The International Journal of Management Education 22 (2024) 101085

Contents lists available at ScienceDirect

The International Journal of Management Education

journal homepage: www.elsevier.com/locate/ijme

How can digital innovation capabilities of Chinese college students be cultivated?

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ARTICLE INFO

Keywords:
Digital innovation capabilities
Innovation education
University talent cultivation

ABSTRACT

This study employs the competency theory model and utilizes Necessary Condition Analysis (NCA) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) to analyze data from 71 excellent universities in mainland China, which host national-level innovation and entrepreneurship colleges and education practice bases. The research investigates how various elements combine to impact the digital innovation capabilities of college students. The study identifies three configurations that lead to high digital innovation capabilities among students and categorizes them into three modes: the capability-motivation combination mode, the internal-external linkage mode, and the capability-willingness combination mode. The findings provide valuable insights for universities in cultivating digital innovation talent.

1. Introduction

Digital innovation stands as a pivotal engine for economic growth (Bansal et al., 2023; Kroh et al., 2024). With the widespread adoption of emerging technologies such as big data, artificial intelligence, blockchain, and the Internet of Things, various sectors are experiencing profound digital transformation (Chen & Shu, 2021), reshaping the demands of the labor market (Dengler & Matthes, 2018). As the vanguard of the future workforce, college students must actively develop their employability skills to meet the evolving market demands and thrive in the complex, dynamic landscape of digital employment (Kopackova et al., 2024). Among these employability skills, digital innovation capability has emerged as a core competence essential for career success in the digital era (Van Laar et al., 2017). Consequently, cultivating college students' digital innovation capabilities is now a key priority in higher education, as it directly enhances their employability and equips them to navigate future job markets more effectively (Jackson, 2019; Leal Filho et al., 2024; Santoveña-Casal & López, 2024).

Digital innovation capability represents a burgeoning concept within academia, addressing the digital upgrade of organizational innovation capabilities in the context of digital transformation (Annarelli et al., 2021). Annarelli et al., (2021) were the first to introduce this notion in the study of digital capabilities, defining it as the capacity for innovation specifically related to digital technologies. This capability encompasses not only the mastery of technology but also a keen insight into the evolution of digital advancements, alongside the creative application of these technologies to products, services, and business models. It relies on

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https://doi.org/10.1016/j.ijme.2024.101085
Received 3 September 2024; Received in revised form 30 October 2024; Accepted 6 November 2024
Available online 15 November 2024
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individuals' technical skills while simultaneously necessitating support from creative thinking and interdisciplinary knowledge (Fichman et al., 2014; Mann et al., 2019). In a globalized world, a nation's technological innovation level significantly influences its global standing (Fang & Liu, 2024; Zhang et al., 2024). College students, as future researchers and technical experts, can greatly enhance national innovation through their digital capabilities (Helmer & Rossano-Rivero, 2022; Kaputa et al., 2022). Furthermore, by mastering digital technologies, these students can address societal challenges and contribute to areas like smart city development, healthcare, and environmental sustainability (Barra et al., 2024; Claro et al., 2024). In education, enhancing students' digital innovation skills can drive reform by utilizing online education, virtual reality, and AI tutoring to provide personalized learning experiences, thus promoting equity and quality improvement (Chen & Xiao, 2024; Helmer & Rossano-Rivero, 2022; Sakellari et al., 2024).

However, existing research reveals three main deficiencies. First, Most studies tend to focus on specific innovation entities, such as governments, enterprises, and higher education institutions, and analyze how certain external factors—like policy support, institutional resources, social resources, technological infrastructure, and cultural context—affect students' digital innovation capabilities (Edu et al., 2020; Okunlaya et al., 2022; Ramdani et al., 2022; Vicente et al., 2020; Wang & Fu, 2023). This perspective fails to account for the complexity involved in developing these capabilities, which are shaped by a network of interconnected and mutually influencing factors, including essential internal attributes like individual competencies (Kohli & Melville, 2019; Mohamed Hashim et al., 2022; Vicente et al., 2020). Second, there is a lack of investigation into how different universities differentially affect students' digital innovation capabilities, neglecting institutional heterogeneity (Huang, 2021). Third, in the realm of research methodologies, the majority of studies investigating university students' digital innovation capabilities predominantly employ either singular qualitative approaches (Lanford et al., 2019) or exclusively quantitative methods (Jackson, 2019; Mann et al., 2019). This reliance on a singular methodological framework, or the utilization of small sample quantitative studies (Agélii Genlott et al., 2019; Lopez-Fernandez & Rodriguez-Illera, 2009), raises concerns regarding the generalizability of their findings. Therefore, this study aims to make the following contributions:

This study explores pathways to enhance college students' digital innovation capabilities under varying conditions of higher education institutions, drawing on multi-factor co-evolution and the competency theory of complementary advantages. The research addresses the following questions:

RQ1: What individual factors influence students' digital innovation capabilities?
RQ2: How can universities tailor strategies to enhance digital innovation based on their unique conditions?

To address these questions, the study examines 71 national-level innovation and entrepreneurship colleges and education practice bases at leading universities in mainland China. Utilizing the competency theory model's four dimensions, the research identifies factors that enhance students' digital innovation capabilities. It employs Necessary Condition Analysis (NCA) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) methods to analyze the configurations of knowledge, skills, traits, and motivation. Unlike traditional regression methods that focus on the "net effect" of individual variables, QCA is based on configurational theory and addresses the complex causes of outcome variables through the interplay of multiple factors, providing a comprehensive explanation (Ragin, 2008). QCA is effective with small sample sizes and adept at handling asymmetric causal relationships, overcoming the methodological limitations of previous studies.

