



Perceived control over attitude: the psychological drivers of sustainable smart courses learning among economically disadvantaged undergraduates

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ABSTRACT

Smart courses, being the effective tool for education equity, are faced with high dropout. This study investigates the factors affecting the complete of the smart courses of economically disadvantaged undergraduates from the psychology drive perspective. Nvivo tool was used to encode the screened 392 literature from Web of Science and the Engineering Index to explore the generic relationship among free nodes. According to the Theory of Planned Behavior, 17 hypotheses and corresponding Structural Equation Modeling were established, and 257 valid questionnaires (age of participants from 19 to 24) were collected for analyzing, and experts were invited to do an interview. The results indicated that behavioral attitude, subjective norms, and perceived behavioral control all had significant positive effects on students' intention to engage in sustainable learning. Among them, perceived behavioral control demonstrated the strongest path coefficient ($\beta = 0.499$, $p < 0.001$), highlighting students' self-efficacy and perceived resource controllability as key driving forces in promoting continuous learning. Although the effects of behavioral attitude ($\beta = 0.343$, $p < 0.001$) and subjective norms ($\beta = 0.274$, $p < 0.001$) were relatively weaker, the clarity of learning goals, expectations from others, and social support still played a positive role in motivating learning engagement. Different from the conventional view, this paper finds out that the most effective point is perceived behavioral control instead of attitudes for economically disadvantaged undergraduates for persistent learning behavior. This study provides a novel perspective on explaining economically disadvantaged undergraduates' sustainable smart courses learning behavior and offers practical recommendations to enhance course completion rates.

1. Introduction

Educational equity is an important foundation for social equity and sustainable development smart courses learning is of great importance to promote world sustainable development at the societal level, especially for those economically disadvantaged undergraduates (with an annual household income below 50%-60% of the national/regional per capita disposable income from China Statistical Yearbook standards). Further, this study analyzes the implementation of sustainable smart courses learning of these students' behavior aspects for the first time. Smart courses learning, facing with the high dropout and low finish rate(Willging and Johnson, 2019; Rahmani et al., 2024), despite with spreading, there are doubts about their intended outcomes, for instance, self-regulated learning, learning engagement and persistence (Jung and Lee, 2018; Li and Liu, 2023b; Yu, 2023). As for smart courses learning influencing factors, the learning design(Reilly and Reeves, 2024),flexibility(Xavier and Meneses, 2021), play a pivotal role in learner engagement, retention and persistence. For most of the studies related with sustainable learning intention, however, focused on how learners' characteristics, such as motivation, affected learning outcomes (Jung and Lee, 2018; Wang and Zhan, 2020b; Kara, 2022). The paper focuses on the "high dropout rate" and "low finish rate" of the users' participation on the



platforms (Park and Choi, 2009b), taking “English courses” as the exemplary model, intending to study the factors of exercising the sustainable learning intention of the users for those economically disadvantaged undergraduates. Smart education courses have actually served as the driven force for prime education sources. Except the compensatory courses required by the teachers or college, a large number of state-class courses have not been finished completely, which can contribute to the incomplete knowledge module. Facing with high dropout of the courses, the study intends to study the factors of exercising the sustainable learning intention of the users for those economically disadvantaged undergraduates. Previous research indicated that learner engagement, motivation, and self-regulation are critical factors influencing learning outcomes and the willingness to continue learning (Jung and Lee, 2018).

In recent years, studies have been conducted on learners’ characteristics, such as motivation, affected learning outcomes. Li and Liu (Li and Liu, 2023a) identified intrinsic motivation, course design quality, teacher support, and platform interactivity greatly affected learning behavior. Reilly and Reeves (Reilly and Reeves, 2024) concluded active learning design was of importance. Additionally, Xavier and Meneses (Xavier and Meneses, 2021) suggested optional learning design from the users could enhance the complete of the courses. Yağcı (Yağcı, 2022) proposed a machine learning algorithm-based midterm grade prediction model using students’ midterm exam grades as the source data, which can predict students’ final study outcome. Huang (Huang, 2023) found out that self-efficacy has a positive impact on perceived usefulness and perceived ease-of-use for online learning behavior. Wu et al (Wu et al., 2019) found out that the top five critical criteria impacting college students’ Learning are enhancing learning performance, increasing learning participation, altering learning habits, access anytime, and quick usage of learning resources

