Understanding adoption of artificial intelligence-enabled language e-learning system: an empirical study of UTAUT model

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Abstract: The use of artificial intelligence is becoming a reality in the educational field. The development of AI technology, in addition to demand and popularity of technological innovations, has given rise to a large number of AI-education companies, and e-learning is poised to enter the advanced stage. The activities in which it is beginning to be implemented are the assessment of users' achievement and provision of a live environment. In this study, a model of the willingness to continuously use AI-enabled language online e-learning products is constructed. The survey participants comprised users of online learning product in China and conclusions are drawn from the users' perspective through empirical analysis based on the unified theory of acceptance and use of technology, combined with perceived risk and perceived entertainment variables. Therefore, based on a theoretical framework, suggestions are provided to optimise the design and marketing of AI-enabled e-learning products and leverage the users' experiences to satisfy their needs. According to the results, from the perspective of users, we propose suggestions for the sustainable development and optimisation of AI-enabled online education products and strategies to help operators reconcile the experiences and needs of the users.

Keywords: e-learning; artificial intelligence; UTAUT model; adoption behaviour; language learning.

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1 Introduction

E-learning was first proposed by Cross (1999). It refers to a digital learning method comprising information technology, multimedia technology, network technology and computer technology. With the development of technology, technology-enhanced learning has gradually change the learning environment and experienced four changes: e-learning, mobile learning, ubiquitous learning and smart learning (Adu and Poo, 2014). Sharma and Kitchens (2004) defined mobile learning as new type of learning supported by mobile devices. Mobile learning is largely self-directed and these individual factors may act as a barrier in using mobile learning (Karimi, 2016). The development of mobile technologies has enabled learning on the move (Han and Shin, 2016). Ubiquitous learning takes advantage of digital content, physical surroundings, mobile devices, pervasive components and wireless communication to deliver teaching–learning experiences to users at anytime, anywhere, and anyway (Cárdenas-Robledo and Peña-Ayala, 2018). Against such background, the technology-enhanced learning environment has also evolved from an e-learning environment to a smart learning environment (Huang et al., 2012). Smart learning is built with two types of technologies: smart devices technologies (such as the Internet of Things, wearable devices) and intelligent technologies (Gros and García-Peñalvo, 2016). These two types of technologies enabled education to have features of tracking learning process, recognising learning scenario, awareness of physical environment, connecting learning communities, adaptive function and natural interaction (Huang et al., 2012; Zhu et al., 2016), which bring learners more flexibility, effectiveness, adaptation, engagement, motivation and feedback (Spector, 2014). Considering the increasing importance of Artificial Intelligence in education, the scholar conducts a comprehensive and systematic review of influential AI in education studies (Chen et al., 2020). With the help of AI technologies education systems can provide personalised guidance, supports, or feedback to students as well as assisting teachers or policymakers in making decisions (Hwang et al., 2020). The prospect of use of AI technologies includes how teachers would enrich them, how students would learn, and how accurate and prompt decisions can be taken in education (Chatterjee and Bhattacharjee, 2020). Further, user capabilities were classified and every type of user can learn from the type and level of the content (Peng et al., 2019; Bose et al., 2020). AI in education will initiate datafication on an unprecedented scale. All these disparate forms of artificial intelligence are undeniably hungry for data (Selwyn et al., 2020). Researchers could also take into serious consideration about effectiveness, efficiency, or usefulness of AI in education (Yu, 2020). AI-enabled e-learning is still in its early stages of development. There is a worldwide interest in the topic and that the literature on this subject is just at an incipient stage. Although AI is a reality, the scientific production about its application has not been consolidated (Hinojo-Lucena et al., 2019).

E-learning in China has evolved from a number of rocky starts in 2014, and has witnessed new market substitutions and iterations (iResearch, 2020). Artificial Intelligence enabled smart learning and the global educational landscape has been changing (Bose et al., 2020). The development of AI technology, in addition to demand and popularity of technological innovations, has given rise to a large number of AI-education companies, and e-learning is poised to enter the advanced stage of "AI plus Education." Decision makers need to know the issues that influence the use of a particular technology so they would be able to take them into account during the development phase (Taherdoost, 2018). This study addresses the gaps in the literature in the users' adoption behaviour of AI-enabled products. The focus of this study is on the most comprehensive application of these products and the most popular English education products in China. One is "Fluent English" by LAIX Inc., which is an AI company that popularises English online learning services (https://www.liulishuo.com). The other is "Scallop Words", a mobile English learning app, by Nanjing Beiwan Education & Technology (https://www.shanbay.com). The third is "Microsoft Xiaoying" founded in 2015 by the Microsoft Research institute in China; it is based on AI English learning products (https://www.engkoo.com). The survey participants comprised users of Microsoft Xiaoying and conclusions are drawn from the user's perspective through empirical analysis based on the unified theory of acceptance and use of technology, combined with perceived risk and perceived entertainment. Therefore, suggestions are provided to optimise the design and marketing of AI-enabled e-learning products and leverage the users' experiences to satisfy their needs.