2. Theoretical framework

2.1. Competency theory

The theory of competence, proposed by McClelland (1973), posits that individuals must possess specific key competencies and traits to achieve effective performance in their respective roles. He challenges the validity of traditional intelligence assessments and academic achievements, arguing that outstanding performance in the workplace is contingent upon deeper personal characteristics. These attributes encompass not only knowledge and skills but also encompass traits and motivations. Spencer and Spencer (2008) expanded this theory with the competency iceberg model, distinguishing between explicit competencies (e.g., knowledge and skills) and implicit competencies (e.g., motivation and traits). In education, competency-oriented reforms focus on developing students' comprehensive abilities to enhance their adaptability and competitiveness in real-world environments (Lifen et al., 2023).

Digital innovation capability refers to an individual's ability to leverage digital technologies for innovation within a digital context (Helmer & Rossano-Rivero, 2022). This capability encompasses technical skills such as programming and data analysis, alongside broader qualities such as innovative thinking, problem-solving skills, and collaboration abilities (Helmer & Rossano-Rivero, 2022). Developing digital innovation capability is crucial for addressing the evolving needs of an information-driven society.

According to competency theory, digital innovation capability includes both technical knowledge and implicit competencies like innovative thinking and motivation (Yang & Ren, 2024). A competency-oriented educational model emphasizes practical application, enhancing students' digital innovation capabilities through project-based learning and interdisciplinary collaboration. This approach acknowledges individual differences and advocates for tailored teaching based on students' abilities. To effectively cultivate college students' digital innovation capabilities, it is essential to create personalized development paths that align with their interests and strengths, fostering the growth of their unique talents.

2.2. Connectivism learning theory

Connectivism, a learning theory proposed by George Siemens, posits that learning is profoundly influenced by the technologies and communications of the digital age. It represents an emergent paradigm that emphasizes networking. Siemens argues that knowledge resides within the connections enabled by digital technology, and learners acquire new knowledge and skills through the continuous expansion of nodes and links (Thoma et al., 2023). This theory particularly highlights the interactivity between learners and digital information, asserting that learning is founded on a diverse and dynamic flow of information, which can be effectively expanded and connected through network technologies(Clarà & Barberà, 2014). Students autonomously search for, select, and analyze digital resources to broaden their knowledge networks, thereby enhancing their motivation and creativity. Furthermore, connectivism underscores the social nature of learning; students utilize various digital tools, such as online collaboration platforms and shared documents, to develop projects within team settings, thereby strengthening their digital innovation capabilities (Dziubaniuk et al., 2023).

Based on the integration of Competency Theory and Connectivism Learning Theory, the theoretical framework has been developed, as shown in Fig. 1.

2.3. Knowledge and college students' digital innovation capability

The investigation into the role of knowledge in enhancing university students' digital innovation capabilities has garnered significant attention and in-depth exploration in recent years (Al-Samarraie & Saeed, 2018; Eid & Al-Jabri, 2016). Two critical dimensions influencing students' digital innovation skills are curricular knowledge and textbook knowledge (Timotheou et al., 2023). Curricular knowledge encompasses the subject matter and professional skills imparted through formal educational systems, providing students with a theoretical foundation and practical guidance essential for comprehending and applying contemporary digital technologies and innovative methodologies. Its systematic and cutting-edge nature is pivotal for augmenting students' digital competencies (Zhou et al., 1996; Luckett, 2009). A high-quality curriculum design should integrate the latest technological trends and theoretical advancements, enabling students to stay abreast of industry developments and master core competencies in digital innovation (Madzík et al., 2024). Conversely, textbook knowledge refers to the specific information acquired through textbooks and other learning resources, often comprising case studies, practical guides, and recent technological advancements. This knowledge equips students to apply theoretical insights in real-world contexts, fostering their innovative thinking and problem-solving abilities. Its applicability and practicality play a vital role in nurturing students' digital innovation skills (Bakken & Andersson-Bakken, 2021). Modern textbooks frequently incorporate a wealth of real-life cases and projects; through hands-on activities and simulated experiments, students can better grasp and master intricate digital technologies and innovative methods (Kopackova, 2024). Furthermore, the proliferation of open educational resources and online learning platforms offers students more flexible and diverse learning pathways, further enhancing their autonomy and digital innovation capabilities (Li, Yang, et al., 2024; Mishra, 2017). In summary, both curricular knowledge and textbook knowledge possess distinctive yet complementary roles in fostering university students' digital innovation abilities, with systematic curricular knowledge providing a theoretical framework and practice-oriented textbook knowledge enriching students' application skills and creative thinking. Based on these observations, this study proposes the following hypothesis:

H1. Knowledge influences college students' digital innovation capability.

2.4. Skills and college students' digital innovation capability

The definition of digital skills can typically be traced back to Gilster (1997), who characterized them as the ability to comprehend and gather information from a variety of formats and diverse sources within an information environment. By adeptly utilizing search engines, databases, and other online resources, students can swiftly locate the most current information and data pertinent to their research topics (Lavidas et al., 2020). This efficient means of information acquisition provides students with a wealth of materials and inspiration, fostering the emergence and development of innovative thinking (Garay et al., 2017). In today's rapidly evolving digital

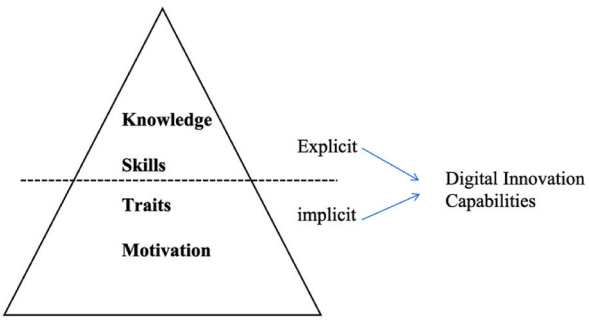

Fig. 1. Theoretical model.