Application of the Theory of Planned Behavior (TPB) in Education

The Theory of Planned Behavior (TPB), proposed by Ajzen (1991), aiming at explaining the relationship between individuals’ behavioral intentions and their actual behaviors. Three variables are included in the TPB that serve to predict an individual’s intent to engage in a behavior: attitude, subjective norms, and perceived behavioral control. This theory has been widely applied in various fields, including health behavior, environmental conservation, and educational behavior (Armitage and Conner, 2001b). In the field of education, the Theory of Planned Behavior (TPB) has been used to explain students’ and teachers’ behaviors. For instance, Gómez-Ramírez, Valencia-Arias, and Duque combines the theory with the Technology Acceptance Model (TAM) to investigate students’ acceptance of mobile learning, finding that perceived behavioral control was a key factor influencing students’ actions. Similarly, Xu et al (Xu et al., 2023a) explored the impact of peer pressure on students’ learning behaviors, revealing that subjective norms contributed a significant role in students’ learning decisions. Other researchers such as Teo and Lee (Teo and Beng Lee, 2010) focuses on the teachers’ behavior and found out that attitude toward usage and subjective norms were significant predictors of behavioral intention to use technology while perceived behavioral control was not.

Research on Continuance Intention in Learning

Lin (Lin, 2011) found out that perceived ease of use has a more critical effect on the attitude and continuance intention of less experienced users, whereas perceived usefulness is found to be a stronger determinant of the attitude and behavioral intention of more experienced users. Dai et al (Dai et al., 2020) adds new variables (attitude and curiosity) to the ECM, which is significant in explaining continuance intention. Park and Choi (Park and Choi, 2009a) found that adult learners’ continuance intention is influenced by multiple factors, including course quality, learning motivation, and social support. Wang and Zhan (Wang and Zhan, 2020a) used structural equation modeling (SEM) to analyze the relationship between English learners’ online self-regulation and their learning behaviors. However, previous research has focused on limited attention and characteristics to mechanisms of the influencing factors instead of focusing on the implementation of continuous behavior. Moreover, focusing on the groups such as teachers and general students, which is not that effective for education gap is actually among special economically disadvantaged undergraduates. Therefore, based on the theory of planned behaviors, this research uses SEM to fully analyze the impact of behaviors and implementation of willingness of economically influential students to learn smart lessons. These searches will provide theoretical insights into the design and optimization of these courses for these groups.

2. Method

The paper uses the Theory of Planned Behavior to analyze the intention of exercising the sustainable learning, one social psychology theory that aims to explain both the intention to participate in an activity and the behavior itself (Armitage and Conner, 2001a), which can not only explain the individual behavior out of reasonable thinking, but can also presume the behavior. Icek Ajzen originated the idea in the early 1980s, and it has been tested in a range of



situations, including health, education, and marketing already. (Jalilvand and Samiei, 2012; Chen, 2016; Wang et al., 2018; Gómez-Ramírez et al., 2019; Knauder and Koschmieder, 2019). In recent years, the theory has been used to explain and predict the behavior of teachers and students in the education domain, for example, students’ voluntary learning intention, teachers’ intention of exercising the smart teaching technology.(Hadadgar et al., 2016; Gómez-Ramírez et al., 2019; Xu et al., 2023b). Three variables are included in the TPB that serve to predict an individual’s intent to engage in a behavior: attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). Attitude is defined as the positive or negative values an individual has about carrying out specific behaviors. Subjective norms are defined as how specific behaviors are viewed by others who are important to an individual and if they expect the behavior to be performed or not. Perceived behavioral control is defined as how an individual’s perception of a behavior is under volitional control(Ajzen, 1991). The strongest predictor of an individual’s behavior change is an intention to engage in that specific behavior. To understand the factors influencing the learning persistence actions, two steps are demanded. (1) What are the key factors affecting the continuous learning action? (2) What is the structural relationship and mechanism among these influencing factors?

