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Drivers of Generative AI Adoption in Higher Education: A fsQCA Study on Student Motivations and Technology Perceptions

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Abstract: Generative Artificial Intelligence (GenAI) is reshaping higher education, yet the drivers of students' continuance intention in academic contexts remain underexplored. Building on the Rich Intrinsic Motivation (RIM) framework and technology adoption theories, this study investigates the configurational effects of intrinsic motivations (accomplishment, knowledge, stimulation), extrinsic motivation (perceived usefulness), and technology characteristics (ease of use, novelty) on GenAI adoption. Using Fuzzy-Set Qualitative Comparative Analysis (fsQCA) on data from 238 university students, the study reveals that no single factor is necessary for adoption. Instead, four distinct sufficient configurations drive high continuance intention: (1) "Happy Achievers" (Hedonic-Mastery), (2) "Curious Explorers" (Hedonic-Knowledge), (3) "Conquerors" (Pure Mastery), and (4) "Determined Strivers" (Utilitarian-Striving). These findings highlight the complex interplay between motivational and technological factors, offering tailored insights for educators to foster sustainable GenAI integration in learning.

Keywords: Generative Artificial Intelligence (GenAI); higher education; motivations; technology adoption; fsQCA (Fuzzy-Set Qualitative Comparative Analysis)

1. Introduction

Generative AI, capable of producing novel content rapidly, is poised to revolutionize education by providing students with new information and learning possibilities beyond the scope of traditional instruction [1]. Previous research has begun to explore the multifaceted drivers of generative AI continuance intention through a mixed-methods design and fuzzy-set qualitative comparative analysis (fsQCA), revealing the complex interplay of motivational factors and technology perceptions in explaining sustained usage among general users [2]. However, there remains a lack of focused inquiry into how these factors operate specifically among students engaged in academic tasks. Building upon the theoretical and methodological framework established by Wolf and Maier, this study aims to investigate the configurations of motivational factors and technology perceptions that drive generative AI adoption among students in higher education, thereby addressing this critical gap in the literature.

2. Literature Review

This section reviews the applications of GenAI in academic tasks and discusses the theoretical foundations of technology adoption in this context.

2.1. Artificial Intelligence and Technology Adoption

Generative AI (GenAI) offers significant benefits in higher education. It assists in academic tasks such as drafting content, checking grammar, and generating creative ideas or visuals (e.g., ChatGPT, Grammarly, DALL-E). It also supports problem-solving, code generation, and debugging in technical fields. When integrated with creativity techniques, GenAI enhances innovation and learning efficiency. Research emphasizes that with responsible and ethical use, GenAI serves as a valuable partner in enriching the educational process and developing essential student competencies [3,4]. Consequently, the adoption rate of GenAI among university students has risen sharply [5].

While AI enhances student efficiency, it also presents risks of misuse. For instance, AI-assisted cheating may undermine critical thinking, creativity, and academic integrity, which in the long term could impair the quality of the workforce and erode societal trust [1]. However, rather than viewing AI as a threat to education, it is better to explore how to properly utilize it [6]. Therefore, it is necessary to adopt the fsQCA method to examine the drivers of students' intention to continue using GenAI from a configuration perspective.

Building on the theoretical framework established by Wolf and Maier, this study investigates GenAI usage by distinguishing between intrinsic and extrinsic motivations, alongside contextual technology characteristics. To understand the drivers of sustained use, we focus on continuance intention, defined as the willingness to continue using a currently used information system, which serves as a proxy for actual continued use behavior [7]. While previous research often under-conceptualized intrinsic motivation merely as enjoyment, this study adopts the Rich Intrinsic Motivation (RIM) framework to capture its complexity. RIM decomposes intrinsic motivation into three distinct components: the intrinsic motivation to accomplish (satisfaction from mastering difficulties), to know (pleasure from learning new things), and to experience stimulation (sensory excitement) [8]. Complementing these is the extrinsic motivational factor of perceived usefulness, where usage is driven by the reinforcing value of outcomes such as enhanced performance or efficiency [9]. Furthermore, given that GenAI represents a disruptive innovation, specific technology characteristics are critical [10,11]. Perceived ease of use reflects the degree to which utilizing the system is free of effort, while perceived novelty captures the user's subjective evaluation of the technology's newness: a significant antecedent of behavioral intention for innovative systems that distinguishes them from traditional tools [12]. These factors do not operate in isolation; rather, they interact in complex configurations to drive high continuance intention.