landscape, digital innovation frequently hinges on the prompt understanding and application of emerging technologies; proficient mastery of data analysis tools enables students to uncover the latent value within data, thereby supporting the formulation of more forward-looking innovative solutions (Mariani & Nambisan, 2021). Moreover, digital skills enhance students' capabilities for online collaboration, allowing them to engage in cross-regional and interdisciplinary teamwork through platforms such as cloud computing and collaborative software, which catalyze the generation of innovative ideas through broader exchanges (Bampasidou et al., 2024). However, in an era inundated with digital information, the authenticity and reliability of that information become paramount concerns. Students must develop critical thinking and metacognitive skills to discern the sources and quality of information, employing cross-validation and consulting authoritative materials to ensure accuracy (Audrin et al., 2024). Metacognitive abilities facilitate a more rational and strategic planning and implementation of innovative projects within the digital innovation process, encouraging reflection not only on current outcomes but also on long-term sustainability (Wang et al., 2023; Wang et al., 2023). Students with strong metacognitive skills tend to prioritize the adaptability of solutions and the potential for future improvements, ensuring that innovations evolve and optimize over time (Urban & Urban, 2024). Thus, while digital skills provide the technological foundation for innovation, metacognitive abilities enable deep reflection and strategic adjustments throughout the innovation process; their synergistic interaction effectively enhances the digital innovation capabilities of university students. Based on these insights, this study proposes the following hypothesis:

H2. Skills influences college students' digital innovation capability.

2.5. Traits and college students' digital innovation capability

Traits play a pivotal role in an individual's successful execution of tasks, with technological awareness and innovation willingness identified as two crucial characteristics (Huang et al., 2023; Lingmont & Alexiou, 2020; Top et al., 2011). Technological awareness refers to an individual's sensitivity to and understanding of technological advancements and their potential applications. Students endowed with high levels of technological awareness can more swiftly identify and leverage emerging technologies—an ability that is particularly significant in the realms of digital tool utilization, data analysis, and interdisciplinary integration (Lingmont & Alexiou, 2020). Research indicates that an enhancement in technological awareness enables students to employ digital technologies more flexibly when confronted with complex tasks, thereby augmenting their capacity for creative problem-solving (Moravec et al., 2024). This awareness transcends mere recognition of technology; it encompasses a profound understanding of how technology drives innovation, thereby allowing individuals to remain competitive in a rapidly evolving digital landscape (Choi-Lundberg et al., 2023). Conversely, innovation willingness reflects an individual's proactive attitude toward seeking novel ideas and methods in the face of uncertainty. Students with high innovation willingness are typically more inclined to experiment with new approaches, engage in collaborative efforts, and embrace challenges. This enthusiasm can significantly enhance their performance in practical projects, making them more likely to take initiative in digital innovation activities (Alshebami, 2021). Based on these observations, this study proposes the following hypothesis:

H3. Traits influences college students' digital innovation capability.

2.6. Motivation and college students' digital innovation capability

In recent years, the role of innovation motivation in the development of digital innovation capabilities has increasingly drawn scholarly attention (Stumbrienė et al., 2024). According to self-determination theory, individuals' innovation motivation can be categorized into intrinsic and extrinsic forms, each capable of stimulating university students' digital innovation potential in distinct ways (Chiu et al., 2024). Research indicates that intrinsic motivations, such as curiosity, a desire for discovery, and a sense of achievement, can encourage students to actively explore new knowledge and technologies, thereby exhibiting higher levels of creativity and problem-solving skills in the digital innovation process (King et al., 2024). Conversely, extrinsic motivations, including reward systems and career advancement opportunities, have also been shown to foster engagement in digital innovation activities; however, their effectiveness often depends on students' perceptions and acceptance of these external factors (El-Bassiouny & El-Naggar, 2023). Existing studies underscore that the effective integration of intrinsic and extrinsic motivations is crucial in unlocking students' innovation potential. When extrinsic motivators align with students' self-value systems, their driving force is amplified, allowing students to pursue not only external rewards but also engage in deeper learning and practical application driven by intrinsic motivations within the digital innovation process (Park & Kang, 2016). Based on these insights, this study proposes the following hypothesis:

H4. Motivation influences college students' digital innovation capability.

3. Methodology

3.1. Method selection

The questionnaire utilized in this study was part of a sampling survey conducted across China. The study was conducted by publicly recruiting researchers at various universities and randomly selecting samples from students across different grade levels for an online survey. The survey was carried out in three phases: the first phase involved the development of a 5-point Likert scale, spanning from