In terms of research methodology, the literature analysis method and interviews were used for the study of the first question. For the second question, the Delphi method and Interpretative Structural Modeling Method were used (ISM).ISM is one widely used analytical method in the field of modern systems engineering for system structure analysis and model construction, and can clarify the relationship between complex elements through mathematical operations and matrix description, revealing the correlation of internal elements of the system and forming a relatively complete multi-level hierarchical structure model(Haleem et al., 2012). According to the basic steps of ISM, the design of this study is as follows: A. Nvivo tool is used to analyze the sustainability, parameters of smart courses learning conducting and summarize the influencing factors of continuous learning behavior; B. For those who have used the online education platforms, interviews will be conducted, which would supplement, delete or revise related influencing factors; C. Consulting with the higher education Academic experts and practitioners in the field to devise the influencing factors.

Data Collection

This paper aims to summarize the influencing factors of sustainable learning from the previous literature, which is mainly from two sections: Web of Science and the Engineering Index. As for the Web of Science, the search query is TS =(“MOOC” or “Smart Courses Learning” or “Distance Education”) and TS =(“Continuance Intention” or “Continue to Use” or “Continuance” or “Usage Behavior” or “Persist” or “Persistence Rates” or “Dropout Rates” or “Drop Out”));Language: (English) and Publication Year: 2014-2024 and Document Types: (Article); The search result is 166 from all databases. As for the Engineering Index, the search query is All Fields (“MOOC” or “Smart Courses Learning” or “Distance Education”) and TS =(“Continuance Intention” or “Continue to Use” or “Continuance” or “Usage Behavior” or “Persist” or “Persistence Rates” or “Dropout Rates” or “Drop Out”));Language: (English) and Publication Year: 2014-2024 and Document Types: (Article); The search result is 392 from all databases. In this paper, NVivo software is used to encode the screened literature to explore the generic relationship among free nodes. After the dealing of data of domestic and foreign literature, the factors influencing continuous learning behavior were preliminarily obtained. In order to extract more information, the interviews were conducted with 12 English courses teachers (experts), along with questionnaires. After all these steps, the influencing factors were generally selected as in the Table1.

Table 1. Influencing Factors

Number	Item
1	Perceived Useful
2	Learning Objective and Internal Motivation
3	Interactive Behavior
4	Teacher Assistant
5	Curriculum Quality
6	Platform Service
7	School Teaching Management Regulations



8	Social Assessment
9	Learning Satisfaction
10	Learning Capability
11	Learning Style
12	Cost Assessment
13	Knowledge Foundation
14	Consistent Learning Intention

Theory of Planned Behavior Modeling

According to the Theory of Planned Behavior, attitude, subjective norms, and perceived behavioral control are the significant influencing factors of intended behavior (Ajzen, 1991). As described in the introduction, attitude is defined as the positive or negative values an individual has about carrying out specific behaviors. Subjective norms are defined as how specific behaviors are viewed by others who are important to an individual and if they expect the behavior to be performed or not. Perceived behavioral control is defined as how an individual's perception of a behavior is under volitional control (Haleem et al., 2012). The strongest predictor of an individual's behavior change is an intention to engage in that specific behavior. According to the Theory of Planned Behavior Modeling, the influencing factors listed in the Table 1 can be divided into three parts as in the Table 2.

Table 2 . TPB Modeling

Parts	Factors	Explaining of the Factors
Attitude (AT)	Perceived Useful	Perceiving Possible Improvement
	Learning Objective and Internal Motivation	Learning Objective and Internal Incentive
Subjective Norms (SN)	Interactive Behavior	Interactive with Content, Mates, Platforms and Teachers
	Teacher Assistant	Teachers' General Influence, Including Academic Level, Guidance
	Curriculum Quality	Curriculum Resource, Value
	Platform Service	Platform Designing, Interactive and Satisfaction
	School Teaching Management Regulations	Administration Management
	Social Assessment	Assessment from Social of the Platform
Perceived Behavioral Control (PBC)	Learning Satisfaction	Level of Satisfaction with the Smart courses learning Experience and Participation
	Learning Capability	Students' Metacognitive Abilities, Cognitive Strategies, Self-management and Regulation Skills, Interpersonal Skills
	Learning Style	Study Habits and Personal Preferences
	Cost Assessment	Expected Cost of Completing the Course, Such as Effort, Time Invested, Expense
	Knowledge Foundation	Knowledge Base
	Consistent Learning Intention	Continue to Use Online Teaching Platforms (e.g., MOOCs) for Learning and Recommend to Others for Learning

Referring to the Theory of Planned Behavior modeling and influencing factors, the hypothesis is made as the following Table 3.

