011; Teo, 2010; Venkatesh et al., 2003) (Appendix A). The survey items were pilot tested and revised in several iterations with language learners at the university where the study was conducted.

Modeling and Analysis

The survey response data were analyzed using structural equation modeling (SEM) to evaluate and modify the hypothesized theoretical model (i.e., the preliminary conceptual model) so as to capture the complex relationships between various constructs that affect students' self-regulated use of technology for language learning. SEM was used as the analytical approach because it allows the modeling and testing of complex patterns of relationships as a whole. SEM also helps to capture the relationships more accurately through taking into account the measurement errors of observed indictor variables (i.e., the variables that can be directly observed) and controlling for correlations between dimensions of latent constructs (i.e., the variables that cannot be directly observed but assessed indirectly through a number of indicator variables). SEM captures the relationships of indicating items to the measured latent constructs in the measurement model, namely how well the items relate to the specific construct they intend to measure (Appendix A). For example, the dependent variable (*technology use for language learning*, henceforth abbreviated as *technology use*) was measured by five indicating items. SEM also examines the relationships between the latent constructs (the independent and dependent variables) in the structural model, namely how the constructs relate to each other (Figure 2). It allows us to understand the total effect, direct effect, and indirect effect of the 10 independent variables (*language learning approach*, *situated interpretation*, *educational compatibility*, *perceived usefulness*, *subjective norm*, *facilitating conditions*, *computer self-efficacy*, *self-regulation*, *language learning motivation*, and *attitude to technology use*) on the dependent variable (*technology use*). The total effect refers to the magnitude of one variable's influence on another. The total effect of a variable on another can be decomposed into direct effects and indirect effects. Direct effects refer to the part of the influence that is not transmitted by intervening variables. For example, *perceived usefulness*'s effect on *technology use* was hypothesized to consist of two parts: a direct effect (*perceived usefulness* → *technology use*) and an indirect effect mediated by *attitude to technology use* (*perceived usefulness* → *attitude to technology use* → *technology use*).

The model was estimated using Amos 20.0. Maximum Likelihood Estimation was used to fit the models and estimate parameters. The absolute fit indices, the χ^2 statistic, the parsimonious indices, root mean square of approximation (RMSEA), and the incremental fit indices, the comparative fit index (CFI) and Tucker-Lewis index (TLI), were used to assess the model fit. The absolute fit indices measures whether the variables are orthogonal (i.e., independent). Ideally, a non-significant χ^2 value would indicate good fit of the research data to the model; however, because the χ^2 statistic is very sensitive to the effect of sample size, normed χ^2 statistics—adjusted by their degrees of freedom—are used often used to assess model fit. The recommended threshold for χ^2/df is less than 2.0. The parsimonious index, RMSEA, indicates the badness-of-fit of the model (larger values signal worse fit), and these indices favor models with fewer parameters. The cut-off point for RMSEA is .06. The incremental fit indices—the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI)—measure the goodness-of-fit of the model; values close to .95 indicate good-fit (Hu & Bentler, 1999; Tabachnick & Fidell, 2007).

RESULTS AND DISCUSSION

Conceptual Model

Table 1. *Comparison of Conceptual and Final Structural Models (Standardized Regression Coefficients, Two-Way Correlations of the Constructs, and Goodness-Fit Indices)*

	Conceptual Model						Final Model				
IV	DV	Mediator					DV	Mediator			
	TU	AT	PU	SR	CSE	EC	TU	PU	SR	CSE	EC
	β	β	β	β	β	β	β	β	β	β	β
AT	-.06										
PU	.15*	.01					.26**				
CSE	-.10										.42***
FC	.02		.19**		.20***			.35***	.37***	.15*	
EC	.11	.89***	.18**					.17**			
SN			.11^								.16**
SR	.07				.49***					.47***	
LLM	.43***	.05	.40***	.70***			.40***	.26***	.64***		
LLA						.23***					.15*
SI						.47***					.26***
Two-Way Correlation		SN		SI		EP	SN		SI		EP
FC				.13***			.58***		.35***		
SN				.47***					.48***		
LLM						.35***					.31***
Model fit index											
χ^2 (N, df)				χ^2 (339, 644) = 1463.97					χ^2 (339, 544) = 1122.86		
χ^2/df				2.27					1.87		
CFI				.89					.93		
TLI				.88					.92		
RMSEA [95% CI]				.061 [.057, .065]					.051 [.046, .055]		

Note. *** = p < .001; ** = p <.01; * = p < .05. CFI = comparative fit index; TLI =Tucker–Lewis index; RMSEA = root-mean-square error of approximation; CI =confidence interval. N = 339.

The conceptual model had poor model fit indices (χ^2/df = 2.27, CFI = .89, TLI = .88, RMSEA = .06) and high correlation between *educational compatibility* and *attitude to technology use* (r = .82, p < .001). This resulted in a negative regression coefficient of *attitude on technology use* (β = -.07, p = .71), and thehypothesized mediating effects of *attitude on technology use* were not working properly either (see Table 1). Therefore, we removed *attitude to technology use* from the model and its associated direct and indirect effects, a typical solution for problems with multicollinearity (Tabachnick & Fidell, 2007).