June 2022 to August 2023; the second phase consisted of pilot testing and revision, from August 2023 to October 2023; and the third phase entailed the formal survey and data collection, scheduled from November 2023 to January 2024. It investigated 71 national-level innovation and entrepreneurship colleges and educational practice bases located within premier universities in mainland China, encompassing 14 disciplines and spanning 27 provinces, autonomous regions, and municipalities. A total of 13,500 questionnaires were collected, and after excluding 710 invalid responses due to excessively short completion times or incorrect institutional names, 12,790 valid questionnaires remained, yielding an impressive response rate of 94.7%. This study employs fsQCA analysis to examine the configurations that foster high levels of digital innovation capabilities among university students, demonstrating a commendable fit. fsQCA is specifically designed to address the complexities of causal relationships and the intricacies of multiple path dependencies. Its inherent advantages facilitate the elucidation of the causal complexity underlying the development of digital innovation capabilities, aspects that traditional statistical analysis methods typically overlook (Meyer et al., 1993; Fiss, 2011). First, the fsQCA methodology synergizes fuzzy set theory with comparative analysis, effectively bridging the realms of case studies and quantitative analysis. By systematically comparing multiple variables, it unveils the multifaceted causal relationships among them, enabling researchers to discern effective causal pathways amidst uncertainty and complexity. This capability is instrumental in exploring the concurrent relationships between various conditions(López-Carril et al., 2024; Vis & Dul, 2018). Second, the fsQCA approach is adept at identifying diverse causal pathways that lead to the enhancement of digital innovation capabilities among university students, exemplifying the notion that different routes can yield similar outcomes(Liu & Zhang, 2022). Various conditions can culminate in multiple configurations, each of which has the potential to foster digital innovation capabilities. Lastly, fsQCA infers causal relationships between conditions and outcomes through set relations rather than mere correlations, thereby enriching the understanding of the causal mechanisms at play(Pappas & Woodside, 2021).

Before conducting the sufficiency analysis using fsQCA, this study employed R software to perform necessity condition analysis (NCA). NCA aims to identify and validate the key conditions required for a specific outcome, centering on the concept of "necessary conditions" and emphasizing that the presence of certain factors is essential for achieving particular results. Unlike the necessity condition tests in the fsQCA methodology, NCA not only determines whether conditions are necessary for the emergence of outcomes but also quantifies their contribution through ceiling regression (CR) and ceiling envelopment analysis (CE), thereby generating corresponding functions(Bu et al., 2023; Dul, 2016). Furthermore, NCA facilitates bottleneck level analysis, identifying the specific levels of necessary and other antecedent conditions required to attain varying outcome levels, thus addressing the shortcomings of fsQCA in necessity analysis. Consequently, this study combines the fsQCA and NCA methods to fully leverage the strengths of both approaches in conducting a configurational analysis of the factors influencing college students' digital innovation capabilities(Vis & Dul, 2018).

3.2. Data

The questionnaire used in this study was designed by the research team of a project funded by the Ministry of Education of China. Based on previous research, this study selected course knowledge, textbook knowledge, digital information collection ability, technological awareness, metacognition, innovation willingness, and innovation motivation as antecedent conditions. Drawing on competency theory, these factors were categorized into four dimensions: knowledge, skills, traits, and motivation. The specific indicators are explained in **Table A**.

4. Results

4.1. Calibration and measurement

This study uses fsQCA to analyze the seven variables of course knowledge, textbook knowledge, digital information collection skills, technological awareness, metacognition, innovation willingness, and innovation motivation. In fsQCA, calibration is the process of assigning cases to set membership, with membership scores ranging between 0 and 1 (Ragin, 2008). Researchers can perform direct or indirect calibration of data (Pappas & Woodside, 2021). Direct calibration ensures that the results are verifiable (Pappas & Woodside, 2021). Therefore, following the literature (Tóth et al., 2015; Romero-Castro et al., 2022), this study uses three

Table 1
Calibration criteria and descriptive statistics.

		Variable	Calibration anchors		
			Fully in(75%)	Crossover(50%)	Fully out(25%)
Outcome variable		Digital Innovation Capability	3.760506588	3.580399259	3.412085385
Antecedent variable	Knowledge	Course Knowledge	4.48832693	4.333333333	4.059803922
		Textbook Knowledge	4.297715895	4.128682555	3.947619048
	Skills	Digital Information Collection Ability	4.055738598	3.957342996	3.771960183
		Metacognitive Ability	4.408005211	4.258292712	4.09507722
	Traits	Technological Awareness	4.693643461	4.609507262	4.501373626
		Innovation Willingness	4.174836601	4.020139839	3.882213698
	Motivation	Innovation Motivation	4.217700779	4.034916184	3.840902443

thresholds—0.75, 0.5, and 0.25—for direct calibration. The full membership points of all seven antecedent variables and the outcome variable are set at the top 75% of the case data, the intersection points at the middle 50%, and the complete non-membership points at the bottom 25% of the case data. For details on anchor point calibration, refer to Table 1.

4.2. Necessary Condition Analysis (NCA)

According to Ragin (2008), a condition is termed a necessary condition when it is always present whenever the outcome occurs. Dul et al. (2016) stipulate that, within NCA, necessary conditions must meet two criteria: the effect size (d-value) must exceed 0.1, and it must demonstrate significance in the Monte Carlo simulation permutation test (p-value <0.01). The effect size (d-value) represents the minimum level of necessary conditions required to produce a specific outcome, with values ranging from 0 to 1, where the lower threshold is set at 0.1. A value approaching 1 indicates a greater effect size. Ceiling regression (CR) and ceiling envelopment analysis (CE) can be utilized to analyze the corresponding effect sizes.

Table 2 shows that the Monte Carlo permutation test P-values for course knowledge, technological awareness, metacognition, innovation willingness, and innovation motivation are all above 0.01, with effect sizes under 0.1. This means these variables are not necessary conditions for the outcome. Although the P-value for CR of textbook knowledge is 0, indicating significance, its effect size is 0, disqualifying it as a necessary condition. For digital information collection ability, CE and CR both have P-values of 0 but effect sizes of 0.018 and 0.026, respectively, which do not meet the criteria. In NCA, the effect size is also referred to as the bottleneck level. Bottleneck level analysis examines the required level of antecedent conditions when the maximum observed range of outcomes reaches a specific threshold (Dul et al., 2016). To attain a 90% level of digital innovation capability, a digital information collection capability level of 8.6% and a metacognitive ability level of 0.5% are necessary. If the goal is to elevate the digital innovation capability to 100%, the required levels for digital information collection capability and metacognitive ability must increase to 13.8% and 1%, respectively. Table 3 confirms that none of the seven variables independently fulfill the criteria for being a necessary condition for digital innovation capabilities. Further validation with fsQCA was conducted. Consistency levels, with a 0.9 threshold (Fiss, 2011), were assessed. Table 4 shows that the consistency for individual variables is below 0.9, meaning no single condition is sufficient as a necessary condition for students' digital innovation capabilities. Thus, no single condition alone is necessary for achieving high digital innovation capabilities among college students.