**Table 3.** Hypothesis of Influencing Factors

Modeling Hypothesis	H1: Students' online using attitude (AT) has positive influence on persistent use of smart courses platform.
	H2: Students' subjective norms have positive influence on persistent use of smart courses platform.
	H3: Students' perceived behavioral control has positive influence on persistent use of smart courses platform.
Attitude Hypothesis	H1.1 Students perceive useful has positive influence on persistent use of smart courses platform.
	H1.2 Students' learning objective and internal motivation have positive influence on persistent use of smart courses platform.
Subjective Norms (SN) Hypothesis	H2.1 Students' interactive behavior has positive influence on persistent use of smart courses platform.
	H2.2 Students with teacher assistant has positive influence on persistent use of smart courses platform.
	H2.3 Curriculum quality has positive influence on students' persistent use of smart courses platform.
	H2.4 Platform service has positive influence on students' persistent use of smart courses platform.
	H2.5 School teaching management regulations has positive influence on students' persistent use of smart courses platform.
	H2.6 Social assessment has positive influence on students' persistent use of smart courses platform.
Perceived Behavioral Control (PBC) Hypothesis	H3.1 Learning satisfaction has positive influence on students' persistent use of smart courses platform.
	H3.2 Learning capability has positive influence on students' persistent use of smart courses platform.
	H3.3 Learning style has positive influence on students' persistent use of smart courses platform.
	H3.4 Cost assessment has positive influence on students' persistent use of smart courses platform.



H3.5 Knowledge foundation has positive influence on students' persistent use of smart courses platform.

H3.6 Consistent learning intention has positive influence on students' persistent use of smart courses platform.

Profile of the Questionnaire

To ensure the accuracy and complacency of the study, the questionnaire aiming at economically disadvantaged undergraduates was designed in four parts: 1. Personal Information: personal information such as name, age, gender, phone number. 2. Smart courses learning intention, behavior, and platform. 3. Smart courses learning persistent use. 4. Behavior Influencing factors, Attitude, Subjective Norms, Perceived Behavior Control.

Structural Model Design

In order to better identify the influencing factors of exercising the behavior of continuous learning, this study furthered the theory of Planned Behavior model based on Ajzen's theoretical model (Ajzen and Fishbein, 1970; Ajzen, 1985; 1991), combining with the characteristics of group interaction and behavior in the smart courses learning. Behavioral attitudes, subjective norms, and perceived behavioral control collectively affect behavioral intentions (BI), which in turn affect students' willingness of continuous learning. The following Figure 1 shows the analytical framework of individual behavior and behavior intention of students' continuous learning.

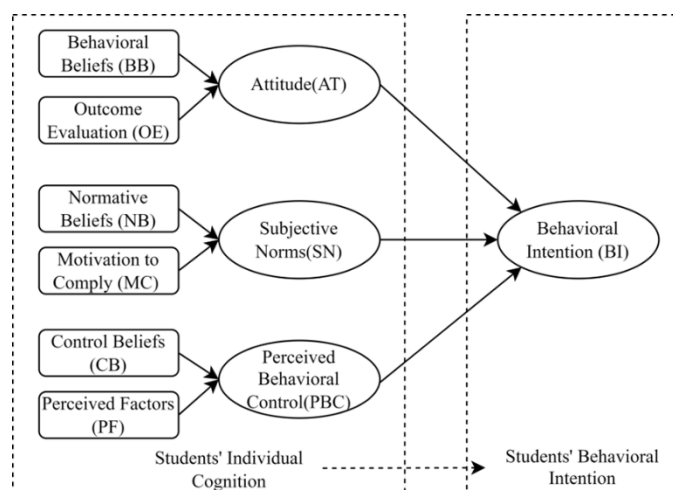


Figure1. Individual Behavior and Behavior Intention

Structural Model Construction

The theory of Planned Behavior proposes that behavioral intention is determined by three main factors: Behavioral Attitude, Subjective Norms and Perceived Behavior Control. Based on the analysis of the influencing factors of these three main factors, the following model equations are constructed to explain students' exercising of intention to continue learning online. Attitude: The main factors of these students' attitude towards exercising smart courses learning behavior are their perception of the usefulness of the course, learning objectives and intrinsic motivation.