2 Literature review

Because of the current e-learning product diversification, several classic models have been used in the study of e-learning. The main classical theories aim to confirm the theory, Technology Acceptance Model (TAM) (Davis, 1986), unified adoption, and integration of the technology acceptance model (Venkatesh et al., 2003). These theories are mainly used for general online education products. However, there are a limited number of studies, both nationally and internationally; regarding the continuance behaviour of the users toward AI-enabled language e-learning products (self-adjusted learning system). Self-adjusted learning systems offer personalised learning experience to students' characteristics and abilities. Studies have shown these systems can be effective learning tools (Li et al., 2018). With the development of many AI online education products, the key to the future success of e-learning is the optimisation of the user experience, such that the Continuance Intention (CI) is encouraged. In this paper, we comprehensively discuss the CI based on relevant concepts, such as perceived risk and perceived entertainment. We study the introduction of AI education learning products from the perspective of the user's CI, keeping up with the existing technology trends and application scenarios. The research topic is in line with studies on emerging business trends.

2.1 Artificial intelligence-enabled language e-learning system

Because of the popularisation of the AI technology, its auxiliary and application scenarios are gradually becoming diversified. AI-enabled language education products are also known as "AI plus education" in China,"which is a collection of AI technologies, models, and practices applied in the field of education. It can be divided into "computing intelligence + education," "perception intelligence + education," and "cognition intelligence + education"; this implies that AI + education is progressing from "storage and computing" to "listening, speaking, watching, and understanding"; ultimately, it will achieve "understanding and thinking." There are two main categories of the application of AI technology in online education (iResearch 2020).

The first category is the use of tools or identification availed by AI, such as image recognition assistance to homework. The intelligent problem bank, iFLYTEK, launched the English-composition revision service, and voice, brain waves, and expression recognition based on cloud knowledge; the aim of this category is to assist teachers, rather than replace them. The second category is self-learning, also known as the "strategy AI." Self-learning does not rely on real teachers in the language learning process, and the teacher is supplanted by AI. Because everyone has their own unique learning path, self-adjustment is a key characteristic of effective and extensible personalised online education (iResearch 2019). For example, AI can provide personalised language education by determining the problem with the user's questions, mastering the user's knowledge and making recommendations to the user. AI can collect considerable amounts of data to optimise user-specific characteristics. However, this is dependent on continuous use, through which the AI technology, based on methods, such as data analysis and machine learning, can build a data-driven personalised language education platform.

2.2 Theory of technology acceptance model

Davis (1986) proposed the TAM, to explain the factors that influence user acceptance of information systems and the degree of acceptance. It is based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1977). This model includes three factors that affect the user's confidence, attitude and CI, which can impact the use of technology, and can be used to predict the major influences on people using information systems.

According to the TAM theory, when people are presented with new technology, they are influenced by two main factors: the cognitive usefulness and cognitive ease of use. These factors are independent variables, and the user's attitude, user, and intention are dependent on them. When people use technology products and emerging technologies, the perceived ease of use and usefulness will frame their attitude, which will affect the usage behaviour. In sum, the following two points are considered: The perceived ease of use when people use the emerging technology or product that can improve efficiency and streamline workflow. The cognitive usefulness, that is, how much the emerging technology or product can enhance job performance.

Li et al. (2016) identifies the platform interactive features and personalised recommendation in a study on an interactive English learning platform, and, based on the users' individual needs and expectations, confirms that the perceived usefulness has a significant impact on the user's CI. In this study, the extension of the "perceived usability" and "perceived usefulness" variables as "function" is defined; it is used to explain the user friendliness of the applications, and to discuss CI, rather than the adoption behaviour. The TAM model is applied in the application of Artificial Intelligence techniques to analyse students' behaviour. The students' perceptions on this subject of Artificial Intelligence and Education is been studied (Cruz-Benito et al., 2019).

2.3 Unified theory of acceptance and use of technology (UTAUT) model

The UTAUT model, which mainly integrates related models and variables in different fields, was proposed by Venkatesh et al. (2003). It mainly integrates the following eight theories: the motivational model (Davis et al., 1992), TAM (Davis, 1986; Venkatesh and Bala, 2008), the Theory of Planned Behaviour (TPB) (Ajzen, 1985), social cognitive theory (Compeau and Higgins, 1995), TRA (Fishbein and Ajzen, 1977), innovation diffusion theory (Moore and Benbasat, 1991), model of PC utilisation, task-technology-fit (Goodhue and Thompson, 1995), and combined TAM and TPB. The model is based on four core concepts, which include one of the most valuable variables: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC). It has been demonstrated in empirical studies that the UTAUT, with up to 70% explanatory power, is more persuasive than previous models.

Although the UTAUT was proposed only recently, because of its strong explanatory power, and the way it systematically integrates other theories, it lends greater diversity and practicality to the empirical analysis by scholars than other theories. It is still widely used in practical applications. The academic community has used this theory to confirm many remarkable hypotheses. Mehta and Morris et al. (2019) integrated human values with technology adoption models and apply the novel conceptual model to the context of digital education using UTAUT as a base model. Nie et al. (2020) study the evidence of TPB and provide a deeper understanding of human-computer interactive behaviour and individual behaviour of technology adoption. With advances in science and technology, the application fields of research are also more diverse. UTAUT is applicable in the context of mobile learning/technology and has been reported as the optimal model for mobile learning (Venkataraman and Ramasamy, 2018).

