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Identifying dominant and heterogeneous factors influencing students' future capabilities under the digital transformation of higher education: a machine learning approach

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ABSTRACT

In the context of digital transformation of higher education, an in-depth analysis of the key factors influencing students' future capabilities is crucial for optimizing curriculum design and resource allocation. This study combines Self-Determination Theory (SDT) with interpretable machine learning methods, and uses 1,083 valid questionnaires from the German Forum for Digitalization of Higher Education (HFD) from November 2023 to March 2024 as samples to construct and prune the J48 decision tree model to systematically identify the dominant and heterogeneous conditions of students' future capabilities. The results show that the high-frequency use of diversified learning forms is the core driving force for improving students' future capabilities. When the sense of autonomy is insufficient, high-quality learning space and positive evaluation of AI tools can effectively compensate for students' intrinsic motivation. This study provides empirical evidence for educational practitioners and policymakers to cultivate students' adaptability, innovation and interdisciplinary capabilities in digital learning environments.

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Digital transformation of higher education; students' future capabilities; self-determination theory; machine learning; decision tree (J48)

1. Introduction

Digital technology has a transformative impact on educational development. Global higher education is undergoing a profound digital transformation. According to the OECD *Digital Education Outlook 2023*, governments have built a more efficient digital education ecology through strategic procurement, AI-driven learning analytics and online collaborative platforms to cope with increasingly complex social and technological challenges (Bo, 2025). At the same time, the acceleration of technological iteration and industrial structure upgrading has led to an increasing demand for digital literacy, innovation ability and interdisciplinary thinking in graduates' workplace and social participation (UNESCO, 2019). In view of the above background, this study focuses on students' "future capabilities", that is, comprehensive competence that is particularly critical to career development and social participation in the next five years has become the core of higher education training goals, including the mastery of transformative technologies and key digital and non-digital abilities, and aims to analyze its influencing factors and action paths (Kirchherr et al., 2018).

Having a high level of future capabilities can not only significantly improve students' employment competitiveness, but also enhance their adaptability and innovation in complex situations, thereby promoting lifelong learning and social coordinated development (OECD, 2019; World Economic Forum, 2020). In the context of digital transformation of higher education, it is of great significance to study students' future capabilities. It can not only help colleges and universities to grasp the new requirements of the labor market for digital literacy, innovative thinking and interdisciplinary collaboration in a timely manner, optimize talent training goals and curriculum structure, but also guide teaching model innovation, such as blended teaching, project-based learning and generative AI-assisted teaching, so as to improve students' key soft skills such as problem analysis, innovative practice and teamwork literacy (OECD, 2020). At the same time, through technical means such as learning analysis and intelligent recommendation, it supports

the construction of personalized learning paths and lifelong learning systems, thereby improving students' independent learning and self-driving abilities. The research results can also provide data basis for colleges and universities to make strategic decisions in digital infrastructure construction, teacher training and teaching reform, and optimize resource allocation (Bayly-Castaneda et al., 2024; Komljenovic et al., 2025; Ning et al., 2025).

Existing literature mainly explores the influencing factors, participation effects and action mechanisms of digital transformation of higher education on students' ability acquisition through traditional statistical methods, qualitative interviews, systematic literature reviews and case studies. The systematic literature review of Zhao et al. (2021) summarizes the main results of digital capabilities research in colleges and universities in the past few years, pointing out that the vast majority of studies focus on capabilities assessment and model construction, and there are few empirical studies that combine capabilities training intervention with transformation practice. Papagiannis and Pallaris (2024) evaluated the impact of workshops on "future capabilities" such as critical thinking, collaboration, and creativity through pre-test and post-test designs. The results showed that practical and project-based teaching significantly promoted the improvement of students' key abilities. Fernández et al. (2023) reviewed the digital transformation initiatives of 39 universities around the world, and it was found that many colleges and universities took "student digital literacy and innovation ability cultivation" as the strategic core, and implemented this goal through specific practices such as school-enterprise collaborative projects, virtual laboratories and AI-assisted learning platforms. Reviewing the existing literature, existing research has not systematically identified which single factors constitute "necessary and sufficient conditions" in improving or inhibiting students' future capabilities, nor has it explored in-depth how multiple factors work together through complementary or compensatory paths. Moreover, it has not used large-scale questionnaires and interpretable machine learning methods to reveal the dynamic evolution mechanism of factor configuration in the context of digital education. Therefore, a method that can both quantitatively evaluate and explain is urgently needed to fill this gap.