The constitutive relationship of behavioral attitudes can be expressed as:

$$AT = \alpha_{AT} + \beta_1 \sum_{i=1}^n (b_i + e_i) + \varepsilon_i \quad (1)$$

AT represents individual behavior attitude; α_{AT} is constant term; β_1 is a regression coefficient to be estimated that reflects the effect of the independent variable on the dependent variable AT ; b_i indicates the intensity of a



particular belief; e_i indicates an evaluation of the outcome of the belief; n indicates the total amount of beliefs and outcome evaluations; ε_1 indicates the error term.

Subjective Norms: Subjective norms are defined as how specific behaviors are viewed by others who are important to an individual and if they expect the behavior to be performed or not (Ajzen, 1991). The constitutive relationship of SN can be expressed as:

$$SN = \alpha_{SN} + \beta_2 \sum_{i=1}^n (n_i + m_i) + \varepsilon_2 \quad (2)$$

SN represents individual subjective norms; α_{SN} is constant term; β_2 is a regression coefficient to be estimated that reflects the effect of the independent variable on the dependent variable SN ; n_i indicates the expectation from others and groups; m_i indicates the motivation to obey the expectation; n indicates the total amount of perceived beliefs and obeying motivation; ε_2 indicates the error term.

Perceived Behavioral Control: The controlling factors of students' behavior in exercising online continuous learning behavior in English courses mainly include self-learning efficacy and sense of controlling over the difficulties they may encounter. The constitutive relationship of perceptual behavioral control can be expressed as:

$$PBC = \alpha_{PBC} + \beta_3 \sum_{i=1}^n (c_i + p_i) + \varepsilon_3 \quad (3)$$

PBC represents perceived behavioral control; α_{PBC} is constant term; β_3 is a regression coefficient to be estimated that reflects the effect of the independent variable on the dependent variable PBC ; c_i indicates the intensity of beliefs; p_i indicates the perception of controlling factors; n indicates the total amount of perceived beliefs and controlling factors; ε_3 indicates the error term.

Behavior Intention: According to the above three factors, the constitutive relationship of BI can be expressed as:

$$BI = \alpha_{BI} + \beta_{AT} AT + \beta_{SN} SN + \beta_{PBC} PBC + \varepsilon \quad (4)$$

BI represents behavior intention; AT represents individual behavior attitude; SN represents subjective norms; PBC represents perceived behavior control. α_{BI} is constant term; β_{AT} 、 β_{SN} 、 β_{PBC} reflect regression coefficients of AT 、 SN 、 PBC to be estimated on BI, and ε indicates the error term.

3. Result

To ensure the accuracy and complacency of the questionnaire, the designing contains four parts: 1. Personal Information: personal information such as name, age, gender, phone number. 2. smart courses learning intention, behavior, and platform. 3. smart courses learning persistent use. 4. Behavior Influencing factors, Attitude, Subjective Norms (SN) and Perceived Behavioral Control (PBC). In this study, Likert scale was used to design questionnaires and distributed to students through the questionnaire platform, and a total number of 268 questionnaires were distributed for economically disadvantaged undergraduates. After excluding 18 questionnaires that were filled up with incomplete and obvious errors, 257 valid questionnaires remained, and the efficient rate was 95.1%. The table 4 shows the profile of the questionnaire.

Table 4. Questionnaire Basic Information (n=257)

Classification Standard	Item	Amount	Percentage
Gender	Male	136	52.92
	Female	121	47.08
E-learning Tool	Phone	90	35.02
	Pad	96	37.35
	Computer	71	27.63
Starting Age of E-learning	Primary School	3	1.17



	Middle School	18	7.00
	High School	146	56.81
	College	90	35.02
Learning Driven Force	Totally Self Motivation	48	18.68
	Totally Task Completion	46	17.90
	Mainly Self Motivation	51	19.84
	Mainly Task Completion	112	43.58
E-learning Duration	Fragmentation Duration	122	47.47
	Whole Period of Time	135	52.53
E-learning Courses	Famous Specialized Courses	69	26.85
	General Courses	39	15.18
	Hobbies Courses	51	19.84
	Further Development Course	98	38.13
Way to Learn About Online Courses	Classmates & Teachers	73	28.40
	Social Media	165	64.20
	Searching	19	7.39
E-learning Platform Choosing	Chinese University MOOC	40	15.95
	Smart Education of China	37	14.40
	Treenity	42	16.34
	Bilibili	53	20.62
	Others	85	33.07

