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Determinants of Students' Behavioral Intention to Use Online Learning Platforms in Chengu, China: An Application of the Technology Acceptance Model

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ABSTRACT: Online learning has become a society-wide learning infrastructure of online intention. This study aims to: 1) measure the relationship between Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention. 2) analyze whether Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention. 3) construct a model of online learning adoption for students in Chengdu. A mixed-methods design was adopted: 400 valid questionnaires were collected from five learner categories through stratified balanced quota sampling and analyzed with SPSS 26.0 and AMOS 26.0, including structural equation modeling and Bootstrap mediation tests; semi-structured interviews with 18 learners were coded thematically to triangulate the findings. The results show that: 1) The factors, effect online learning intention of learners in Chengdu were Online Learning Intention, Perceived Ease of Use, Perceived Usefulness, Subjective Norm Dynamic Capability, and Innovation at high level respectively. 2) Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention have relationship mean all factor has directly affect each other. 3) Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention.

INTRODUCTION

In the third decade of the twenty-first century, the reshaping of education by digital technology has moved from prophecy to everyday reality. Online education is no longer merely a supplementary means for schools; it has become a society-wide learning infrastructure spanning from children to retirees and from classrooms to workplaces. Although market research estimates differ in caliber, they are highly consistent in direction: the global online education market reached a scale of tens to hundreds of billions of US dollars by 2025 and has maintained double-digit compound annual growth, widely regarded as the fastest-growing segment of education. North America holds the largest market share, while the Asia-Pacific region has become the most promising market with the highest growth rate, with China serving as the main engine of Asia-Pacific growth. Efremova, N., and Huseynova, A. (2023). The global pandemic of 2020 was a watershed in the history of online education. More than 1.5 billion learners were forced to move online, completing the largest migration of educational form in human history within weeks. Capital markets boiled in response, and education technology investment hit a historical record that year. However, the explosive growth catalyzed by the pandemic also planted hidden dangers: users who had flooded in passively drained away in large numbers after schools reopened, and the industry shifted from “savage growth” into an adjustment period of “refined operation.” Since 2023, the explosion of generative artificial intelligence has injected new variables into the industry; applications such as intelligent tutoring, personalized learning paths, and automated assessment are rewriting the experiential structure of

online learning, with large technology platforms and traditional educational institutions competing head-on in the same arena. Efremova, N., and Huseynova, A. (2023). In contrast to the carnival of scale stands the embarrassment of quality. Completion rates of massive open online courses have long hovered between 5% and 10%, with the vast majority of registered learners failing to reach the end of their courses. Learner isolation, the mismatch between courses and individual differences, and the absence of learning support services have been repeatedly identified as the main causes of attrition. The deeper contradiction lies in the “technology investment paradox”: platforms invest heavily in technology development and content production, yet user retention and paid conversion do not improve in step. The industry has gradually realized that competition in online education has shifted from “whether courses exist” to “whether learners stay,” and that the foundation of retention is quality — not the quality on an acceptance report, but the quality that learners vote for with their feet. Efremova, N., and Huseynova, A. (2023). The above background, this study states the research problem along four dimensions the practical paradox: the dislocation between functional completeness and missing intention. Online learning platforms are far more functional than before — high-definition video, multi-device synchronization, intelligent recommendation, and online assessment are all in place — yet learner attrition has not improved significantly as a result. The completeness of technical functions has not automatically converted into enhanced learning intention, indicating that intention formation follows another mechanism.

RESEARCH OBJECTIVES

Corresponding to the first three research questions, this study sets three objectives:

- 1) To determine the level factors of Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention., effect online learning intention of learners in Chengdu.
- 2) To measure the relationship between Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention.
- 3) To analyze whether Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention

RESEARCH HYPOTHESES

- H1: Perceived Usefulness has a positive influence on Dynamic Capability.
- H2: Perceived Usefulness has a positive influence on Innovation.
- H3: Perceived Ease of Use has a positive influence on Dynamic Capability.
- H4: Perceived Ease of Use has a positive influence on Innovation.
- H5: Subjective Norm has a positive influence on Dynamic Capability.
- H6: Subjective Norm has a positive influence on Innovation.
- H7: Dynamic Capability has a positive influence on Online Learning Intention.
- H8: Innovation has a positive influence on Online Learning Intention.
- H9: Dynamic Capability plays a mediating role between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention.
- H10: Innovation plays a mediating role between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention.