Final Model

The final model had a χ^2/df value was 1.87 and a RMSEA value of .05, suggesting a good fit of the model for the data. The CFI value was .93 and the TLI value was .92, which were close to .95. All indicators significantly loaded on their specified latent construct, and the means were all above the neutral point of the Likert scale (3.5) (Appendix A). The results of the analysis of the final structural model are listed in Table 1 and illustrated in Figure 2.

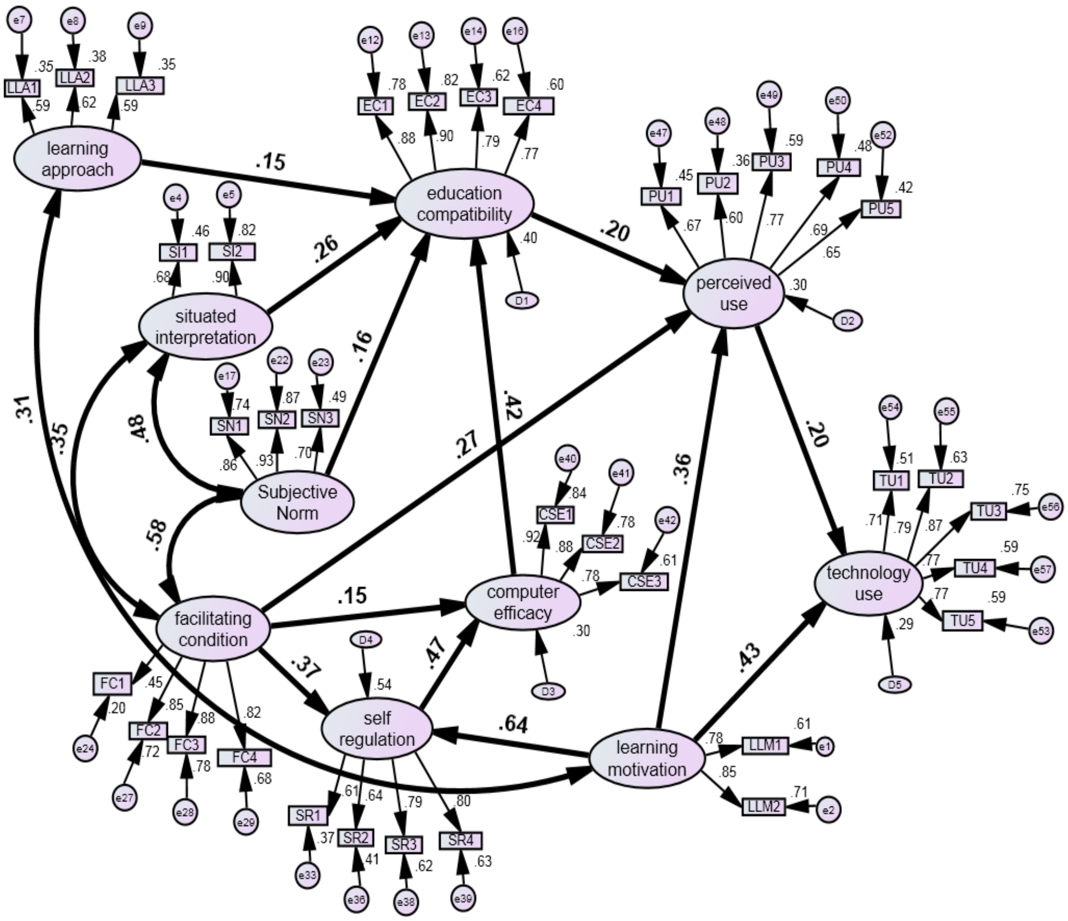

Figure 2. The structural model. All the effects and relationships were significant at p < .05.

Determinants of the Five Endogenous Variables

As hypothesized, *perceived usefulness* and *language learning motivation* directly and significantly predicted language learners' self-directed use of technology for language learning, resulting in an R^2 of .29. The other hypothesized independent variables affected technology use indirectly through intricate interactions with these two direct determinants and between themselves. The final model also illustrated the determinants of four additional endogenous variables: *perceived usefulness*, *educational compatibility*, *computer self-efficacy*, and *self-regulation*. These four endogenous variables were explained by their determinants in the amounts of 30%, 40%, 30%, and 54%, which is to say that the determinants could account for 30%, 40%, 30%, and 54% of the variations within *perceived usefulness*, *educational compatibility*, *computer self-efficacy*, and *self-regulation*.