Scale Reliability and Validity Test

Based on the 257 valid questionnaires, SPSS 26.0 was used to test the reliability and validity of 17 items, and the results are listed in table 5. In terms of reliability analysis, Cronbach's alpha was used to evaluate the internal consistency and reliability of the scale. The results showed that the Cronbach's alpha of the overall scale was 0.914, and the coefficients of Behavioral Intention (BI), Behavioral Attitude (AT), Subjective Norm (SN) and Perceptual Behavior Control (PBC) were 0.894, 0.780, 0.880 and 0.915 respectively, all exceeding the critical value of 0.7, indicating that each scale had high internal consistency and verified the reliability of its reliability (Bagozzi, 1981). In terms of validity analysis, factor analysis was performed on 17 scale items by principal component analysis and Varimax Rotation. The KMO measure was 0.941 and the significance of Bartlett's Test of Sphericity was $P < 0.001$, suggesting that the data could be conducted with the factor analysis (Wu et al., 2021). Further exploratory factor analysis (EFA) results showed that the factor loading of all scale items was higher than 0.7, and the cumulative variance explained reached 80.13% after factor rotation. A total of four factors were extracted, which corresponded with the individual's continuous learning intention, the overall evaluation of smart courses learning behavior, the perceived expectation and pressure from significant others for their continuous learning behavior, and the evaluation of their own ability and external resources. These results show that the theoretical research dimensions determined by exploratory factor analysis have a good correspondence with the variable structure constructed in this paper, and prove that the structural validity of each latent variable of the scale is accepted (Straub and Gefen, 2004).

Table 5. Reliability and Validity Test Results of the Scale

Content	Sample Amount	Num of Item	Item	Reliability		Validity	
				Cronbach's α	KMO	Factor Loading	
AT	257	2	AT1、AT2	0.780		0.869、0.854	
SN	257	6	SN1、SN2、SN3、SN4、SN5、SN6	0.914	0.880	0.941***	0.815、0.823、0.789、0.852、0.809、0.791



PBC	257	6	PBC1、PBC2、 PBC3、 PBC4、PBC5、 PBC6	0.915	0.809、0.795、0.807、 0.781、0.767、0.754
BI	257	3	BI1、BI2、BI3	0.894	0.843、0.787、0.814

Notes : “***” indicates significance level $P < 0.001$; The factor loads are calculated by principal component analysis and varimax rotation.

Structural Equation Model Analysis

Based on the existing theoretical model and scale data, this study established one structural equation model with latent variables and observed variables through confirmatory factor analysis. The data were empirically tested by using AMOS 28.0 software. The fit indicators of the model refer to Table 6. The results show that the fit indicators meet the requirements of the standard, indicating that the constructed model has a high degree of consistency with the sample data (Zheng et al., 2023). This indicates that the proposed model has good robustness and explanatory ability, and can be effectively used to analyze college students' implementation of willingness of continuing learning in online English courses. According to the above analysis results, these students' implementation of willingness to continue learning in smart English courses is significantly positively affected by behavioral attitudes, subjective norms and perceived behavior control. Specifically, students' behavioral attitudes towards online English courses significantly positively affect their behavioral intentions ($\beta = 0.343$, $P < 0.001$), validating hypothesis H1. The factor loading coefficient of AT1 and AT2 is 0.78 and 0.71 respectively, both of which were statistically significant at the 0.05 level, indicating that AT1 and AT2 had a significant measurement relationship with behavioral attitudes (AT) and supported the H1.1 and H1.2 hypotheses. When students have a positive attitude towards online English lessons, they are more inclined to continuous learning, especially if they feel that the course meets their self-learning goals and is of high value. This is because clear learning goals help students stay focused and motivated during the learning process, and positive behavioral attitudes are a key for continuous learning (Locke and Latham, 2002), increasing students' implementation willingness to continue learning online English courses.