4.3. Sufficiency analysis

This study analyzed the configurations of seven antecedent conditions affecting digital innovation capabilities among college students. Configuration analysis involves two main steps: truth table analysis and standard analysis. To construct the truth table, thresholds for consistency and minimum case frequency are set. According to Ragin (2008), a consistency threshold typically ranges from 0.75 to 0.85. For small sample studies, a minimum case frequency of 1 is often used. In this study, the case frequency was set to 1, the consistency threshold to 0.8, and the proportional reduction in inconsistency (PRI) to 0.7, following Misangyi and Acharya (2014). According to Fiss (2011), this study prioritizes intermediate solutions while also considering parsimonious solutions to identify core conditions. Specifically, conditions that are present in both the intermediate and parsimonious solutions are classified as core conditions, whereas those appearing only in the intermediate solution are categorized as marginal conditions. Different configurations represent distinct combinations of conditions that yield the same outcome. The sufficiency analysis identified three configurations that lead to high digital innovation capabilities among college students. Details of these configurations are presented in Table 5, and the regions covered by the configurations are listed in Table B.

P1: The Capability-Motivation Combination Model. According to Configuration P1, high digital innovation capability can be achieved when there is substantial capacity for digital information collection coupled with motivation and a certain degree of innovative willingness. This can occur even in the absence of technological awareness and despite shortcomings in knowledge.

Table 2
Necessary condition analysis (NCA) result tables.

Variable	Method	Accuracy	Ceiling zone	Scope	Effect size (d)	P-value
Course Knowledge	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Textbook Knowledge	CR	100%	0.000	1	0.000	0.000
	CE	100%	0.000	1	0.000	1.000
Digital Information Collection Ability	CR	97.2%	0.018	1	0.018	0.000
	CE	100%	0.026	1	0.026	0.000
Metacognitive Ability	CR	100%	0.000	1	0.000	0.063
	CE	100%	0.002	1	0.002	0.055
Technological Awareness	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Innovation Willingness	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Innovation Motivation	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000

Note: $0 < d < 0.1$: Low level; $0.1 \leq d < 0.3$: Middle level; $0.3 \leq d < 0.5$: High level; CR: ceiling region; CE: ceiling envelope. $P < 0.01$: Significant.

Table 3
The bottleneck table of digital innovation capability.

Digital Innovation Capability	Course Knowledge	Textbook Knowledge	Digital Information Collection Ability	Metacognitive Ability	Technological Awareness	Innovation Willingness	Innovation Motivation
0	NN	NN	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN	NN	NN
50	NN	NN	NN	NN	NN	NN	NN
60	NN	NN	NN	NN	NN	NN	NN
70	NN	NN	NN	NN	NN	NN	NN
80	NN	NN	3.4	NN	NN	NN	NN
90	NN	NN	8.6	0.5	NN	NN	NN
100	NN	NN	13.8	1.0	NN	NN	NN

Table 4
Necessity test for a single condition.

Conditions	High		Low	
	Consistency	Coverage	Consistency	Coverage
Course Knowledge	0.686	0.682	0.444	0.441
~Course Knowledge	0.438	0.441	0.680	0.684
Textbook Knowledge	0.704	0.704	0.421	0.416
~Textbook Knowledge	0.411	0.415	0.695	0.701
Digital Information Collection Ability	0.803	0.823	0.316	0.323
~Digital Information Collection Ability	0.340	0.332	0.827	0.807
Metacognitive Ability	0.711	0.726	0.383	0.390
~Metacognitive Ability	0.402	0.395	0.730	0.716
Technological Awareness	0.615	0.634	0.463	0.477
~Technological Awareness	0.493	0.480	0.644	0.625
Innovation Willingness	0.797	0.766057	0.360	0.345
~Innovation Willingness	0.319	0.333	0.756	0.788
Innovation Motivation	0.780	0.762	0.360	0.351
~Innovation Motivation	0.335	0.344	0.756	0.774

Metacognitive abilities do not influence the outcome. For college students, strong digital information collection skills and motivation for innovation are crucial conditions in this model. The consistency score for P1 is 94.5%. This model suggests that students with robust digital information collection skills and ample innovative motivation will effectively enhance their digital innovation capabilities.

Fudan University and the China Academy of Art are exemplary institutions that match this model. Specifically, Fudan University has a strong academic foundation in digital technology and information science. The School of Information Science and Technology offers courses in big data, artificial intelligence, and digital technology, fostering students' data processing and information-gathering skills and emphasizing the importance of digital literacy. With a robust ability to collect information in a digital environment, students can quickly and accurately extract relevant information from various digital resources (Marcon & Sehnem, 2024). Additionally, Fudan University has established dedicated innovation platforms, providing students with information on a series of innovation and entrepreneurship competitions. This initiative promotes innovation among students and young faculty, cultivating students' innovation consciousness and supporting various innovation activities through resources and platforms. Innovation motivation can be reflected in a strong internal drive, the desire for personal fulfillment, and the ambition to tackle complex problems. In June 2018, the China Academy of Art founded the Innovation Design College, with the mission of "building design humanity, focusing on art-technology integration, integrating interdisciplinary teaching, and nurturing innovative talents." Its teaching goals emphasize the development of students' abilities in "aesthetic judgment, social perception, technical learning, and innovative breakthroughs." This targeted educational model enhances students' motivation for innovation, encouraging them to break traditional thinking patterns, actively explore new technological applications or solutions, and transform collected information into meaningful, innovative outcomes (Ceipek et al., 2021). Additionally, the academy addresses social issues across culture, lifestyle, and environment in the context of the big data and media age by proposing solutions and theories based on innovative design, stimulating students to engage in social innovation and realize their unique value through digital innovation.