LITERATURE REVIEWS

Perceived usefulness: The degree to which a learner subjectively believes that online learning can improve his or her learning or work performance (Davis, F. D. 1989.)

Perceived ease of use: The degree to which a learner subjectively believes that using online learning platforms and resources is free of effort (Davis, F. D. 1989.)

Subjective norm: the degree of expectation and support that a learner perceives from significant others, teachers, colleagues, peers, family members parents, spouse, children, regarding his or her participation in online learning perceived expectations, opinions, or judgments of specific reference groups. (Hafram, Maryam & Hasim, Abdul Hafid, 2018; Fei et al., 2026).

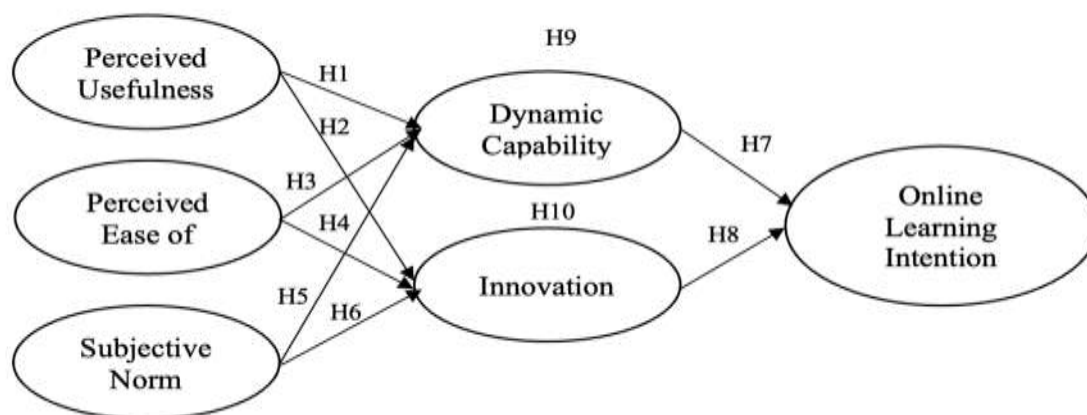
Dynamic capability: the organizational capability of an online learning provider to sense environmental ch dynamic capabilities include absorptive capacity, entrepreneurial leadership, intellectual capital, and information technology flexibility. angel, integrate internal and external resources, and reconfigure online learning products and services (Akkadet Uppachai (2025) and Photchanachan et al. (2026).

Innovation: New practices implemented by providers in online courses, teaching models, technology application, and learning services, and the degree to which they are perceived by learners. Innovation for online learning is the use of new technologies, digital tools, and creative teaching methods to make education more engaging, personal, and effective. It moves virtual classrooms past simple video calls and static text into dynamic environments that fit each student's needs

Online learning intention: A learner's subjective tendency to continue participating in online learning, increase investment in online learning, and recommend it to others in the future, student's motivational drive, goal orientation, or psychological commitment to enroll in, participate in, or continue using digital education platforms and courses. In educational research and instructional design, these intentions are generally split into specific behavioral and motivational dimensions: Key Types of Online Learning Intentions. (Z. Guo et al., 2023; Channuwong et al., 2026)

- Enrollment Intentions (OLEI): The initial goals or reasons driving a learner to sign up for a course, such as acquiring specific career skills, earning a certificate, conducting academic research, or interacting socially.
- Continuance Intentions: A learner's motivation to persist with an online learning system or complete subsequent digital modules after initial adoption. (Z. Guo et al., 2023)

CONCEPTUAL FRAMEWORK



METHODOLOGY

This research employed a mixed-methods design was adopted for quantitative 443 valid questionnaires were collected from target population of this study comprises learners aged 16 and above residing in the administrative region of Chengdu, China, who have prior online learning experience. For qualitative use semi-structured interviews with quantitative analysis, semi-structured interviews were conducted with 15–20 learners purposefully selected to represent the four learner segments (universities, vocational colleges, online Student and corporate employees t. Data analyze Descriptive statistics, Reliability and validity testing, Exploratory factor analysis (EFA), Correlation analysis, and Structural equation model (SEM) (Hair et al., 2017). For qualitative data were analyzed using thematic coding (DeLone, W. H., & McLean, E. R. (2003)