2.4 Perceived risk

The perceived risk was conceptualised by Bauer (1960b); it has its root in psychology. According to Bauer (1960a), consumers have certain psychological expectations that cannot be validated before making a purchase. Therefore, when the result matches the expectation, it is easy to be satisfied. However, a mismatch between the results and expectations results in dissatisfaction. Therefore, this uncertainty underlies consumer purchase decisions; this situation is the perceived risk at its most basic form. Cox and Rich (1964) averred that consumers will have certain purchase decision settings and expectations before making purchases. Cunningham (1967) divided the perceived risk into uncertainty (whether the product cannot be expected to meet expectations) and consequences (the degree of harm arising from the product not meeting the expectations) (Cunningham, 1967; Cox, 1967) If the customer pays more attention to the undesirable degree of harm, the perceived risk is greater. Later scholars used Cox and Cunningham's explanation to define the perceived risk.

According to Jacoby and Kaplan (1972), the perceived risk could be functional, physical, financial, social, or psychological. The focus of this research is on the characteristics of the AI-enabled e-learning products that require the collection of user data. With the wide range of applications of the Internet for life, consumers are also paying increasing attention to user privacy. In recent years, user privacy infringement has become the biggest challenge in the advancement and optimisation of AI products. In the application of AI technologies to the analysis of educational data, issues concerning ethical and privacy are worth noting. The application of AI technologies commonly requires large amounts of data, involving confidential information about students and faculty. Thus, issues concerning privacy and data protection may involve, which should be considered seriously (Chen et al., 2020). Expectedly, finance is a key source of privacy and security concerns in the context of AI products, especially as it pertains to personal data such as credit card information and transaction behaviour. In using AI products, users will be conscious of this risk. Therefore, in this study, the perceived risk variables examined include the concept of psychological and financial risk.

2.5 Perceived entertainment

Perceived entertainment is different from "perceived enjoyment." Perceived entertainment refers to the degree of entertainment derivable from the use of the computer itself (Davis et al., 1992). It refers to the fun generated through the behaviour of using the technology (Dennis et al., 2007). In developing and designing a product, it is important to ensure that the interface is entertaining, as this is positively correlated to the user's interest in using the product. Therefore, if the programmer can make the interface entertaining, the users' interest in it will be aroused. Consequently, they will feel happy using it, and be more willing to use it (Koufaris, 2002; Leng et al., 1970). Dennis et al. (2007) discovered that the functions and entertainment properties of products and systems are the key to determining user acceptance and adoption behaviour.

Research on the entertainment impact factors has extended beyond advertising and marketing; it has also begun to receive attention in the field of education. The perception of entertainment can have a positive impact on users' learning behaviour (Feng et al., 2015; Khalil and Rintamaki, 2014).

3 Research model

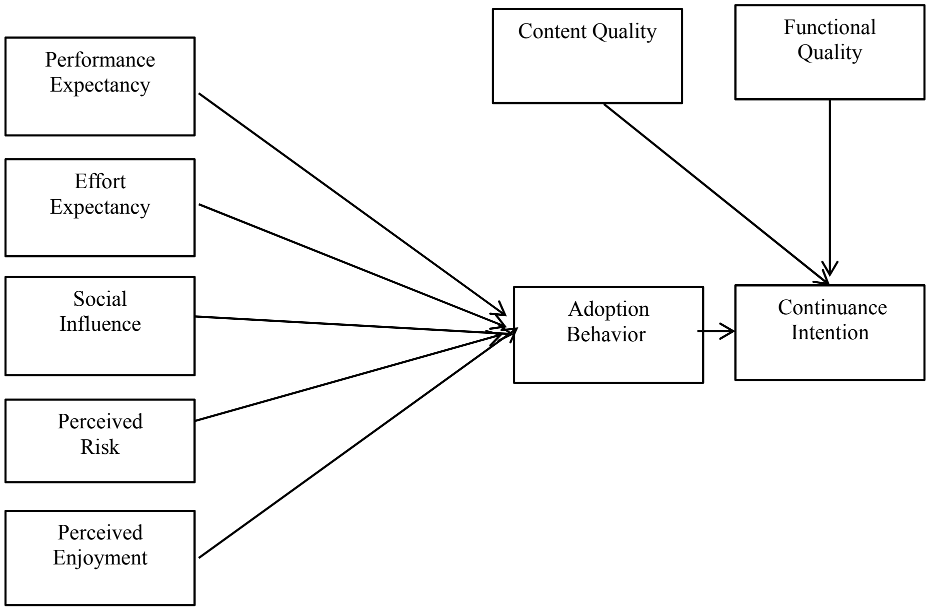
The characteristics of the AI-enabled online education products, necessitate extensive data collection and the use of machine learning to optimise personalised recommendations and analyse students' needs, such as weaknesses improvement. On the other hand, learning products need human-machine interaction with users to enhance learning and entertainment perception, and the essence of educational products is the content quality. In this study, the key factors influencing the users' continued usage of online education products are examined using the TAM, PR theory and consumer willingness, based on UTAUT. The model has four dimensions: PR, PE, content and functions. The user adopts a product. Subsequently, due to many reasons, the user ceases to use the product, which causes the waste of human and material resources. For the development of online education, and to maintain the number of active users continue to use, in order to bring the industry shuffle and achieve the essence of education. Therefore, exploring the continuous usage of the product, rather than the initial adoption behaviour, is the key to the competitive optimisation of AI online education products.