Therefore, this study is based on a survey of 1,083 students enrolled in German universities conducted by the Forum on Higher Education in the Digital Age (HFD) from November 2023 to March 2024. Based on the questionnaire data, the three dimensions of competence, autonomy and relatedness in the Self-Determination Theory (SDT) were first analyzed in correspondence with the various factors that affect the generation of students' future capabilities, and then integrated into a unified research framework. Then, the filter and wrapper were used to select features, and finally the decision rules were extracted based on the J48 decision tree to deeply analyze the dominant effect and combination path of the factors. This study focuses on the following three questions:

RQ1: Which individual factor(s) serve as the dominant and necessary conditions for enhancing students' future capabilities in the context of educational digital transformation?

RQ2: Which combinations of factors are most likely to lead to an improvement in students' future capabilities under the digital transformation of education?

RQ3: Which combinations of factors are most likely to result in a lack of improvement in students' future capabilities under the digital transformation of education?

Through this design, this paper will not only enrich the theoretical perspective of the study of students' future capabilities, but also provide empirical evidence for universities to optimize teaching and space resource allocation in the digital era.

2. Theoretical background and literature review

2.1. Students' future capabilities and its influencing factors

In the context of digital transformation of higher education, students are facing a career environment reshaped by digital information and processes, while the speed of technological iteration and social change is also unprecedentedly accelerated. This dual background puts forward higher requirements for students' digital literacy and innovation capabilities, and promotes the digital transformation of education and the upgrading of industrial structure to continuously improve the standards of talent cultivation. Future capabilities have become a key goal of the digital transformation of education. Having future capabilities

can not only significantly improve graduates' employment competitiveness, but also enhance their adaptability and innovation in complex situations, which can promote lifelong learning and social participation, and achieve the coordinated development of individuals and society.

At present, there is no consensus in the academic community on the definition of "future capabilities". Early studies were mostly based on the three-dimensional perspective of "knowledge-skills-literacy", while in recent years, more attention has been paid to the cultivation of interdisciplinary learning and innovation capabilities. To adapt to the changes brought about by digital transformation, students' future capabilities encompass not only basic knowledge and skills, but also the ability to master transformative technologies such as artificial intelligence, smart hardware, and robotics, as well as non-digital competencies required in a highly digital environment – including interdisciplinary competence, innovation capacity, and social responsibility. There are several authoritative frameworks in the world, such as the OECD 2030 Skills Framework, which divides future capabilities into Learner Competencies, Life Competencies and Citizenship Competencies. In *The Future of Jobs Report*, the World Economic Forum (WEF) pointed out that in the era of automation and artificial intelligence, there is an increasing demand for transferable skills such as complex problem solving, critical thinking and emotional intelligence (World Economic Forum, 2020). McKinsey Global Institute (MGI) divides competencies into basic skills (such as reading and arithmetic), social-emotional skills (such as teamwork) and advanced cognitive skills (such as innovative thinking) (Bughin et al., 2018). The Ashoka Foundation focuses on students' social innovation and civic participation awareness (Ashoka Canada, 2025). Although these frameworks have international influence and have been applied to varying degrees in higher education practices in various countries, the operational exploration of the "future capabilities" indicator system still needs to be strengthened. While the aforementioned framework provides an international perspective on "future capabilities", how to accurately define the indicator system for "future capabilities" amid digital transformation remains an urgent issue to be addressed. In this study, future capabilities are operationalized as the specific competencies that students need to navigate future professional life and social engagement in the context of digital transformation. Based on the "Future Skills" framework jointly developed by Stifterverband and McKinsey, this study identifies several key competency dimensions, including: mastery of transformative technologies such as artificial intelligence, smart hardware, and robotics (i.e. digital literacy); the ability to analyze data and make decisions (i.e. data-driven decision-making capability); the capacity for continuous learning and self-improvement (i.e. lifelong learning ability); adaptability to change and innovative thinking (i.e. adaptability and entrepreneurial mindset); and the ability to analyze and solve complex problems (i.e. critical thinking). These capabilities are quantified and evaluated through questionnaires, interviews, and students' participation in digital learning activities, thereby providing specific criteria for the improvement of students' future capabilities. Through such an operationalized framework, this study can not only be implemented and validated in German higher education institutions but also provide a flexible and adaptable tool for competency assessment in other educational contexts (Kirchherr et al., 2018).