2.2. Research Framework

Building upon the established framework, our research model investigates the interplay of three distinct groups of antecedents -- intrinsic motivational factors intrinsic motivation to accomplish (InMaccomplish), intrinsic motivation to know (InMknow), intrinsic motivation to experience stimulation (InMstimulation), extrinsic motivational factors -- perceived usefulness (ExMPU), and technology characteristics -- perceived ease of use (TeCPEOU), perceived novelty (TeCNVL). This structure allows for a comprehensive analysis of the drivers behind students' continuance intention to use GenAI.

3. Research Design

This study employed a multi-wave survey and fsQCA to identify the configurations of factors driving high and low continuance intention among university students in their use of GenAI.

3.1. Method

This study adopted a cross-sectional survey design. Data were collected using a structured questionnaire divided into two main parts. The first part gathered demographic information and GenAI usage patterns. The second part measured the core constructs of the research model using established scales adapted to the GenAI context in education. All items, except demographics, were measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree).

3.2. Data Collection and Sample

Data were collected via an online survey platform Wenjuanxing in September 2025. Participation was voluntary and anonymous. To qualify, participants needed to be currently enrolled in a higher education institution and have prior experience using generative AI tools for academic purposes. A total of 260 responses were received. After removing incomplete and inconsistent responses (e.g., straight-lining, reverse scoring), 238 valid questionnaires were retained for analysis, resulting in an effective response rate of 91.5%. The demographic profile and GenAI usage characteristics of the sample are presented in Table 1.

Table 1. Demographics of 238 survey participants.

Gender (in Percent)	Grade Level (in Percent)	Most Used GenAI Tools (in Percent)	Learning Activities with GenAI (in Percent)	First Exposure Pathway to GenAI (in Percent)
Male 56.7 Female 43.2	Year 1 25.2 Year 2 25.2 Year 3 28.6 Year 4 21.0	Doubao 92.4 DeepSeek 87.4 Kimi 32.4 ChatGPT 13.0 BaiduERNIE 9.2 Xunfei Xinghuo 8.4 Others <5.0each	Writing texts 84.4 Integrating info 82.7 Translation 79.4 Preparing exams 58.0 Drawing/video 45.4 Programming/data 35.4 Other activities 5.04	Social media 44.5 Self-exploration 19.0 Peers 18.1 Course 14.3 News 4.2 Others 0

Note: Percentages exceed 100% because participants were allowed to select multiple options.

As shown in Table 1, the study collected data from 238 survey participants. The demographic profile reveals a gender distribution of 56.7% male and 43.2% female. Participants were distributed across grade levels: Year 1 (25.2%), Year 2 (25.2%), Year 3 (28.6%), and Year 4 (21.0%). The most frequently used GenAI tools were Doubao (92.4%) and DeepSeek (87.4%), which are leading Large Language Models (LLMs) in China, followed by Kimi (32.4%) and ChatGPT (13.0%). In terms of usage, students primarily utilized GenAI for writing texts (84.4%), integrating information (82.7%), and translation (79.4%)

3.3. Measurement Items

The present survey was constructed based on established measures from prior research; a full listing of all survey items can be found in the Appendix (Table A). The questionnaire incorporated InMaccomplish (four items), InMknow and InMstimulation (each with three items), and ExMPU (six items). Continuance intention was assessed using three items, one of which was reverse-scored. To address the fact that GenAI is a comparatively novel technology for university students, we measured TeCPEOU with six items and TeCNVL with three items. All measures were adapted to the GenAI context; instruments originally developed in everyday-life settings were modified to reflect academic tasks. For instance, "Using ChatGPT enables me to accomplish tasks more quickly." was reworded as "Using GenAI enables me to accomplish my academic tasks more quickly." (the first item of ExMPU). Responses to all items were recorded on a seven-point Likert scale.A pilot test with 30 students confirmed the clarity and face validity of the questionnaire.