Table 6. Model Fit Indicators

Fit Index	Absolute Fit Indices			Relative Fit Indices			Parsimonious Fit Indices	
	CMIN/DF	GFI	RMSEA	NFI	CFI	IFI	PNFI	PGFI
Standards	<3.000	>0.800	<0.080	>0.900	>0.900	>0.900	>0.500	>0.500
Fit Index	1.296	0.883	0.011	0.919	0.927	0.916	0.782	0.549

Secondly, subjective norms also have a significant positive impact on students' behavioral intentions ($\beta = 0.274$, $P < 0.001$), which validates hypothesis H2. The factor loading coefficients of the six measures of the subjective specification (SN1, SN2, SN3, SN4, SN5, and SN6) were 0.72, 0.78, 0.69, 0.79, 0.72, and 0.75 respectively, all of which were statistically significant at the 0.05 level, indicating that these items had a significant measurement relationship with the subjective norm (SN), which supported the H2.1 to H2.6 hypothesis. However, the path coefficient of subjective norms is relatively small, indicating that its influence on behavioral intentions is weak, which is consistent with the results of the TPB theory that subjective norms have less influence (Ajzen, 1991; Hogg and Terry, 1996; Armitage and Conner, 2001c). In online English courses, students are often influenced by the expectations and pressure of society, school, and significant personnel (e.g.: teachers, family, and classmates). These external expectations and pressures can motivate students to pay more attention to online courses, especially in the context of the gradual popularization of online education. The support from teachers on online platforms, encouraging feedback, and positive interaction among classmates can help to enhance students' motivation and sense of urgency to learn online English courses, and thus increasing students' exercising willingness to continue learning online English courses.

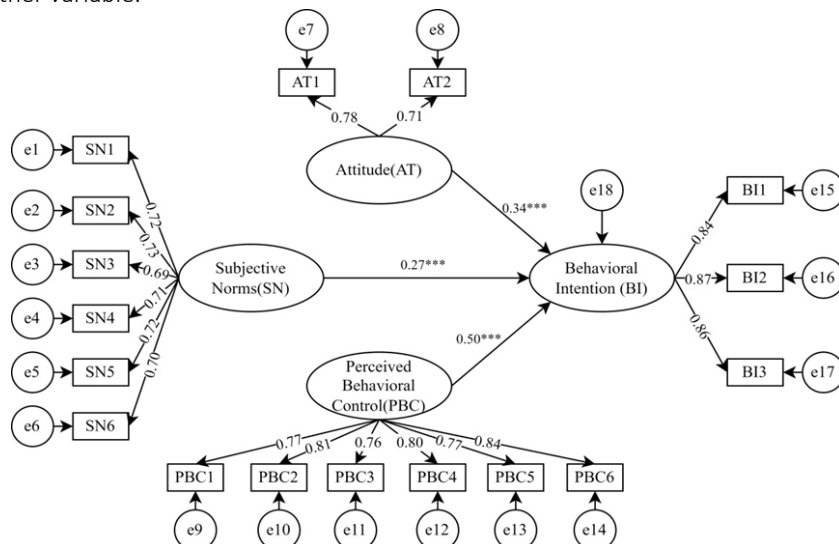


Finally, perceptual behavior control has the most significant effect on behavioral intention ($\beta = 0.499$, $P < 0.001$), which verifies hypothesis H3. The factor loading coefficients of the six measures of perceptual behavior control (PBC1, PBC2, PBC3, PBC4, PBC5 and PBC6) are 0.77, 0.81, 0.76, 0.80, 0.77 and 0.84 respectively, which are all statistically significant at the 0.05 level, indicating that these items had a significant measurement relationship with the perceptual behavior control (PBC), supporting the hypothesis of from H3.1 to H3.6. When students perceive that they are in control of the learning process, their implementation of willingness to continue learning is significantly enhanced (Pintrich and Groot, 1990). This is consistent with the previous analysis, suggesting that students' reliance on the technology and support services of smart courses learning platforms, as well as the importance of their own learning abilities, which are key factors influencing their willingness to continue learning. When teachers have rich knowledge and experience in online education, the quality of the courses is high, the paid courses are reasonable, the platform is rich in functions and the services are high-quality, the smart courses learning satisfaction of students will be improved. In other words, students are more willing to continue learning when they perceive that they have sufficient capabilities and resources, and are confident in their ability to learn when encountering with difficulties. The hypothesis test results are listed in the Table 7. Students Continuous Learning Structural Equation Model and Standardized Path Coefficients are presented in Figure 2.