In summary, this research model proposes nine research variables to study the CI using the product. The parameters are: PE, EE, SI, PR, perceived entertainment, function quality, content quality and adoption behaviour. The dependent variable is the continued usage, and the adopted behaviour is the mediation variable. The specific study design variables defined are shown in Table 1, and the research model is shown in Figure 1.

Table 1 Defined studied variables

Variables	*Defined*	*Reference*
Performance expectancy (PE)	Users feel the extent of the work has been defined when using the AI-enabled English e-learning products	Venkatesh et al. (2003)
Effort expectancy (EE)	The effort users expect to expend when using the AI-enabled English e-learning products	Venkatesh et al. (2003)
Social influence(SI)	The influence exerted on the users by the surrounding communities in the use of the AI-enabled English e-learning products	Venkatesh et al. (2003)
Perceived risk (PR)	Users ponder the impact of different risks, such as technology and economy, which influences their adoption intentions when using the AI-enabled English e-learning products	Jacoby and Kaplan (1972)
Perceived entertainment (PEU)	The subjective pleasantness or enjoyment derived from using the AI-enabled English e-learning products	Koufaris (2002)
Adoption behaviour (AD)	Users' willingness to adopt and use emerging technologies, specifically the AI-enabled English e-learning products	Venkatesh et al. (2003)
Content quality (CQ)	Users practical assessment of whether the content and the personalisation of content meets their learning needs and other needs when using the AI-enabled English e-learning products	Qian (2015)
Function quality (FQ)	The functional interface design and technical implementation, and whether it meets the needs of the users more than traditional e-learning products	Kolekar et al. (2018)
Continuance intention (CI)	the psychological state of users, their intention to continue using the AI-enabled English e-learning products	Bhattacherjee (2001)

Figure 1 User acceptance model of AI-enabled language e-learning system



4 Research Hypotheses

Based on research model, we propose the following research hypotheses:

- *H1: Performance expectancy of users have a significant positive effect on AI-enabled e-learning products adoption behaviour.*

According to the UTAUT, the main factor that directly affects consumers' willingness to use a product is the PE (Li et al., 2016). In the context of the use of IT systems, the PE implies the degree to which the system improves job performance. In this study, the PE is defined in the context of the usage of the AI-enabled products; thus, the PE indicate that the users can achieve better learning performance. The PE also covers the degree of convenience afforded by e-learning. Particularly in the era of the mobile web, mobile phones are commonly used to learn, and access knowledge.

Based on this analysis, it can be seen that users' willingness to use information systems will increase, when they think it can improve their personal work performance or benefit them.

- *H2: Effort expectancy of users has a significant positive impact on the adoption of AI-enabled e-learning products.*

In terms of the EE, users do not desire to expend too much effort and time on learning a new system (Li et al., 2016). The EE also refers to the degree to which it is easy to use the AI-enabled online education products.

Roger posits that when users perceive that a new product or system is easy to operate, the acceptance level increases (Rogers, 2010). According to Venkatesh's theory, satisfying expectations affects the performance of the behavioural intentions (Venkatesh et al., 2003). The effort required is the difficulty operating and applying the technology pose. Nov and Ye (2008) defined effort expectancy as the user's subjective evaluation of the ease of operating the new technology system, which is an interaction between individuals and technology, one of the internal motivations influencing the usage behaviour.

- *H3: Social influence on users has a significant positive impact on the AI-enabled e-learning products adoption behaviour.*

The SI will affect the performance of the behavioural intentions. Venkatesh et al. (2003) defined it as the extent to which users are affected by others when using new technology systems. Agarwal and Prasad (1998) and Venkatesh et al. (2003) and other scholars believe that users' willingness to use the system increases, when people around them adopt it. The above research results demonstrate that if the system is recommended by important people around the users, they become more willing to use it. The stronger the SI, the greater the intention of adoption.

- *H4: Perceived risk to users has a significant negative impact on AI-enabled e-learning products adoption behaviour.*

The introduction of the concept of the PR into research on user behaviour dates back to as early as 1960. Bauer posits that when consumers decide to purchase a product, they face many uncertainties; and the decision is based on the assumption that the results will exceed their expectations (Bauer, 1960a).

Wu and Wang (2006) divided the PR that influence consumers' adoption intentions into four in his research model: technical risk, economic risk, behavioural risk and functional risk. The results confirmed that economic risk has a very significant negative influence.

- *H5: Perceived enjoyment has a significant positive effect on the AI-enabled e-learning products adoption behaviour.*

The perceived entertainment factor when consumers use information systems was defined by Davis (1993; Davis et al., 1992). Davis was the earliest researcher to discuss information systems in the context of the perceived entertainment. Subsequently, many scholars confirmed that this variable had a promoting effect on the CI. Based on the motivational theory research, Deci and Ryan (1985) and Davis (1993) studied consumers' use of information systems, and opined that their usage behaviour would be affected by external motives, such as the perceived usefulness, as well as internal motives such as the perceived entertainment (Deci and Ryan,1985).

Cui (2014) studied the influencing factors of mobile learning users, and confirmed that the impact of the perceived entertainment on behaviour is significant. Ma (2009) studied the attitudes of the users of mobile learning, and verified the impact of the perceived entertainment on the user attitudes.