MEASUREMENTS

This study used the questionnaire to collected data the measurement of each variable as follow:

Perceived usefulness (PU) : Measurement is 5 items, PU1: The platform's courses improve my learning/work efficiency,PU2: The course content helps my learning or career development, PU3: Through this platform, I can master needed knowledge and skills faster, PU4: Overall, the platform's services are very useful to me, and PU5: I am willing to recommend the platform's courses to others.

Perceived Ease of Use (PEOU) Measurement is 5 items, PEOU1: The platform's system is simple and easy to operate, PEOU2: I can easily find the courses and learning resources I need, PEOU3: The platform's interface design is clear and friendly, PEOU4: When I encounter operational problems, I can conveniently get help, and PEOU5: Overall, I find using the platform's services easy

Subjective Norm (SN), Measurement is 5 items, SN1: People important to me think I should participate in online learning,SN2: My organization encourages or requires online learning,SN3: Classmates/colleagues around me generally recognize the value of online learning, SN4: Society's evaluation of online learning is generally positive, and SN5: Overall, people around me support my online learning

Dynamic Capability (DC). Measurement is 6 items, DC1: The platform can keenly sense changes in learner needs, DC2: The platform can adjust course content promptly based on feedback,DC3: The platform's teaching services keep up with technology trends, DC4: The platform can effectively integrate various teaching resources, DC5: The platform can flexibly respond to policy and market changes, DC6: Overall, the platform has good dynamic quality improvement capability.

Innovation (INN), Measurement is 6 items,INN1: The platform frequently launches new courses or learning models, INN2: The platform has distinctive innovation in teaching methods,INN3: The platform is adept at using new technologies to improve learning experience,INN4: The platform's service design embodies innovative ideas, INN5: Compared with similar institutions, the platform's innovation level is relatively high, INN6: The platform's innovation outcomes can tangibly improve learning effectiveness.

DATA ANALYSIS

Demographics Result

The majority of respondents were male of 51.50%, the age distribution concentrates in the 18–45 range of (77.40%), which dominates online learning consumption in Chengdu, education bachelor's degree of 34.30% , learning-behavior profile is equally informative. More than half of the respondents of (57.80%) have more than one year of online learning experience, and of 24.50% study online more than five hours per week. Paid courses account for a substantial share of current enrollment of (37.80%).

Table 1 Descriptive Statistics Results

Variable	Mean	SD	Level	Skewness
Perceived Usefulness	3.67	1.058	High	-.641
Perceived Ease of Use	3.59	1.811	High	-.487
Subjective Norm	3.78	.890	High	-.546
Dynamic Capability	3.79	.779	High	-.551
Innovation	3.91	.098	High	-.440
Online Learning Intention	3.71	.052	High	-.327

Result objective 1) To determine the level factors of Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention., effect online learning intention of learners in Chengdu

Research found that: the factors, effect online learning intention of learners in Chengdu were Online Learning Intention, Perceived Ease of Use, Perceived Usefulness, Subjective Norm Dynamic Capability, and Innovation at high level respectively.

KMO and Bartlett's Test

KMO and Bartlett's tests are used to find out if the factor analysis of a particular study is useful or not. In this regard, it is estimated that if the value of the KMO test is very close to 1.00, it will be beneficial for the study. In addition, it has also been estimated that if the value of Bartlett's test is less than 0.05). it will also be beneficial for the study. The fulfillment of both conditions can be seen in table 2.

Table 2 KMO and Bartlett's Test

Kaiser-Meyer-Olkin.		.898
Sampling Adequacy.		
Bartlett's Test of Sphericity	Approx. Chi-Square	5533.373
	Df	120
	Sig.	.000

Convergent and discriminant validity

In Table 4, the results of convergent and discriminant validity can be seen evidently. According to the results presented in the table, the composite reliability CR values for all variables are more than 0.7 while average variance extracted AVE values are more than 0.5. The researcher has also found out that the variables have loadings different from each other. This confirms the authenticity of the collected data.