Technology Use: The Direct Product of Personal Will and Buy-in and the Indirect Product of Social Support

Within this model, *language learning motivation* and *perceived usefulness* were the two dominant predictors of *technology use*. *Language learning motivation*, operationalized as *interest* and *task value beliefs*, was found to be a major attitudinal construct that drives self-initiated technology use for language learning with a total effect size of .50 ($p < .001$). It not only influenced technology use directly ($\beta = .43$, $p < .001$), but also exerted an indirect effect of .07 ($p < .01$) via perceived usefulness and self-regulation. This finding confirms the importance of students' motivational beliefs, including task value beliefs, as the imperative precursor of self-regulated behavior (Weinstein et al., 2007; Winnie & Hadwin, 1998; Zimmerman, 2011). The more motivated students are towards learning the target language, the more likely they will exert their agency in using technology to support their learning experience outside their language classes (Lai & Gu, 2011; Mercer, 2011).

Table 2. *Standardized Direct-, Indirect-, and Total-Effects of the Research Model*

Outcome	Determinant	Mediator	Standardized Estimates		
			Direct Effect	Indirect Effect	Total Effect
Technology Use ($R^2 = .29$)	Language Learning Motivation (LLM)		.43 (.07)***		.50***
		Perceived Usefulness (PU)		.07 (.03)**	
		Self-Regulation (SR)		.01 (.00)**	
	Perceived Usefulness (PU)		.20 (.09)**		.20**
	Educational Compatibility (EC)	Perceived Usefulness (PU)		.04 (.02)**	.04**
	Computer Self-Efficacy (CSE)	Educational Compatibility (EC)		.02 (.01)**	.02**
	Self-Regulation (SR)	Computer Self-Efficacy (CSE)		.01 (.01)**	.01**
	Facilitating conditions (FC)	Perceived Usefulness (PU)		.09 (.04)**	.10**
		Self-Regulation (SR)		.01 (.00)**	
		Computer Self-Efficacy (CSE)		.004 (.00)**	
	Language Learning Approaches (LLA)	Educational Compatibility (EC)		.01 (.01)*	.01*
	Situated Interpretation (SI)	Educational Compatibility (EC)		.01 (.01)**	.01**
	Subjective Norm (SN)	Educational Compatibility (EC)		.01 (.00)**	.01**

Note: ***$p < .001$; **$p < .01$; *$p < .05$. The first number reports the effect size; the number in the parentheses is the standard error.

Consistent with previous literature, *perceived usefulness* was found to be a significant predictor of students' *technology acceptance for language learning*, with a significant direct effect of .20 ($p < .01$) (Clark et al., 2009; Lee et al., 2003; Šumak et al., 2010). *Perceived usefulness*, an important attitudinal construct, also functioned as the only venue through which the other predictors exerted their influences on *technology use*. When facing various potential resources and venues that they can potentially utilize to construct their personalized language learning ecologies, language learners' buy-in of the usefulness of technologies for various learning purposes is particularly crucial in influencing their decisions on whether or not to use technologies to support language learning (Lai & Gu, 2011).

The other seven independent variables, with the exception of *facilitating conditions*, all had significant yet minimal indirect effects on *technology use* mainly through perceived usefulness or educational compatibility (see Table 2). *Facilitating conditions* had a small significant indirect effect on *technology use* through *perceived usefulness*, *self-regulation*, and *computer self-efficacy* ($\beta = .10$, $p < .01$). Thus, these findings are in line with previous studies showing that technological resources shared by teachers and peers and the tips and technical support from peers help students to realize the potentials of technology for language learning, encourage them to take up control in learning, and boost their confidence in their ability to capitalize on the potentials. This increased confidence ultimately increases the frequency of their use of technology to support language learning (Hartshorne & Ajjan, 2009; Lai et al., 2012).

Thus, *technology use* appears to be reliant upon students' interest and task value beliefs in learning the language, their perceptions of the usefulness of such an activity for language learning, and the perceived availability of support, both pedagogical and technical, from their language instructors and peers. Since *perceived usefulness* is a strong direct predictor and the major mediator for *technology use*, and is an attitudinal component that is subjective to intervention (Venkatesh et al., 2007), it is crucial to understand its antecedents.

Table 3. *Determinants of Perceived Usefulness*

Outcome	Determinant	Mediator	Standardized Estimates		
			Direct	Indirect	Total
Perceived Usefulness ($R^2 = .30$)	Educational Compatibility (EC)		.20 (.05)**		.20**
	Computer Self Efficacy (CSE)	Educational Compatibility		.06 (.02)**	.06**
	Self-Regulation (SR)	Computer Self-Efficacy (CSE)		.04 (.01)**	.04**
	Facilitating conditions (FC)		.27 (.09)***		.30***
		Self-Regulation (SR)		.02 (.01)**	
		Computer Self-Efficacy (CSE)		.02 (.01)**	
	Language Learning Approaches (LLA)	Educational Compatibility (EC)		.04 (.02)*	.04*
	Situated Interpretation (SI)	Educational Compatibility (EC)		.05 (.02)**	.05**
	Subjective Norm (SN)	Educational Compatibility (EC)		.02 (.01)**	.02**
	Language Learning Motivation (LLM)		.37 (.05)***		.39***
		Self-Regulation (SR)		.02 (.01)*	

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$. The main number reports the effect size; the number in the parentheses is the standard error.