P2: The Internal-External Interaction Model. Configurations P2a and P2b share core conditions, making them equivalent second-order configurations. P2a demonstrates that high digital innovation capability can be achieved with ample course knowledge, robust digital information collection skills, strong metacognitive abilities, substantial innovation willingness, and sufficient innovation

Table 5
Configurations for high digital innovation capability.

Conditions		high			
		P1	P2a	P2b	P3
Knowledge	Course Knowledge	△	●	●	▲
	Textbook Knowledge	△	◎		▲
Skills	Digital Information Collection Ability	●	●	●	●
	Metacognitive Ability		●	●	▲
Traits	Technological Awareness	▲		◎	◎
	Innovation Willingness	◎	●	●	●
Motivation	Innovation Motivation	●	●	●	△
Consistency		0.945133	0.856014	0.870152	0.914573
Raw coverage		0.129051	0.541066	0.429523	0.100999
Unique coverage		0.0477524	0.130688	0.0199778	0.0396781
Overall solution consistency		0.876417			
Overall solution coverage		0.667064			

Note: ● = core causal condition (present); ▲ = core causal condition (absent); ◎ = contributing causal condition (present),△ = contributing causal condition (absent); Blank spaces indicate a "don't care" condition.

motivation, regardless of technological awareness. The consistency score for P2a is 85.6%. This model indicates that students excelling in these areas are likely to effectively stimulate their digital innovation capabilities. P2b shows that high digital innovation capability results from adequate course knowledge, powerful digital information collection skills, strong metacognitive abilities, substantial innovation willingness, and sufficient innovation motivation, regardless of technological awareness. Conversely, when these conditions are met along with a degree of technological awareness, high digital innovation capability will also emerge, with the presence or absence of textbook knowledge not affecting the configuration. The consistency score for P2b is 87%.

For example, Peking University exemplifies this model by providing systematic support in course knowledge, resources, and innovation incentives, creating a comprehensive innovation pathway from theoretical learning to practical application. Students in Peking University recognize for their top-tier capabilities, exhibit outstanding performance in digital information-gathering skills, metacognitive abilities, innovation willingness, and motivation. Additionally, it boasts a vast and deep curriculum spanning sciences, humanities, and engineering, and emphasizes interdisciplinary integration. Through innovative courses and development programs, Peking University provides a solid knowledge base for students. This educational ecosystem not only enhances students' competency across multiple dimensions but also gives them a significant edge in digital innovation capability.

P3: The Capability-Willingness Combination Model. According to Configuration P3, when college students exhibit strong digital information collection capabilities coupled with a pronounced willingness to innovate, their digital innovation capability correspondingly reaches a high level.

Hefei University of Technology exemplifies this model. Specifically, the university has invested in course resources, digital platforms, and innovation practices to create an educational environment where students develop robust digital information skills and a strong inclination for innovation. This demonstrates that when students simultaneously possess strong digital information collection ability and innovation willingness, their performance in digital innovation is significantly stimulated (Chen et al., 2024; Li et al., 2024). Furthermore, this model underscores that digital innovation capability can be more effectively cultivated through a combination of institutional innovation resources and students' innovation motivation. By providing rich course resources, the university prepares students to navigate an uncertain, complex, and ambiguous world (Liu et al., 2023; Wang et al., 2024; Wang et al., 2024). In line with trends in modern technology, multidisciplinary integration, and digitalization, Hefei University of Technology has adapted its curriculum to meet the demand for new engineering talents in the evolving economy. The school has implemented policies that address gaps in course integration, humanities education, and practical skills in engineering, ultimately establishing a comprehensive curriculum structure that includes general education, required and elective courses, foundational subjects, and specialized innovation and entrepreneurship modules. This curriculum shift includes adjustments in course proportions, such as interdisciplinary courses, frontier courses, and innovation-focused content, to build students' digital knowledge and skills. Additionally, the university encourages students to explore data analysis and online information-gathering techniques, fostering innovative thinking in engineering.

4.4. Robustness testing

Common methods for robustness testing include adjusting calibration, modifying consistency thresholds, and adding or removing cases (Greckhamer et al., 2018; Leppänen et al., 2019). In this study, the consistency threshold was raised from 0.8 to 0.85, while the frequency threshold remained at 1, and the Proportional Reduction in Inconsistency (PRI) was set at 0.8. The configurations from the analysis remained consistent, confirming the robustness of the results.

5. Discussion

This study investigates how various factors in competency theory influence college students' digital innovation capabilities. Analysis shows that at least two core conditions are needed to stimulate these capabilities, highlighting the importance of multiple interacting factors. The study identifies three models for promoting digital innovation capabilities: the Capability-Motivation Combination Model, the Internal-External Interaction Model, and the Capability-Willingness Combination Model. These findings offer higher education institutions and researchers insights into enhancing students' digital innovation skills, aiding their preparation for the digital age.