Table 3: Convergent and Discriminant Validity

	CR	AVE	PU	PEU	SM	DC	INN
PU	0.933	0.873	0.785				
PEU	0.952	0.772	0.298	0.773			
SM	0.872	0.773	0.298	0.534	0.646		
DC	0.920	0.816	0.324	0.435	0.503	0.613	
INN	0.920	0.816	0.324	0.435	0.503	0.513	0.710

Confirmatory Factors Analysis

According to the results of confirmatory factor analysis CFA given in table 5, it can be observed that the values for all the indicators linked with CFA are present within the appropriate range given in the table (Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. 2022). This indicates that the hypothetical model is fit for use in the study

Table 4: Confirmatory Factors Analysis

Indicators	Cut-Off Value	Results
CMIN/DF	Less or equal to 3	2.94
GFI	Equal or greater than .80	.916

CFI	Equal or greater than .90	.941
TLI	Equal or greater than .90	.930
RMSEA	Less or equal to .08	.061

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). confirmatory factors indicators.

PATH COEFFICIENT ESTIMATION RESULTS

1. Direct effect

Result of objective 2) To measure the relationship between Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention.

From The path hypothesis test results. All seven direct paths reach the 0.001 significance level with directions consistent with theoretical expectations, so hypotheses H1 through H7 are all supported the mean all factor has directly affect each other.

Table 5 Path Hypothesis test direct effect Results

Hypothesis	Path	Standardized β	SE	t	Significance	Conclusion
H1	PU $\rightarrow$ DC	0.28	0.05	5.8	$p < 0.001$	Supported
H2	PU $\rightarrow$ INN	0.23	0.05	5.1	$p < 0.001$	Supported
H3	PEOU $\rightarrow$ DC	0.25	0.05	4.7	$p < 0.001$	Supported
H4	PEOU $\rightarrow$ INN	0.23	0.05	4.2	$p < 0.001$	Supported
H5	SN $\rightarrow$ DC	0.19	0.04	4.5	$p < 0.001$	Supported
H6	SN $\rightarrow$ INN	0.32	0.06	5.9	$p < 0.001$	Supported
H7	DC $\rightarrow$ OLI	0.31	0.06	4.8	$p < 0.001$	Supported
H8	INN $\rightarrow$ OLI	0.34	0.71	5.12	$p < 0.001$	Supported

The coefficient structure exhibits three features. First, the influence of dynamic capability on online learning intention (0.32) is the strongest single path in the model—learners' perception of providers' capability-building outcomes is the most direct support for intention. Second, the three perceptual factors influence innovation with nearly equal strength (0.23, 0.25, and 0.23)—usefulness, ease-of-use, and normative feedback jointly constitute the demand coordinates for innovation output. Third, the influence of dynamic capability on innovation (0.19) is significant but limited in strength—the conversion from capability building to innovation output suffers attenuation.

The regression equations are highly significant: the dynamic capability equation has $R^2 = 0.48$, $F = 34.03$; the innovation equation has $R^2 = 0.35$, adjusted $R^2 = 0.34$, $F = 52.01$; and the online learning intention equation has $R^2 = 0.45$, adjusted $R^2 = 0.44$, $F = 67.23$, with all F tests significant below 0.001. The model explains 34.50% of the variance in innovation, a moderately high level, and 25.30% of the variance in online learning intention, within the acceptable range for cross-sectional intention research

2. Indirect effects

Result of objective 3) To analyze whether Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention.

From The path hypothesis test results. Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention. Bootstrap Mediation Test Results

Table 6. presents the Bootstrap test results for mediation effects. The 95% confidence intervals of all six indirect effects exclude zero, all reaching significance.

Table 6 Bootstrap Test Results of Mediation Effects (5,000 Resamples)

Indirect Effect Path	Effect	SE	Z	Significance	95% CI
PUE → DC → OLI (H9)	0.08	0.02	4.9	$p < 0.001$	[0.05, 0.13]
PU → INN → OLI (H9a)	0.07	0.02	3.9	$p < 0.001$	[0.04, 0.11]
PEOU → INN → OLI (H9b)	0.07	0.02	4.2	$p < 0.001$	[0.04, 0.10]
SN → DC → OLI (H10c)	0.07	0.02	4.0	$p < 0.001$	[0.04, 0.10]
DC → INN → OLI(H10b)	0.06	0.02	3.8	$p < 0.001$	[0.03, 0.09]
PU → DC → INN → OLI (H10)	0.02	0.01	3.0	$p < 0.01$	[0.01, 0.03]

Note. PU = perceived usefulness, PEOU = perceived ease of use, SN = subjective norm, DC = dynamic capability, INN = innovation, OLI = online learning intention.