- *H6: Adoption behaviour has a significant positive impact on the continuance use of AI-enabled e-learning products.*

Adoption behaviour is the main reason for exploring the consumer acceptance, adoption, and use of emerging technologies, according to Keramati et al. (2012).

Bhattacherjee (2001) summarised the relationship between the TRA and EDT in relation to the theory of CI, and observed that the CI was influenced by the perceived usefulness after use. Further, according to the rational behaviour theory, the user adoption behaviour directly affects his or her behaviour (continuance intention).

- *H7: Content quality has a significant positive effect on the continued use of the AI-enabled e-learning products.*

The essence of online learning is education itself, and the essence of education is the content quality of the course and lesson plans. For users to continue using the online learning, the most important factor is their interest in the content. The users of e-learning are mainly preoccupied with the practicality of the knowledge and whether the teaching content meets their needs. Based on the literature relevant in investigating the post-adoptive behaviour, The users' intentions to continue to use the e-learning system should be oriented mainly by the fact that the system can bring critical benefits in enhancing learning. (Lin and Wang, 2012; Chang, 2010; Vatanasombut et al., 2008), The measurement of information quality was adopted from the study of Wu and Wang (2006). Further, we are convinced that the content of online education products is not based on customised teaching according to the users' aptitude, and cannot break through the individual differences of students. Traditional education in China deploys duck teaching to a large extent; therefore, the content of online education at that time did not have a positive impact on the users' continuous use. In a research on the influencing factors of online learning users' continuous use behaviour, Qian (2015) found that although the content had a significant impact on the satisfaction derived from English e-learning products, it is not attractive for users' continuous use.

By collecting the user's past learning content, the AI-enabled e-learning system can analyse the user's strengths and weaknesses, and then push the learning lesson plans that are more suitable for the user. The content of the push mechanism is the key to whether users continue to use the system or not.

- *H8: Function quality has a significant positive effect on continuance intention of AI-enabled e-learning products.*

AI-enabled education products are also committed to facilitating immersive learning experience through voice interaction, animation function, and movie scenarios using AI. It simulates the real learning experience. Liu and Sun (2011) researched mobile reading services, and confirmed that the interface of the electronic screen was important. Compared with the traditional paper-based reading method, the user's actual feelings and expectations after initial adoption can be affected by the interface. Kolekar et al. (2018) studied e-Learning portal framework, and stated that the portal identifies the students learning style and accordingly provide material and customise the user interface based on that learning style. This will improve the learning capacity of the students. The student generally does not have the time to browse through all types of material for a particular topic, so the portal will customise and provide only those materials which will enhance the learning experience of the student. It also confirms that the functional interface has a strong positive correlation with user satisfaction. The functions include the layout and user interface design. When the mobile reading system has good interfaces, the user satisfaction is higher. In past related user behaviour research. The function quality is the same as content quality, and may affect the investigation of post-adoption behaviour.

Mobile reading and online education also serve as an online content service; the users' satisfaction with the functions is significant. The UTAUT extends from satisfaction to the CI, which are directly proportional to each other (Venkatesh et al., 2003).

5 Research methodology

In this study, the following comprehensive methods are adopted. First, a questionnaire based on the domestic and foreign mature measurement table design. Through a pre-survey, the reasonableness of the questionnaire was tested; following which it was then distributed through the Internet for research. The statistical analysis included credibility analysis, validity analysis, descriptive statistical analysis, related analysis, regression analysis and Statistical Package for Social Sciences (SPSS).

5.1 Sampling

The purpose of this study was to investigate the CI to use the AI-enabled English e-learning products. A nonrandom purposive sampling (non-probability sampling) was adopted. The study samples were collected through the "Microsoft Xiaoying" user channel distribution in China. The selected users used a variety of English learning and education products at the same time; they are also current users of the "English fluent" app, the first educational product on the China App store, China. "Scallop Word" is one of the earliest e-learning products in China.

After research and interviews with experts, we found that the Microsoft Xiaoying's target users were similar to those of the other two products; the majority of them were students under the age of 24, followed by white-collar workers. Approximately 60% of the users were female. Male users accounted for approximately 40% of the total. The target users were distributed across provinces and regions with developed economies and a large population base. These users have a strong desire to improve their English, and usually try many products to learn English. The users of "Microsoft Xiaoying" have almost had the experience in using the other products. Therefore, the "Microsoft Xiaoying" user group is representative of the users of the AI-enabled English e-learning products. It was necessary to filter the interviewees to obtain the appropriate sample for the research. The online questionnaire was also linked to the public account of Microsoft Xiaoying to facilitate the collection of the questionnaire. In addition, in all the questionnaire questions, "application of this product" refers to using the AI-to the products most commonly used by AI-enabled e-learning products; thus, the questions were based on the usage situation, rather than the special features.

The focus of this study is on the intended user's continuous usage of the AI-enabled English e-learning education product, not the initial adoption behaviour; therefore, to obtain an effective result, we examined only the use of the AI-enabled e-learning products information, and distinguish whether there are any in the questionnaire scale, so that in the subsequent options for the use of products and functions, you can truly answer. If there is no experience in using AI-enabled e-learning products, the respondent's answer is considered invalid.