3.4. Data Analysis Using FsQCA

FsQCA as an asymmetrical modeling approach estimating different combinations of the measured variables in line with the logical tenets of complexity theory [13]. In this analysis, independent variables are termed conditions and dependent variables outcomes. The method employs fuzzy-set membership, meaning both conditions and outcomes are measured on a continuous scale from 0 (no membership/agreement) to 1 (full membership/agreement).

Calibration. The questionnaire employed a seven-point Likert scale, with the 5th percentile set as the threshold for full non-membership, the 50th percentile for the cross-over point, and the 95th percentile for full membership in the questionnaire data (Table 2). Since fsQCA cannot operate with exact values of .50, we modified this value to .49999 for inclusion in the analysis.

Table 2. Calibration of anchor points for conditions and results.

	Full Membership	Cross-over Point	Full non-Membership
Continuance	7	5	3.5
InMaccomplish	7	5	3
InMknow	7	5.33	3
InMstimulation	7	5	3
ExMPU	7	5.5	4
TeCPUEOU	6.71	5	3.43
TeCNVL	7	5	4

Analysis for sufficient configurations. First, a truth table was constructed, representing all $2^6 = 64$ possible logical combinations of the six conditional constructs under study. This initial table was then refined by applying a frequency threshold of 3 to mitigate potential bias from rarely observed configurations; only combinations evidenced in at least three participant datasets were retained for subsequent analysis. This step aligns with recommendations for samples exceeding 150 cases [14]. Subsequently, a raw consistency threshold of .85 was applied to ensure robust causal relationships [15]. Finally, to avoid configurations that simultaneously account for both high and low outcomes, a proportional reduction in inconsistency (PRI) threshold was set at 0.75 [16].

3.5. Results

3.5.1. Reliability and Validity

Table 3 presents the descriptive statistics and reliability measures. The Cronbach's alpha (CA) for all constructs ranged from 0.90 to 0.92, exceeding the 0.7 threshold, indicating high internal consistency. The means suggest high levels of perceived usefulness (M=5.34) and novelty (M=5.24).

Table 3. Descriptive statistical analysis results of each condition.

Constructs			M	SD	CA
1	Intrinsic motivational factors	Intrinsic motivation to accomplish	4.93	1.11	.90
2		Intrinsic motivation to know	5.15	1.20	.90
3		Intrinsic motivation to experience stimulation	4.85	1.16	.90

4	Extrinsic motivational factor	Perceived usefulness	5.34	0.89	.90
5	Technology characteristics	Perceived ease of use	4.99	0.98	.91
6		Perceived novelty	5.24	1.06	.90
7	Continuance intention		5.09	1.02	.92

Note: M = mean, SD = standard deviation, CA = Cronbach's α.

3.5.2. Necessary Condition Analysis

Table 4 details the necessary condition analysis. A condition is typically considered "necessary" if consistency exceeds 0.9. The results show that no single factor achieved a consistency score above 0.9 for high continuance intention (the highest was TecNVL at 0.825) and low continuance intention (the highest was ~ExMPU at 0.856). This indicates that no single motivational or technological factor is solely responsible for GenAI adoption; rather, it is the combination of factors that matters.

Table 4. Necessary condition Analysis.