Perceived Usefulness: The Combined Effect of Personal Will, Social Support, and Perceived Fit

Three factors influenced *perceived usefulness*: *language learning motivation* ($\beta = .39$, $p < .001$), *facilitating conditions* ($\beta = 0.29$, $p < .001$), and *educational compatibility* ($\beta = .20$, $p < .01$). These three determinants accounted for 30% of the variance in *perceived usefulness* (see Table 3). The stronger the interest and task value beliefs students have for learning a particular language, the greater the teacher and peer support for technology-enhanced language learning, and the closer the connection the students feel between technology use and their language learning expectations, the more likely they will perceive the usefulness of technology use for language learning (Lai et al., 2012; Pynoo et al., 2011). In particular, educational compatibility served not only as a significant direct predictor of but also as the major mediator of other variables' effects on perceived usefulness.

Educational Compatibility: The Interactive Outcome of Personal Psychological Traits and Contextual Expectations

Educational compatibility was found to be determined by a combination of psychological and contextual factors. The influential personal psychological traits included *computer self-efficacy* (direct effect: $\beta = .42$, $p < .001$), *self-regulation* (indirect effect: $\beta = .23$, $p < .01$), *epistemological belief* (direct effect: $\beta = .15$, $p < .05$) and *language learning motivation*. The affecting contextual expectations included *situated interpretation (*direct effect: $\beta = .26$, $p < .001$), *facilitation conditions* (indirect effect: $\beta = .23$, $p < .001$), and *subjective norm* (direct effect: $\beta = .16$, $p < .01$). These variables explained 40% of the variance in educational compatibility (see Table 4). The psychological variables had a greater impact on educational compatibility than contextual factors. For students to perceive the compatibility of technology use with their language learning expectations, they need to (a) believe in autonomous out-of-class language use and in constructing learning experience themselves (Tsai & Chuang, 2005), (b) have faith in their abilities to do so and to capitalize on the potentials of technologies (Chow, Herold, Choo, & Chan, 2012), and at the same time (c) perceive the expectations concerning and the supports available for technology use from their educational contexts (Goodyear & Ellis, 2008).

Table 4. *Determinants of Educational Compatibility*

Outcome	Determinant	Mediator	Standardized Estimates		
			Direct	Indirect	Total
Educational Compatibility ($R^2 = .40$)	Computer Self-Efficacy (CSE)		.42 (.05)***		.42***
	Self-Regulation (SR)	Computer Self-Efficacy		.24 (.05)**	.24**
	Facilitating conditions (FC)	Self-Regulation		.12 (.03)**	.23**
		Computer Self Efficacy		.10 (.05)**	
	Language Learning Approaches (LLA)		.15 (.09)*		.15*
	Situated Interpretation (SI)		.26 (.07)***		.26***
	Subjective Norm (SN)		.16 (.05)**		.16**
	Language Learning Motivation (LLM)	Self-Regulation		.11(.02)**	.11**

Note: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$. The main number reports the effect size; the number in the parentheses is the standard error.

Computer Self-Efficacy: The Product of Social Support and Individual Skill

Computer self-efficacy was found to be largely determined by *self-regulation* ($\beta = .47$, $p < .001$), and the effect was completely direct. As is shown in Table 5, *facilitating conditions* also exerted a direct effect on *computer self-efficacy* ($\beta = .15$, $p < .05$) as well as an indirect effect via *self-regulation* ($\beta = .30$, $p < .05$). *Language learning motivation*'s effect was mediated through *self-regulation* ($\beta = .28$, $p < .01$). These three variables accounted for 30% of the variance in computer self-efficacy. This is in line with research showing that the greater the skills learners have in managing their learning process and the more support they have to facilitate their effective use of technology, the greater confidence they have in their ability to use technology effectively for learning (Lai et al., 2012; Moos & Azevedo, 2009).

Table 5. *Determinants of Computer Self-Efficacy*

Outcome	Determinant	Mediator	Standardized Estimates		
			Direct	Indirect	Total
Computer Self-Efficacy (R^2 = .30)	Facilitating conditions (FC)		.15 (.10)*		.45*
		Self-Regulation (SR)		.30 (.07)*	
	Language Learning Motivation (LLM)	Self-Regulation (SR)		.28 (.05)**	.28**
	Self-Regulation (SR)		.47 (.09)***		.47***

Note: $^{***}p$ < .001; $^{**}p$ < .01; $^{*}p$ < .05. The first number reports the effect size; the number in the parentheses is the standard error.