5.2 Data collection

The total number of questionnaires collected was 919. There were 584 valid data for discussion and analysis, after the invalid and null data were deleted. The majority of the respondents were women, accounting for up to 67% of the respondents. Majority of the respondents were college or university students and young people; The respondents with the highest academic qualifications were mostly concentrated in the universities, accounting for 68.32%. Table 2 shows the sample's gender, age, and education.

Table 2 The sample's demographic characteristics (N=584)

	Items	*Number*	*Percentage*
Gender	Male	192	32.88%
	Female	392	67.12%
Age	<19	105	17.98%
	19-22	212	36.30%
	23-30	158	27.05%
	>30	109	18.66%
Education	High School	118	20.21%
	Collage or University	399	68.32%
	Advanced degree	67	11.47%

Among the AI-enabled online education products that have been used, almost all the respondents had used "Fluent English" and "Microsoft Xiaoying." The main motivation to use the AI-enabled e-learning products was self-improvement, followed by "in-school learning test" and "interest."

5.3 Dara analysis

The analysis of the study is presented here, including the descriptive statistics, reliability tests, correlation, and regression. Table 3 presents the matrix of correlations between variables. It can be observed that there are several sets of correlations above 0.30; therefore, the application of the factorial analysis to these variables is appropriate. However, most of the parameters were also significantly positively correlated, which indicates that there may be a collinearity problem, and special tests would be required when performing regression analysis later.

Table 3 Correlation coefficient matrix

	PE	*EE*	*SI*	*PR*	*PEN*	*CQ*	*FQ*	*AD*	*CI*
PE	1.000								
EE	0.657**	1.000							
SI	0.568**	0.524**	1.000						
PR	0.306**	0.382**	0.509**	1.000					
PEN	0.681**	0.694**	0.669**	0.563**	1.000				
CQ	0.672**	0.725**	0.710**	0.611**	0.894**	1.000			
FQ	0.614**	0.691**	0.680**	0.669**	0.879**	0.944**	1.000		
AD	0.605**	0.674**	0.664**	0.655**	0.861**	0.908**	0.929**	1.000	
CI	0.602**	0.679**	0.655**	0.647**	0.870**	0.910**	0.935**	0.939**	1.000

Note: **Significant at 0.01 level (2-tailed).

The regression analysis, correlation analysis and t-test were used to evaluate the hypotheses. The regression analysis was performed to estimate the linear relationship between the dependent variable and the independent variables using the SPSS. Multiple linear regression was used to investigate whether the variables in the constructs positively and significantly predicted overall satisfaction, and determine which constructs had the highest impact. The constructs were the independent variables used in this study. These included the PE, EE, SI, PR, PE, CQ and FQ, which were the dependent variables in the study. Multiple regressions were performed for each construct. Further, correlation analysis was used to identify the connections between the CQ, CI and FQ, CI.

Reliability refers to the degree of consistency between the multiple measurements of a variable. One type of diagnostic measure that is widely used (and has been used in this study) is Cronbach's alpha. This measure, which is known as internal consistency, estimates the reliability of the test scores. The conventionally accepted lower limit for the Cronbach's alpha was 0.70. This rises as the inter-correlations among the test items increase. The inter-correlations among the test items are maximised when they all measure the same construct. Because the reliability test is performed on each of the constructs separately, the results validate the model and factor analyses. The high alpha value of the constructs in this study indicates that the variables within the constructs are correlated, and measure the same thing. The results of the reliability analysis, presented in Table 4, demonstrate that all the constructs included in this study are strongly acceptable and reliable coefficients. Thus, the questionnaire is approved as a reliable instrument.

Table 4 Reliability analysis

Construct	*Cronbach's alpha*	*Number of items*	*Result*
Performance expectancy	0.854	4	High Reliability
Effort expectancy	0.861	3	High Reliability
Social influence	0.878	2	High Reliability
Perceived risk	0.900	3	High Reliability
Perceived enjoyment	0.945	3	High Reliability
Content quality	0.971	5	High Reliability
Function quality	0.959	5	High Reliability
Adoption behaviour	0.943	2	High Reliability
Continuous use	0.978	4	High Reliability

6 Results

Based on the data multicollinearity, collinearity diagnostics were performed. We applied three different regression models. In the first regression model, the collinearity statistics for five independent variables (PE, EE, SI, PR and PEN) and one dependent variable (adoption behaviour) are shown. The second regression model shows the statistics for two independent variables (CQ and FQ) and one dependent variable (continuous use). The third regression model shows the statistics for one independent variable (adoption behaviour) and one dependent variable (continuous use).

The associated Variance Inflation Factor (VIF), Durbin-Watson value and tolerance values are presented in Tables 5, 6 and 7. The significance of the overall model was p-value < 0.001, and the adjusted R^2-squared was 0.798; the Durbin-Watson value was 2.018. A VIP in the range of 1.587 to 3.213 indicates acceptable values, according to the suggested benchmark, i.e., VIF < 10. Similarly, the associated tolerance values, ranging from 1 to 0.63, were also within the acceptable threshold values, i.e., tolerance > 0.1. Thus, the model did not indicate any multicollinearity issues.