5.1. Theoretical implications

This study offers three key theoretical contributions. **(1) Configurational Perspective:** Unlike previous research that examines the isolated effects of individual factors on digital innovation capability, this study uses a configurational approach to explore how various elements within the competency theory model interact to influence college students' digital innovation capabilities. It identifies three distinct configurations for achieving high levels of digital innovation, thereby providing a deeper understanding of the complex mechanisms at play. **(2) Digital Orientation of Competencies:** This research extends the scope of innovation studies to include digital innovation, examining how digitally-oriented competencies affect college students' digital innovation capabilities. It highlights the role of universities and students in driving digital transformation and contributes to understanding digital innovation in developing countries, using Chinese college students as a representative sample. **(3) Methodological Advancement:** By employing fuzzy-set Qualitative Comparative Analysis (fsQCA), this study enhances the methodological framework for researching digital innovation capabilities. The fsQCA method allows for a nuanced analysis of the interactions between multiple factors, offering a more comprehensive view than traditional empirical methods that focus on marginal net effects.

5.2. Practical implications

This study also offers practical implications, particularly in the realm of management. First, the high level of digital innovation capability among college students results from the synergistic interaction of various elements within the competence theory model. This indicates that universities should adopt a systematic configurational approach when formulating measures to enhance students' digital innovation capabilities, reinforcing the integration and coordination of various elements.

The Capability-Motivation Combination Model. This model underscores the crucial role of integrating digital information collection skills with innovation drive in stimulating university students' digital innovation capabilities. Higher education institutions should enhance digital literacy education by establishing dedicated courses and seminars that teach students advanced techniques for data collection, analysis, and management, thereby cultivating their abilities to process and evaluate information. For instance, Fudan University has taken the lead in this regard by offering the "Digital Intelligence Literacy: Developing New Capabilities in the AI Era" summer training program for outstanding high school students in 2024. This initiative targets talented students with a keen interest in artificial intelligence, big data, digital economy, and the societal applications of information technology, aiming to enhance their knowledge and skills in data intelligence ahead of their peers, while fostering innovative thinking, problem-solving abilities, and technological application skills. Simultaneously, this program encourages students to reflect on and discuss the potential risks associated with the development of data intelligence and the corresponding countermeasures. In conjunction with strengthening digital literacy education, higher education institutions should also focus on stimulating students' intrinsic motivation for innovation within the educational environment. This can be achieved by offering innovative courses and providing opportunities and spaces for autonomous exploration, thereby enhancing students' thirst for knowledge and spirit of inquiry. Such initiatives will enable them to maintain a proactive and engaged approach throughout their learning journey.

The Internal-External Interaction Model. This model emphasizes the significant role of integrating curricular knowledge, digital information collection skills, metacognitive abilities, innovation willingness, and motivation in enhancing digital innovation capabilities. Curriculum design should focus on interdisciplinary integration, encompassing cutting-edge fields such as computer science, data analysis, and artificial intelligence, while also incorporating real-world application scenarios. This approach should offer project-based learning and laboratory practice opportunities, encouraging students to apply digital information collection tools and techniques in practical projects. Additionally, students should be taught how to effectively utilize library resources, databases, and online search tools, which will help them develop skills in information filtering, evaluation, and integration. For instance, Peking University's Yuanpei College, in collaboration with the School of Mathematical Sciences and the School of Computer Science, has launched a major in Data Science and Big Data Technology that responds to the demands of the digital age. This program aims to equip students with a solid foundation in theoretical and professional knowledge, fostering their abilities to analyze and solve problems, as well as to continuously update their knowledge and innovate. Simultaneously, higher education institutions should cultivate a campus culture

that supports innovation, thereby stimulating students' willingness to innovate and their proactive creativity. This can be achieved by providing innovation and entrepreneurship platforms, competitions, and project incubators that encourage interdisciplinary collaboration and creative expression.

The Capability-Willingness Combination Model. This model underscores the vital role of integrating digital information collection skills with innovation willingness in enhancing university students' digital innovation capabilities. While higher education institutions establish digital literacy courses aimed at improving students' skills in data retrieval, information evaluation, and analysis, it is equally important to foster a campus culture that supports digital innovation among students.

For instance, universities can create innovation laboratories and implement mentorship programs, providing essential technical support and equipment, while pairing experienced faculty members with students for personalized guidance and consultation. This approach encourages students to pursue independent innovation projects within the laboratory, facilitating exploration and application of digital technologies. Such initiatives can help students overcome challenges in the innovation process and bolster their self-confidence. A case in point is Hefei University of Technology, which has launched an innovative experimental class within its Electrical Engineering and Automation program. This initiative selects mentors and instructors from the entire college to offer comprehensive one-on-one guidance throughout the learning process. Furthermore, the university collaborates with leading enterprises to establish joint talent cultivation bases, engaging in various technological innovation projects and practical activities that emphasize the development of exceptional innovation capabilities and awareness among aspiring electrical engineers.

5.3. Limitations and future directions

This study has certain limitations. First, regarding research methodology, fsQCA offers dual advantages of qualitative and quantitative analysis, effectively dissecting the interplay of antecedent conditions and aligning with the context wherein university students' digital innovation capabilities emerge from the interplay of multiple factors. However, this study only addresses the static influence of each factor on digital innovation capabilities. Future research could incorporate temporal factors by employing Temporal Qualitative Comparative Analysis (TQCA) to explore stable configurations associated with high and low levels of digital innovation capabilities across a time dimension, enabling a dynamic assessment of these capabilities' development over time. Additionally, the current findings do not indicate the intensity of influence among factors, an area future studies could address through alternative measurement methods. Second, in terms of research variables, this study's framework includes explicit knowledge and skills alongside implicit subjective influences, focusing on the individual university student level. Future research might expand this analytical framework by integrating external factors, such as governmental policies, digital infrastructure, and industry partnerships, to provide a more comprehensive perspective on influences impacting digital innovation. Third, regarding sample selection, data for this study were derived from a survey conducted within China by the author's national project team. The sample's restriction to China and reliance on self-reported survey data may limit generalizability and potentially introduce subjective bias. Expanding the sample to include data from other regions—or even undertaking cross-national comparisons—could provide a broader, more nuanced perspective.