Self-Regulation: The Influence of Personal Will and Social Support

Facilitating conditions and *language learning motivation* significantly and directly affected *self-regulation. Language learning motivation* had a large effect size on *self-regulation* (β = .64, p < .001), and *facilitating conditions* also showed a moderate effect (β = .37, p < .001). These two factors accounted for 54% of the variance in *self-regulation* (See Table 6). These findings indicate that self-regulated language learning is influenced both by individual, cognitive variables and by social factors: strong interest and task-value beliefs in learning the language drive learners to exert agency over themselves to control their language learning experience (Artino & Stephens, 2009); and ideas and support from teachers and peers in using technology to support learning also orient learners to play a more active role in their learning process (Hadwin, Oshige, Gress, & Winne, 2009).

Table 6. *Determinants of Self-Regulation*

Outcome	Determinant	Mediator	Standardized Estimates		
			Direct	Indirect	Total
Self-regulation (R^2 = .54)	Facilitating conditions (FC)		.37 (.09)***		.37***
	Language Learning Motivation (LLM)		.64 (.05)***		.64***

Note: $^{***}p$ < .001; $^{**}p$ < .01; $^{*}p$ < .05. The first number reports the effect size; the number in the parentheses is the standard error.

All in all, findings from this study revealed that *language learning motivation*, *perceived usefulness*, and *facilitating conditions* were the major predictive factors for language learners' *self-regulated use of technology for learning*. *Perceived usefulness* and *educational compatibility* were the two major factors that mediated most of the relationships that affected *technology use*. *Language learning motivation* and *facilitating conditions* had the most influence on the majority of the psychological and sociocultural factors that affected *technology use* through either serving as precursors of or holding interactive relationships with them.

Interactions of Attitudinal, Perceived Control, and Social Influence Components in the Model

Ajzen's (1985) Theory of Planned Behavior identified three major determinant components that influence individuals' behavior decision making: an attitudinal component, a perceived control of behavior component, and a social influence component. In this study, the three constructs of the attitudinal component appeared to play major roles in technology use: *language learning motivation* functioned as the dominant predictor, and *perceived usefulness* and *educational compatibility* served as two levels of mediating venues through which the rest of the factors exerted an influence on *technology use*. This finding suggests that in the context of self-directed technology use for language learning, the attitudinal component is most critical in shaping learners' digital choices.

More importantly, the attitudinal component mediated the effects of the other two components on the adoption of technology. The perceived control of behavior component, consisting of *facilitating conditions*, *computer self-efficacy*, and *self-regulation*, exerted its influence on *technology use* through the attitudinal component: *facilitating conditions* exerted its influence through *perceived usefulness* and *computer self-efficacy* via *educational compatibility*. The social influence component interacted with the attitudinal component through the direct effect of *subjective norm* on *educational compatibility*: the positive opinions and expectations of significant others helped language learners become more attuned to the compatibility of technology use with language learning and consequently raised their awareness of its potentials for language learning. The social influence component also interacted with the perceived control of behavior component through a significant positive correlation between *subjective norm* and *facilitating conditions*: on the one hand, the more teachers and peers expected and encouraged students to use technology, the more likely they were to share resources and strategies to help students make effective use of technology for language learning; on the other, the resources and strategies from teachers and peers reinforced students' perceptions of their positive opinions of technology use.

Discrepancies between the Conceptual Model and the Structural Model

Table 7 shows the results of the hypothesis tests and the discrepancies between the conceptual model and the final model. Overall, the ten selected variables were mostly found to affect language learners' self-directed use of technology for language learning as hypothesized except *attitude to technology use.*

Table 7. *Hypothesis Testing and Discrepancies between Conceptual Model and Final Model*

Hypotheses	Direct Paths	Result	Indirect Paths	Result
H1 (effect of *perceived usefulness*, PU)	PU → TU	√		
H2 (effect of *attitude to technology use,* ATU)	ATU → TU	⊗		
H3 (effects of *educational compatibility*, EC)	EC → TU	⊗	EC → PU	√
			EC → ATU	⊗
H4 (effects of *language learning motivation*, LLM)	LLM → TU	√	LLM → PU	√
			LLM → SR	√
			LLM → ATU	⊗
H5 (effect of *language learning approach,* LLA)			LLA → EC	√
			LLA * LLM	√
H6 (effect of *situated interpretation*, SI)			SI → EC	√
H7 (effect of *computer self-efficacy,* CSE)	CSE → TU	⊗		
H8 (effects of *self-regulation,* SR)	SR → TU	⊗	SR → CSE	√
H9 (effects of *facilitating conditions*, FC)	FC → TU	⊗	FC → PU	√
			FC → CSE	√
			FC * SI	√
H10 (indirect effect of *subjective norm*, SN)			SN → PU	⊗
			SN * SI	√
Added Path & Relationships				
SN → EC	FC → SR	CSE → EC	SN * FC	

Note. √ indicates that the result was supported; ⊗ indicates that the result was not supported.