The second model is presented in Table 6. The p-value was 0.001, and the adjusted R^2-squared was 0.881. The Durbin-Watson value was 1.9542, indicating that the strain number has no autocorrelation. The VIF was 9.223. The third model is presented in Table 7. The p-value was 0.001, and the adjusted R^2-squared was 0.882. The Durbin-Watson value was 1.877; and the VIF was 1. These show that the models have good explanatory power and are statistically significant; further, they do not indicate any multicollinearity issues.

Table 5 Model 1: multicollinearity diagnostics result, dependent variable: adoption behaviour

Construct	*B*	*Standard error*	*β*	*t*	*p*	*Tolerance*	*VIF*
Performance expectancy (PE)	0.002	0.028	0.002	0.068	0.946	0.442	2.265
Effort expectancy (EE)	0.14	0028	0.14	5.083	0	.454	2.202
Social influence (SI)	0.087	0.026	0.087	3.306	0001	0.495	2.019
Perceived risk (PR)	0.234	0.023	0.234	9.972	0	0.63	1.587
Perceived enjoyment (PEN)	0.572	0.033	0.572	17.126	0	0.311	3.213
R			0.894				
R^2-Squared			0.799				
Adj R^2-Squared			0.798				
F			460.801***				
Durbin-Watson			2.018				

Table 6 Model 2: multicollinearity diagnostics result, dependent variable: continuous use

Construct	*B*	*Standard error*	*β*	*t*	*p*	*Tolerance*	*VIF*
Content quality (CQ)	0.246	0.043	0.246	5.657	0.001	0.108	9.223
Function quality (FQ)	0.703	0043	0.703	16.175	0.001	0.108	9.223
R			0.939				
R^2-Squared			0.881				
Adj R^2-Squared			0.881				
F			2151.053***				
Durbin-Watson			1.954				

Table 7 Multicollinearity diagnostics result, dependent variable: continuous use

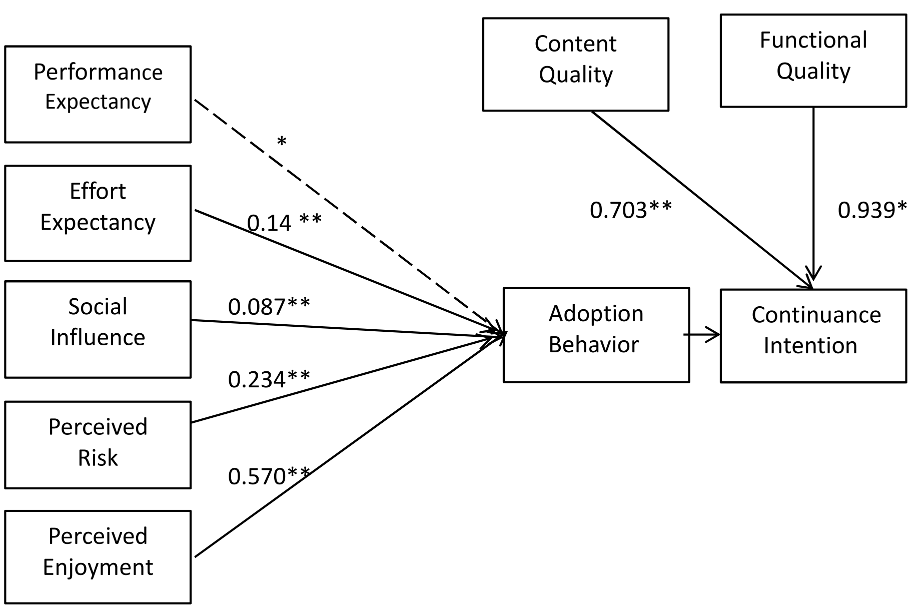
Construct	*B*	*Standard error*	*β*	*t*	*p*	*Tolerance*	*VIF*
Adoption Behaviour	0.939	0.014	0.939	65.97	0.001	1	1
R			0.939				
R^2-Squared			0.882				
Adj R^2-Squared			0.882				
F			4351.99***				
Durbin-Watson			1.877				

Based on the results presented, the hypotheses may be either validated or rejected. To verify the existence of a relationship between the constructs, a Pearson's correlation was run between the two factors. Table 8 presents the results of this correlation. The results of the analyses show that H1 is rejected. The performance expectancy (PE) does not support the use's adoption behaviour (AD). H2, H3, H4 and H5 are significant and each construct contributes to AD, which produces high to moderately low contribution. H5 is deemed more significant than the others. It means that the perceived enjoyment (PEN) is high contribution to AD. The correlation results also reveal H6 and H7 to be significant, as there is a direct relationship between Continuance Intention (CI) with respect to Functional Quality (FQ) and Content Quality (CQ). Finally, H8 is also significant and a strong correlation (coefficient > .5) was found between AD&CI.

Table 8 Summary of results

Hypothesis	*Variable*	*Coefficient*	*Significance*	*Support*	*Contribution*
*H*1	PE&AD	0.002	0.946	No	Significant difference
*H*2	EE&AD	0.14	0.000	Yes	Moderately low
*H*3	SI&AD	0.087	0.001	Yes	Low
*H*4	PR&AD	0.234	0.000	Yes	Moderately high
*H*5	PEN&AD	0.570	0.000	Yes	High
*H*6	FQ&CI	0.246	0.001	Yes	Moderately high
*H*7	CQ&CI	0.703	0.001	Yes	Very high
*H*8	AD&CI	0.939	0.001	Yes	Very high

Figure 2 Results of multiple regression on the model



Source: **Hypothesis is supported. *Hypothesis not supported.