Hypotheses H9 (including three sub-paths), and H10 are all supported. The serial mediation effect (0.02), though numerically small, is statistically significant, confirming the existence of the complete transmission chain of "perception—capability—innovation—intention." The Bootstrap approach also permits a clean comparison of indirect-effect sizes, since all intervals are estimated on the same resampling basis. The usefulness serial chain, the capability parallel channel, and the innovation parallel channel each contribute visibly, and their non-overlapping confidence ranking—usefulness.

CONCLUSION

The integration of quantitative and qualitative findings strengthens the credibility of the conclusions. The quantitative strand provides precise estimates of path coefficients, mediation effects, and group differences, answering the "whether" and "how strong" questions. The qualitative strand explains the "why" questions—especially why payment experience scores lowest among online learning quality items, why normative influence is comparatively strong in Chengdu, and why innovation is valued when it reduces effort or makes progress visible. The two strands converge on the same substantive conclusions, with the qualitative evidence adding mechanism narratives that statistical coefficients alone cannot provide.

1)The factors, effect online learning intention of learners in Chengdu were Online Learning Intention, Perceived Ease of Use, Perceived Usefulness, Subjective Norm Dynamic Capability, and Innovation at high level respectively. 2)Perceived Usefulness, Perceived Ease of Use, learner characteristics, Dynamic Capability, Innovation and Online Learning Intention have relationship mean all factor has directly affect each other.3) Dynamic Capability and Innovation play a mediating role impact between Perceived Usefulness, Perceived Ease of Use, Subjective Norm, and Online Learning Intention.

DISCUSSION

Online learning intention (OLI) had an overall mean of 3.71 (SD = 0.52), indicating a high level of intention among the sample. The highest-scoring item was overall intention strength (3.78), followed by prioritization intention (3.75) and continuance intention (3.73). The lowest-scoring item was payment intention (3.60).

The finding that intention is high (3.71) but payment intention is lower (3.60) reveals the gap between behavioral intention and payment intention in Chengdu's online learning market. While learners express strong willingness to continue participating and prioritize online learning, their willingness to pay for high-quality courses is comparatively lower. This gap reflects the free-to-paid conversion challenge in the online learning industry, where learners have become accustomed to free resources and may be reluctant to pay for courses that they perceive as substitutable (Li & Wang, 2022; Sirathanakul et al., 2023).

The group analysis revealed that intention levels vary in the same direction as learners' degree of autonomous choice: adult learners (3.80) and corporate employees (3.79) report the highest intention, while vocational students (3.62) and basic education learners (3.61) report the lowest. This pattern suggests that intention is highest when online learning is a voluntary, self-directed

choice and lowest when it is a required routine arranged by parents and schools (Ajzen, 2020; Sutthadaanantaphokin et al., 2025). The finding that intention is high but payment intention is lower and has significant implications for providers' business models and for the sustainability of the online learning ecosystem. Providers should recognize that a considerable part of current online learning intention is built on external scaffolding and that the conversion from free to paid learning remains a challenge (Li & Wang, 2022). The findings are consistent with prior research in several respects. The finding that intention is high in post-adoption contexts is consistent with Bozkurt, A., & Sharma, R. C. (2020) expectation-confirmation model. The finding that payment intention is lower than continuance intention is consistent with the free-to-paid conversion challenge documented in the online learning industry (Li & Wang, 2022). The findings suggest that providers should focus on enhancing the perceived value of paid courses to increase payment intention. This may involve clearer articulation of learning outcomes, stronger credential recognition, and more transparent pricing and refund policies. The low payment intention score also suggests that providers should explore alternative business models, such as freemium models, subscription models, or employer-sponsored learning, to monetize their offerings (Teece D.J., 2017).

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