Attitude to technology use was found to be highly correlated with *educational compatibility* and interacted abnormally with other variables due to this high correlation, and was thus subsequently dropped from analysis. The hypothesized effects and relationships of *perceived usefulness*, *language learning motivation*, and *facilitating conditions* were largely supported. The hypotheses of *language learning approaches* and *situated interpretation* serving as antecedents of *educational compatibility* were also supported. However, the hypothesized effects of *attitude to technology use*, *computer self-efficacy*, *subjective norm* and *educational compatibility* on self-directed *technology use* were largely unsupported. Instead, they impacted *technology use* mainly through *educational compatibility*. Thus, the major discrepancies between the conceptual model and the structure model were that *attitude to technology use* did not play the hypothesized significant role, but rather *educational compatibility* replaced it as a more determinant player. *Attitude to technology use*, namely, whether students perceived technology use making learning fun and as something to look forward to, failed to exert the hypothesized effect on Hong Kong undergraduate students' self-directed use technology for learning. A plausible explanation is that people's appraisal of the importance and relevance of an attitude object affects its potential impact on behavior (Ajzen & Fishbein, 2005). Hong Kong students tend to regard learning as a serious undertaking (Rao, 1996) and valued diligence and perseverance in English learning (Shi, 2006). Thus, whether technology use fits their learning expectancies might have mattered more than whether it makes learning fun in shaping their decisions on technology use for learning. Thus, this study joins a few emerging studies to advocate giving greater attention to the importance of the perceived fit between technology use and learning preferences and values in shaping students' technology adoption behavior (Chen, 2011; Slyke, Dick, Case, & Ilie, 2010).

The final model highlighted the effects of *perceived usefulness*, *language learning motivation*, and *educational compatibility* and suggested that the attitudinal factors play the dominant role in shaping self-directed use of technology for language learning. The attitudinal component, although repeatedly shown to be significant, has often been found to work parallel with the perceived control component and social influence component to influence technology adoption. However, in this study we found it played a dominant role and mediated the effects of *perceived control* and *social influence*. This finding makes sense in the context of self-directed technology use for language learning: most of the technology-enhanced language learning opportunities exist in the common information communication technological platforms and venues that learners frequently use in their daily life, and thus the roles of perceived control and social influences might be relatively less critical to technology adoption in this context than other subject matters. The findings suggest that in cases where technological resources for learning are abundant and are incorporated into daily life, what matters more might be the attitudinal factors that drive learners' willingness to actively incorporate these technological resources into their language learning ecology.

IMPLICATIONS ON EDUCATIONAL INTERVENTION FRAMEWORK

This study set out to understand factors that determine language learners' self-directed use of technology for learning. The findings concurred with current literature that educational interventions that aim to enhance self-directed use of technology for language learning should adopt multi-faceted models that focus on fostering both learners' willingness and relevant skills (Holec, 2009; Weinstein et al., 2011). More importantly, this study found that among the various components that affect technology use, attitudinal factors—the driving forces behind learners' willingness to use technology—played the most critical role, and factors in *perceived control* and *social influence* impacted technology adoption mainly through influencing these attitudinal factors. This finding suggests that developing a willingness to use technology should be at the core of educational interventions. This warrants attention given that most of the current literature on enhancing language learners' use of technology has highlighted the importance of enhancing relevant skills for technology-enhanced language learning, namely learners' technological, pedagogical, and content knowledge and skills (Hubbard, 2004; Levy, 2009). As an example, consider the newly released TESOL Technology Standards (Healey et al., 2011). These standards focus heavily on developing students' digital competencies in selecting appropriately technologies and using them in socioculturally and pedagogically appropriate manners. In contrast, learners' attitudinal factors, the most significant determinants of self-directed technology use for language learning, are not given enough attention. Thus, to enhance students' active use of technology outside classrooms for language learning, enhancing learners' willingness for technology use needs to be stressed more consistently.

This study further identified the underlying structures of and psychological antecedents to the key components, and suggested specific aspects that educators can work on to enhance self-directed use of technology for language learning.

First of all, this study identified that *language learning motivation*, *perceived usefulness*, and *educational compatibility* are three major attitudinal factors that drive language learners' willingness to use technology, and thus educational interventions need to work on strengthening these attitudinal factors so as to enhance learners' willingness. It also revealed that self-regulation and efficacy in mapping appropriate technologies with learning purposes and using them in effective manners form the essential skills that language learners need in order to engage in self-regulated technology use, and should be the major targets of the skill enhancement component in educational interventions.