6 Discussion

In addition to the achievement expectations, the main variables of the remaining UTAUT models had significant positive influences on the adoption behaviour of users using AI-enabled online education products, with the highest positive values being for the perceived entertainment (PEU), followed by PR, EE and SI. It was found in this study that the users were mainly college students, and the three products (Fluent English, Scallop Words and Microsoft Xiaoying) were self-adjusting English learning systems, the aim of the users was mainly to improve their English listening and writing ability, rather than a specific expectation to improve their performance.

The effort expectancy had the moderate low impact on the adoption behaviour, the effort required is the difficulty operating and applying the technology pose. The users are accustomed to using mobile devices, and the product developers must consider the user interface, so this factor is positive, but moderate low impact.

The social inference had the low impact on the user adoption behaviour. The research results demonstrate that if the system is recommended by important people around the users, they become more willing to use it. This study show the impact is not so high. Perhaps the reason is that how to improve personal English level is a more personal consideration

The perceived risk had the moderately high positive impact on the user adoption behaviour. The AI technology is enabling a smart learning environment to effectively promote the development of personalised learning and adaptive learning, in this study, the characteristics of the AI technology explicit and ask the user's perspective on that characteristic. We introduce the AI technology as a smart learning tool, which is a form of personalised adaptive learning. But the benefits and concerns for users should be considered. AI-enabled product needs to collect information about personal use behaviour, so the perceived risk should belong to the risk of information security. This study result also supports this personal concern.

The perceived enjoyment had the most positive impact on the user adoption behaviour, perhaps because the new generation of AI-enabled online education product users will strongly demand entertaining learning. In examining the effects of entertainment, the product-aware entertainment function (such as lively images and sounds and combined entertainment function) is the biggest factor in attracting the new generation of users' adoption behaviour.

The CQ and FQ also significantly affected the CI. Whether the product itself could meet the needs of consumers, the CQ and FQ are still very important factors and the FQ impact exceeds that of the CQ; thus, the domain variables had a more positive impact on the CI. Students learn according to their learning styles and determining these is a crucial step in AI-enabled traditional education adaptive. For example, user capabilities were classified using AI. This user ability classification aimed to get material that matched the user's ability, which bring learners more flexibility, effectiveness, adaptation, engagement, motivation and feedback. Our findings demonstrate that the smart leaning system will be the impact for the users. Finally, the adoption of the product significantly improved the CI. Once the user adopts the product, their loyalty increased and they became loyal users.

7 Recommendations and marketing inspiration

Based on the empirical analysis results, it can be inferred from this study that enterprises that develop and operate the AI-enabled e-learning products should adopt the following strategies.

Focus on the entertainment function of the product, as well as the interactive effects, to improve the user adoption behaviour; based on the empirical analysis results, the perceived entertainment can best improve the user adoption behaviour. To meet the preferences of the younger generation, product developers should not only pay attention to the function and content of the product, but also enrich the entertainment level of the product, to attract the attention of the most promising young generation of users. Furthermore, we should reduce the perceived risk of products and the cognitive risks of user adoption, through measures such as improving the stability of the product, information security protection, and user privacy. Users' willingness to adopt the product is also highly socially motivated; therefore, building a discussion-sharing community for products, and improving the interaction between users can positively improve user adoption behaviour.

As shown by this study, the user adoption behaviour significantly increases the CI, making users loyal users. Software development and operators should therefore lower the threshold for user adoption, such as the introduction of free trial versions, or free entry-level versions for users to use first. Further, they should allow these users to access advanced functional versions, before adopting a charging policy. Commencing the use of interfaces should be made as easy as possible, and user barriers should be reduced. These product development strategies can encourage greater user adoption, thereby increasing the CI and creating loyal users, which will increase the profitability of the product in the long run.

Through empirical research, it was demonstrated in this study that the FQ and CQ have a significant positive impact on the CI, which in turn has a more significant impact on the functional quality. Therefore, it is recommended that software developers and product managers designing products should first pay attention to the function of the product; the content will be gradually expanded with the increase in users. Product functionality is the main product attribute, and once the product has been adopted by the user, the power of the functions is the biggest factor determining the user's CI.

Finally, AI-enabled products are becoming more and more popular, and the perceived risk has the impact to the user acceptance. Consumers are considering issues related to personal privacy and information security. For the education industry, decision makers need to know these issues that influence the users so they would be able to take them into account during the product development phase. Companies that develop and operate AI-enabled e-learning products need to provide highly reliable products to the customers.

8 Research limitation and future research

In this study, online questionnaires were designed, and purposive sampling was implemented. The questionnaire was distributed on the "Microsoft Xiaoying" user channel, an AI-enabled English learning product founded by the Microsoft Research Institution in China. Although this sampling method can improve the sample validity and sample quality, and the majority of the respondents are college students, it may not sufficiently cover users at all levels and potential users. In future studies, it is recommended to expand the sampling range.

The impact of user characteristics on the adoption behaviour or CI was not verified in this study. According to result, the perceived risk has the moderately high positive impact on the user adoption behaviour. The major risk of AI-enabled product maybe is data security for the consumers. The user's demographic characteristic and the information security issue may be discussed in the future.

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