6. Conclusion

This study addresses gaps in the fragmented literature on college students' digital innovation capabilities by proposing a framework that combines competence theory with fsQCA. Previous research has focused on isolated factors like coursework and personality traits, while this study examines seven key factors: course knowledge, textbook knowledge, digital information collection ability, metacognitive ability, technological awareness, innovation willingness, and innovation motivation.

The study identifies three key models for enhancing digital innovation capabilities: (1) Capability-Motivation Combination Model: High innovation capability results from strong digital information collection skills and innovation motivation. Institutions like Fudan University and the China Academy of Art exemplify this model. (2) Internal-External Interaction Model: Effective digital innovation requires a mix of course knowledge, digital information collection skills, metacognitive abilities, innovation willingness, and motivation. Nankai University, Shanghai University of Finance and Economics, and Southeast University illustrate this model. (3) Capability-Willingness Combination Model: Strong digital information collection abilities and a willingness to innovate lead to high digital innovation capabilities. Hefei University of Technology aligns with this model.

While digital information collection ability is crucial, it is not a necessary condition for high innovation capability. This study offers actionable insights and recommendations for higher education institutions to boost students' digital innovation capabilities.

CRediT authorship contribution statement

Yangjie Huang: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition. **Jiali Zhang:** Writing – original draft, Data curation. **Ying Xu:** Writing – review & editing. **Yajing Bu:** Writing – review & editing.

Informed consent

No animal studies are presented in this manuscript.
No human studies are presented in this manuscript.

No potentially identifiable human images or data is presented in this study.
Consent from all research participants was obtained by virtue of survey completion.

Ethical statement

All studies in this manuscript were approved by the ethics committee of the first author's institution, Institute of China Innovation and Entrepreneurship Education of Hangzhou Normal University, and were conducted in accordance with the Declaration of Helsinki.

Funding

Major Projects on Philosophy and Social Sciences of The Ministry of Education "Research on Comprehensively Improving the Quality of Domestic Talent Development under New Circumstances"(NO. 23JZD045).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank the editor and reviewers whose suggestions and comments greatly helped to improve and clarify the manuscript. Yangjie Huang and Yajing Bu are co-corresponding authors.

Appendix

Table A

Conditions	Variable	Measurement
Outcome variable	Digital Innovation Capability	1. I am proficient in using web tools and technologies to develop new projects. 2. I recommend new digital software to others. 3. I excel at producing new digital content.
Antecedent conditions	Course Knowledge	1. Our university offers students a solid foundation in mathematics and science, along with advanced specialized courses. 2. Our university provides high-quality general education courses for students. 3. Our university offers courses that promote personalized development for students.
	Textbook Knowledge	1. The current textbook content aligns with the forefront of technological advancements. 2. The current textbook content aligns with the goal of cultivating talent with innovative thinking abilities. 3. The current textbook content aligns with the needs for personal self-development.
	Digital Information Collection Ability	1. I can utilize various databases and online search methods to collect information. 2. I can obtain relevant information using informal online resources. 3. I can quickly find the digital learning materials I need.
	Technological Awareness	1. I feel proud of our nation's breakthroughs in critical core technologies. 2. I am confident in the current advancements in overcoming bottleneck technologies such as high-end chip manufacturing. 3. I believe universities must support the nation's pursuit of high-level technological self-reliance and strength.
	Metacognitive Ability	1. I collect sufficient data to support my judgment before making decisions. 2. During decision-making, I integrate information and refine ideas through inquiry. 3. In the decision-making process, I review and adjust the methods of analyzing information.
	Innovation Willingness	1. I can create plans to seize opportunities for myself or others, such as more efficient work methods or new approaches to solving societal problems. 2. I can identify new opportunities. 3. I can leverage opportunities to integrate necessary resources.
	Innovation Motivation	1. Even in the face of setbacks, I persevere until I achieve my goals. 2. In research projects, I can effectively address any challenges that arise. 3. Despite being warned of numerous difficulties by others, I continue to pursue my goals.

Table B
Case with a membership score greater than 0.5 in the solution and outcome.

	Configuration	University
High	P1	- China Academy of Art - Fudan University
	P2a	- Northeast Agricultural University - China University of Petroleum (East China)

(*continued on next page*)

Table B (*continued*)

Configuration	University
	- Huazhong Agricultural University
	- Northeastern University
	- Harbin Institute of Technology
	- Northwest A&F University
	- Peking University
	- Nankai University
	- Sichuan University
	- East China University of Science and Technology
	- Nanjing University of Aeronautics and Astronautics
	- Southeast University
	- Nanjing Agricultural University
	- Hebei University of Technology
	- Chongqing University
	- University of Science and Technology Beijing
	- Shanghai University
	- Beijing Jiaotong University
	- South China University of Technology
	- Shanghai University of Finance and Economics
P2b	- Northeast Agricultural University
	- China University of Petroleum (East China)
	- Northeastern University
	- Harbin Institute of Technology
	- Northwest A&F University
	- Nanjing University of Aeronautics and Astronautics
	- Southeast University
	- Nankai University
	- Sichuan University
	- South China Normal University
	- Chongqing University
	- Hebei University of Technology
	- East China University of Science and Technology
	- Shanghai University of Finance and Economics
	- Southwest Petroleum University
P4	- Hefei University of Technology

Data availability

Data will be made available on request.

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