Second, the study identified that *perceived usefulness* and *educational compatibility* were shaped by a variety of psychological and sociocultural factors, including (a) students' constructive views of language learning that value experiential learning and out-of-class language use opportunities; (b) students' perceived expectations and support from language course instructors and peers in using technology for learning; and (c) students' abilities to regulate their language learning experience and their confidence in selecting and using technologies effectively for language learning. Thus, to foster these two sets of positive attitudinal beliefs, language instructors and peers have an important role to play. First of all, language instructors need to help students adopt a more experiential and autonomous view of language learning, which could be achieved explicitly through class discussions and explicit strategy training (Macaro, 2006) and implicitly through utilizing more constructivist-oriented language pedagogies, such as task-based language teaching (Lai & Lin, 2012) since learner beliefs are dynamic, socially constructed, and subject to the influence of the instructional context and the instructors' teaching styles (Christison, 2003; Haerle & Bendixen, 2008). Second, language instructors may need to convey explicitly their expectations concerning the use of technology to support language learning. These expectations could be expressed through teachers actively using technologies themselves in language teaching, involving some technology-enhanced language learning activities such as formative or summative assessment components, or through teachers introducing technology-enhanced language learning resources or materials during class instruction or as learning assignments. Third, measures need to be taken to develop students' confidence in using technologies effectively for language learning since such confidence reinforces positive attitudinal beliefs and drives action. Language instructors may develop learners' confidence through helping them to gain successful experience of using technologies for language learning both in and outside class and through forming a positive social environment in the classroom that strengthens students' perceptions of the availability of social support for technology use (Clark et al., 2009; Lai et al., 2012; Moos & Azevedo, 2009).

Third, the study found that self-regulation seems to determine computer self-efficacy, which suggests that developing self-regulation should form the basis of boosting efficacy in selecting and using technologies effectively for language learning. Educational interventions need to increase learners' knowledge and skills of using technologies effectively for various language learning purposes and develop their self-regulation skills simultaneously. Hubbard's (2004) cyclical approach that engages language learners in pedagogical training, personal experimentation with technological applications and collaborative debriefing, and self-reflection is one such good model that incorporate both components to enhance learners' skills in technology use. But at the same time, we need also to attend to the impacts of facilitating conditions on skill development. Thus, in addition to directly training students on relevant skills, we need also to make sure instructional moves are in place that expand and strengthen resources and strategies that learners can access. For instance, language instructors may construct learning activities that engage students in discussing their experience of technology use so as to orient each other towards the potential of technology for language learning or form peer support networks to facilitate and encourage classmates to share resources, tips, and technical support with each other (Lai et al., 2012; McLoughlin & Lee, 2010).

CONCLUSIONS

This study set out to identify key predictors of self-directed use of technology for language learning and their determinants in order to identify potential interventions to boost language learners' self-regulated use of technology. It identified attitudinal factors as the most critical and suggests that they should be the focus of interventions. Through revealing the predictive relationships of various factors, the study further suggests areas and directions for intervention. Future studies may empirically test whether or not and how the manipulation of different variables affect language learners' self-regulated use of technology for learning and explore various intervention models to foster such behaviors.

This study has several limitations. First, the study was based on student self-reported data in one questionnaire, which made it susceptible to common method variance. However, since the study targeted students' opinions on impersonal objects—technology—rather than socially sensitive topics, the elicited data were more likely to represent true opinions and to be less subject to the threat of common method variance (Malhotra, Kim, & Patil, 2006). Second, this study measured a small cohort of learners at a university in Hong Kong and thus, the applicability of its findings may be limited. It would be interesting to examine the predictive relationships in other cultures where students differ in their use of technologies and approaches to learning (Gray, Chang, & Kennedy, 2010). Furthermore, the particular characteristics of the participants in this study might have biased some research findings and cautions need to be taken in interpreting the findings. For one thing, since the majority of the participants self-selected to take the online version of the survey, it is quite likely that the data stood for a cohort of learners who were relatively more comfortable with technology. This potential participant bias might have caused the non-significant direct effect of computer self-efficacy on self-directed technology use. For another, the participants were of relatively high motivation and their learning motivation profiles might have caused the high impact of perceived usefulness and low impact of computer self-efficacy (Huang, Huang, Huang, & Lin, 2012). Third, the research model explained 29% of the variance in language learners' frequency of technology use for learning, and a large portion of the variation remains uncaptured in the current model. Future research should explore potential variables that are not included in the current model, such as affective factors (e.g., students' enjoyment of various technology-enhanced activities; Straub, 2009), and examine various contingency variables that moderate the effects of key constructs on technology adoption, such as gender, espoused cultural values and so on (Venkatesh et al., 2007). Future research could also use more fine-grained measures of some variables to test the effects of these variables, such as assessing the strength of the learners' immediate social network to measure facilitating conditions (Zhang, 2010), or including other dimensions of motivation that are critical to self-regulated behaviors (e.g., goal orientations, learning efficacy, motivational engagement; Artino & Stephens, 2009; Zimmerman, 2011). Finally, using a quantitative lens this study added to our understanding of language learners' self-directed use of technology for learning through constructing a framework that teases apart factors and their interactions in shaping self-directed technology use. However, to understand the nuances of this phenomenon, qualitative studies are very much needed to provide further insights into the nature of the self-directed technology use for language learning and how these and various other factors motivate or inhibit learners' selective use of various technologies for learning.