	High continuance Intention		**Low Continuance Intention**	
	Consistency	Coverage	Consistency	Coverage
InMaccomplish	0.780	0.820	0.541	0.546
~InMaccomplish	0.568	0.563	0.821	0.782
InMknow	0.772	0.797	0.541	0.536
~InMknow	0.550	0.555	0.795	0.770
InMstimulation	0.771	0.836	0.522	0.544
~InMstimulation	0.580	0.558	0.843	0.779
ExMPU	0.759	0.846	0.473	0.507
~ExMPU	0.557	0.524	0.856	0.773
TecPUEOU	0.767	0.802	0.544	0.547
~TecPUEOU	0.567	0.564	0.803	0.768
TecNVL	0.825	0.803	0.540	0.505
~TecNVL	0.491	0.526	0.789	0.813

Note: The tilde (~) indicates low-level conditions.

3.5.3. Sufficient Configurations

The fsQCA analysis identified four distinct configurations that lead to high continuance intention. We assessed the overall quality of these solutions based on their coverage and consistency. The overall solution consistency is 0.877, and the solution coverage is 0.691, indicating high explanatory power for the model. The specific configurations are described below (Table 5):

Table 5. Sufficient configurations for high continuance intention.

	1	**2**	**3**	**4**
InMaccomplish	●		•	●
InMknow		●	⊗	⊗
InMstimulation	●	•	⊗	⊗
ExMPU	●	●	⊗	●
TeCPUEOU	•	●	⊗	⊗
TeCNVL	●	●	⊗	•
Consistency	0.949	0.946	0.819	0.936

Raw Coverage	0.552	0.553	0.304	0.270
Unique Coverage	0.017	0.020	0.080	0.021
Solution coverage	0.691			
Solution consistency	0.877			

Note: ● indicates the presence of a core condition; · indicates the presence of a peripheral condition; ⨂ indicates the absence of a core condition; ⊗ indicates the absence of a peripheral condition; Blank spaces indicate a "don't care" condition (the condition may be either present or absent).

Configuration 1: Hedonic-Mastery Driven The first sufficient configuration describes students driven by a comprehensive set of positive factors. These users are motivated by the intrinsic motivation to accomplish and to experience stimulation, combined with high perceived usefulness, ease of use, and novelty. This group represents "happy achievers" who find the tool not only effective and easy to use but also enjoyable and satisfying to master.

Configuration 2: Hedonic-Knowledge Driven The second configuration represents users similar to the first group regarding technology perceptions but with a different motivational focus. These individuals are driven by the intrinsic motivation to know rather than to accomplish, alongside stimulation, perceived usefulness, ease of use, and novelty. They are "curious explorers" who sustain their usage because they enjoy learning new concepts and the smooth interaction with the technology, prioritizing curiosity over task mastery.

Configuration 3: Pure Mastery Driven The third configuration reveals a unique and counter-intuitive pathway. These users exhibit high intrinsic motivation to accomplish despite the absence of intrinsic motivation to know or stimulation, and notably, despite perceiving the tool as lacking usefulness, ease of use, and novelty. This suggests a "conqueror" mentality where the user persists in using GenAI solely for the personal satisfaction of overcoming the difficulties associated with a challenging, unpolished, or seemingly useless tool.

Configuration 4: Utilitarian-Striving Driven The fourth configuration outlines a pragmatic user group. These students are driven by intrinsic motivation to accomplish, perceived usefulness, and perceived novelty, but they persist despite the absence of ease of use and intrinsic enjoyment (knowledge and stimulation). This characterizes "determined strivers" who recognize the newness and utility of the tool for solving problems and are willing to endure a difficult and boring user experience to achieve their academic goals.

4. Discussion

4.1. Theoretical Implications

This study extends the understanding of technology adoption in education by integrating the Rich Intrinsic Motivation (RIM) framework with fsQCA. Unlike variance-based approaches that seek a "one-size-fits-all" solution, our findings reveal that high continuance intention is equifinal-driven by four distinct pathways [17].