Table 7. Hypothesis Test Results

Hypothesis	Path Relationships	Estimate	S.E.	C.R.	Hypothesis Testing
H1	BI \leftarrow AT	0.343***	0.054	6.538	Support
H2	BI \leftarrow SN	0.274***	0.041	5.719	Support
H3	BI \leftarrow PBC	0.499***	0.067	7.154	Support

Notes : "****" represents significance level $P < 0.001$; " \leftarrow " indicates that the variable toward which the arrow points is influenced by another variable.



Notes : "****" represents significance level . represents Residual Variables.

Figure2. Students Continuous Learning Structural Equation Model and Standardized Path Coefficients



Based on the classical theoretical framework of the theory of Planned Behavior in social psychology, this paper used 257 valid questionnaires to construct a structural equation model of economically disadvantaged undergraduates' implementation of willingness to continue smart English courses. SPSS 26.0 and AMOS 28.0 were used for statistical analysis to explore the factors and mechanisms influencing these students' implementation of willingness to continue learning. Through empirical analysis, this study draws the following conclusions:

Behavioral attitudes have a significant positive impact on economically disadvantaged undergraduates' continuous behavioral intentions' implementation in course learning. Behavioral attitudes reflect students' overall evaluation of online courses, including the quality of course content, the effectiveness of teaching, and the experience of using the platform. These attitudes are based on students' goal satisfaction, past experiences, cognitive evaluations, and emotional responses. Students are more likely to continue to use smart courses platforms for English learning when they find online courses more positively, especially if they believe that the course content helps to achieve learning goals, the quality of teaching is high, and the platform experience is good. Positive emotional responses and cognitive evaluations not only improve students' learning satisfaction, but also enhance their learning motivation and willingness to continue learning.

Subjective norms have a significant positive impact on these students' willingness to implement continuous learning. Subjective norms involve the influence of individuals' perception of social pressure and social role identification on continuous learning behavior, reflecting the students' possible adjustment of their thinking style and motivation under external interference. When students feel positive support and encouragement from their significant other (eg: family, friends, teachers, good platform service, positive school teaching management regulations social assessment), their motivation to learn is enhanced and they are more likely to continue their participation in courses. Perceptual behavior control has a significant positive impact on economically disadvantaged undergraduates' implementation of willingness to continue to behave. Perceptual behavioral control refers to an individual's perception of their ability and resources to complete courses, reflecting students' confidence and self-efficacy in successfully participating in and completing smart courses learning. When students' self-efficacy is higher, they are more confident in their ability to overcome difficulties in smart courses learning and master what they are learning. At the same time, students' sense of control over the learning environment, time management skills, resource adequacy and availability will also affect their willingness to continue learning. When these conditions are met, students perceive fewer barriers to learn, which in turn increases their willingness to continue learning.

Among the above three latent variables, perceptual behavior control has the most significant impact on economically disadvantage college students' willingness to continue learning, while subjective norms have the least influence. The powerful influence of perceived behavioral control suggests that when students perceive themselves to be in effective control of the smart courses learning process, their willingness to continue learning is significantly enhanced. In contrast, the weaker effect of subjective norms suggests that external social pressures and other people's expectations have limited motivation for students to continue smart courses learning. The limitation of the study is the total amount questionnaires could be enhanced as the result of this data was collected by individual.

4. Conclusion

Coping with the strategy, there are several suggestions for these students. Firstly, empower students through Adaptive Learning Systems. Implement AI-driven adaptive learning platforms that personalize course content based on students' progress, knowledge gaps, and learning styles, which can equip students with a sense of control in their learning. And besides, AI tutors are expected in these platforms, which can provide instant feedback, reducing frustration and enhancing perceived controllability over learning challenges. Secondly, leverage Peer and Community-Based Learning Networks. Create small, discipline-specific peer groups to foster accountability and social support (subjective norms). Platforms like Discord or dedicated app spaces can host these communities, which could inspire the motivation and intensify the controllability. Thirdly, predictive analytics could be used to identify at-risk students based on engagement metrics (e.g., login frequency, quiz performance) and trigger personalized interventions (e.g., counselor outreach). Teacher-assisting and peer work could be implemented in these circumstances.

Ethics statement

The studies involving humans were approved by the Ethics Committee of Foreign Languages College, Yibin University. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.



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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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