APPENDIX A. Measurement Model (n = 339)

Latent Construct	Mean	*SD*	Unstandardized Loading	Standardized Loading	*SE*
Technology Use for Language Learning (TU) (α = .89) (adapted from Lai & Gu, 2011)					
Use technology to learn more about the language and culture	2.88	1.11	1.00	$.77^{***}$	.07
Use technology to persist in achieving language learning goals	2.71	1.02	.86	$.71^{***}$	.07
Use technology to expand opportunities to use the language	2.81	1.13	1.05	$.79^{***}$	.07
Use technology to sustain/enhance motivation and interest	2.97	1.15	1.17	$.87^{***}$	.07
Use technology to seek engaging learning activity or experience	2.74	1.13	1.02	$.77^{***}$	.07
Perceived Usefulness (PU) (α = .82) (adapted from Lai & Gu, 2011)					
Useful for improving learning experience and environment	4.40	.97	1.00	$.67^{***}$	.11
Useful for monitor learning progress	3.76	.98	.90	$.60^{***}$	.10
Useful for enhancing motivation and interest	4.50	1.02	1.20	$.77^{***}$	.11
Useful for expanding venues of emotional and learning support	4.21	1.09	1.16	$.69^{***}$	.11
Useful for expanding language use opportunities	4.47	1.07	1.06	$.65^{***}$	.11
Educational Compatibility (EC) (α = .91) (adapted from Chen, 2011)					
Compatible with beliefs about language learning	4.18	.88	1.00	$.88^{***}$	.05
Compatible with goals for language learning	4.11	.86	1.00	$.90^{***}$	.04
Compatible with current learning situation	4.21	.87	.89	$.79^{***}$	.05
Fit into learning style	4.16	.97	.97	$.77^{***}$	.06
Computer Self-Efficacy (CSE) (α = .90) (adapted from Lai et al., 2012)					
Confident with abilities in using technologies effectively for language learning	4.12	.92	1.00	$.92^{***}$	.04
Confident with abilities in selecting appropriate technologies for learning needs	4.02	.93	.97	$.88^{***}$	.04
Confident with abilities in using technologies to create enjoyable learning experience	4.18	.90	.84	$.78^{***}$	.05
Facilitating Conditions (FC) (α = .82) (adapted from Lai et al., 2012)					
Often get ideas from teachers on potential technologies to use	3.80	1.09	1.00	$.45^{***}$	.23
Have friends/classmates who share strategies of using technologies effectively for learning	3.77	1.02	1.76	$.85^{***}$	.21
Have friends/classmates from whom to seek advice on technology use for learning	3.71	1.02	1.83	$.88^{***}$	.22
Have friends/classmates from whom to seek technical help	3.69	1.00	1.68	$.82^{***}$	.20
Subjective Norm (SI) (α = .86) (adapted from Venktesh et al., 2003)					
People who influence learning behaviors think I should use technologies to support language learning	3.75	1.04	1.00	$.86^{***}$	.05
People important to me think I should use technologies to support language learning	3.63	1.02	1.07	$.94^{***}$	.05

Members in learning community support the use of technologies for language learning	4.03	.97	.76	.70***	.05
Language Learning Motivation (LLM) (α = .80) (based on Zimmerman, 2011)					
Highly motivated to grasp the language and understand the target culture	4.45	1.06	1.00	.85***	.08
Invest a lot of spare time in learning the language	4.05	1.08	.94	.78***	.07
Language Learning Approaches (LLA) (α = .63) (adapted from Lai & Gu, 2011)					
Learning well depends on learning and using the language outside the class	5.03	.83	1.00	.59***	.17
Study time best spent in seeking opportunities to use the language in real life	4.93	.80	1.00	.62***	.16
Time spent on learning and using the language outside the class is crucial to ultimate achievement	4.75	.88	1.05	.59***	.17
Situated Interpretation of the Context (SIC) (α = .76) (based on Goodyear & Ellis, 2008)					
Using technologies is part of the language course requirement	3.88	1.05	1.00	.68***	.15
Are expected to use technologies to enhance language learning at this university	3.94	1.05	1.33	.91***	.16
Self-Regulation Skill (SRS) (α = .81) (adapted from Lai & Gu, 2011)					
Constantly monitor learning progress	3.76	1.06	1.00	.61***	.10
Have ways to make learning the language more attractive	4.02	.93	.92	.64***	.10
When learning environment becomes less favorable, try to sort out and address the problem	4.12	.87	1.05	.79***	.10
Know how to arrange time and environment to make learning more efficient and effective	3.99	.97	1.17	.80***	.11

Note. Attitude to technology use was dropped from the measurement model. Attitude to technology use was conceptualized by three items on interest and enjoyment in using technology to support language learning (adapted from Teo, 2010), such as “I enjoy learning language with technologies” or “I look forward to the language learning experience that involves the use of technology.” This construct had an alpha value of .89.

ACKNOWLEDGEMENTS

This article is based on a project (GRF7461/10H) funded by the Research Grants Council of the Government of the Hong Kong SAR. Thanks are expressed to the participating students and the anonymous reviewers of the journal *Language Learning & Technology*.

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