A particularly novel finding is the "Conquerors" profile (Configuration 3). These students persist in using GenAI despite perceiving it as lacking usefulness, ease of use, or novelty. This counter-intuitive behavior challenges traditional adoption models like TAM, which rely heavily on perceived usefulness. It suggests that for this subset of learners, the motivation extends beyond intrinsic mastery to a prevention-focused coping strategy [18]. Driven by the Fear of Missing Out (FOMO) on emerging AI competencies, these students persist in "taming" the complex technology-despite its current flaws-to mitigate the anxiety of future obsolescence, viewing proficiency as a survival skill rather than a source of immediate utility or enjoyment.

4.2. Practical Implications

Our findings suggest that higher education institutions should adopt differentiated strategies to sustain student engagement effectively:

For the majority ("Happy Achievers" and "Curious Explorers"): Educators should focus on reducing friction by enhancing the ease of use and highlighting the practical utility of GenAI in coursework.

For the niche groups ("Conquerors" and "Determined Strivers"): Instructors can design advanced "prompt engineering" challenges that leverage their desire for mastery and novelty, transforming the tool's complexity into a learning opportunity.

4.3. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design captures perceptions at a single point in time. Given the rapid iteration of LLMs like DeepSeek and Doubao, longitudinal studies are needed to track how "novelty" effects fade over time. Second, the sample is specific to Chinese higher education, where native LLMs dominate the market; future research should validate these configurations in other cultural contexts. Finally, future studies should corroborate self-reported data with objective system logs to reduce subjective bias.

5. Conclusion

This study utilized fsQCA to unravel the complex causal patterns driving university students' continuance intention regarding GenAI. We identified four distinct user profiles: "Happy Achievers," "Curious Explorers," "Conquerors," and "Determined Strivers." These configurations demonstrate that GenAI adoption is multifaceted, driven by varying combinations of hedonic, utilitarian, and mastery-based motivations. By acknowledging these diverse pathways, stakeholders can foster a more sustainable and effective integration of AI in higher education.

Funding: Research on the Innovation of MICE-related Courses Empowered by Generative Artificial Intelligence: A 2023 Teaching Reform Project at the School-Level of Swan College, Central South University of Forestry and Technology

Appendix A:

List of survey items:

Construct.	Items
InMaccomplish	1. I use GenAI for academic tasks because I feel personal satisfaction when mastering difficult skills.
	2. I use GenAI for the pleasure I feel when it helps me improve my academic weaknesses.
	3. I use GenAI for the satisfaction I experience when perfecting how I use it for assignments and projects.
	4. I use GenAI for the satisfaction I feel when overcoming challenging academic problems with its help.
InMknow	1. I use GenAI for the pleasure it gives me to learn more about how it works and its academic applications.
	2. I use GenAI for the pleasure I feel while discovering new information and concepts relevant to my studies.
	3. I use GenAI for the pleasure of developing new academic or research relevant skills.
InMstimulation	1. I find using GenAI to complete my academic work enjoyable.
	2. The actual process of using GenAI for my studies is pleasant.
	3. I have fun using GenAI for my coursework.

ExMpu	1. Using GenAI enables me to accomplish my academic tasks more quickly. 2. Using GenAI improves my performance on assignments and in my courses. 3. Using GenAI increases my academic productivity. 4. Using GenAI enhances my effectiveness as a student. 5. Using GenAI makes completing my academic work easier. 6. Overall, I find GenAI useful for my studies.
TeCpeou	1. Learning to use GenAI for my academic needs is easy for me. 2. I find it easy to get GenAI to help me achieve my specific academic goals. 3. My interaction with GenAI for schoolwork is clear and understandable. 4. GenAI is flexible to interact with for different types of academic tasks. 5. It would be easy for me to become skillful at using GenAI for my studies. 6. Overall, I find GenAI easy to use for academic purposes.
TeCnvl	1. I find using GenAI for my academic tasks to be a novel experience. 2. Using GenAI for my studies feels new and refreshing. 3. GenAI represents a neat and novel way of engaging with technology for learning.
Continuance Intention	1. I intend to continue using GenAI for my academic work rather than stop using it. 2. I intend to continue using GenAI rather than use alternative methods for similar academic tasks. 3. If I could, I would not like to discontinue my use of GenAI for my studies.

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