The factors affecting students' future capabilities can be summarized into seven categories: demographics and socioeconomic factors, psychological and motivational factors, material and time resources, social and cultural support, previous ICT training and attitudes, subject background and academic performance, and school organizational support. Existing studies have shown that family socioeconomic status and urban-rural differences significantly shape students' digital capabilities by affecting the acquisition of educational resources (Litina & Miltuze, 2023; Van Laar et al., 2017). Self-efficacy and intrinsic learning motivation directly predict students' persistence and innovative performance in complex tasks (Agusnaya et al., 2024; Bandura, 1997). The availability of digital devices and networks and the time available for learning are key prerequisites for students to develop technology and information processing capabilities. Teacher-student support networks, peer collaboration, and family and community cultural background play an important role in promoting the cultivation of digital interaction and teamwork capabilities (Bach & Thiel, 2024; Kirkwood & Price, 2014). Redecker and Punie (2017) pointed out in the European Framework for the Digital Competence that systematic ICT training and positive technological attitudes significantly improved students' digital literacy and innovation capabilities (Kayyali, 2024). Jaramillo Gómez et al. (2025) also found that differences in professional fields and academic performance levels affect the development of critical thinking and advanced cognitive skills. In addition, OECD (2019) report emphasizes that school organizational support such as digital infrastructure construction, teacher information-based teaching training and blended

teaching design plays a key role in the formation of students' lifelong learning capabilities and entrepreneurial thinking. These studies provide important insights for this study to explore the factors that affect students' future capabilities.

2.2. Research framework based on self-determination theory

Self-Determination Theory (SDT) was first proposed by Deci and Ryan to explain the quality of motivation and the independent motives of behavior (Deci & Ryan, 2013). SDT emphasizes the independent choice of individual behavior and believes that behavioral motivation can be divided into three types: intrinsic motivation, extrinsic motivation and amotivation, presenting a continuum. Intrinsic motivation means that individuals engage in activities out of interest and hobbies, extrinsic motivation involves external rewards or pressure, and amotivation manifests as a lack of motivation. The internalization of extrinsic motivation is a key process in which individuals transform external requirements and values into internal recognition. This process is affected by the satisfaction degree of three basic psychological needs, namely competence, autonomy and relatedness. The three psychological needs are related to three perceptions, namely competence, autonomy and relatedness (Jiang et al., 2024). When these three needs are well met, individuals are more likely to generate high-quality intrinsic motivation and show higher autonomy, persistence and creativity in their behavior. Conversely, the frustration of any need will weaken the intensity of motivation and affect the corresponding learning outcomes.

Drawing on Self-Determination Theory (SDT), this study constructs a "SDT-based framework for the development of future capabilities in the context of digital transformation in higher education." As a theoretical foundation, SDT provides a clear organizational logic for the seven categories of factors influencing future capabilities, aiming to uncover the intrinsic development mechanism of students' future capabilities amid the digital transformation of higher education (Figure 1). First, combined with the literature review, the seven factors that affect students' future capabilities are mapped to the three basic demand dimensions of self-determination theory according to their functions in meeting psychological needs. Among them, autonomy emphasizes learners' autonomous right to choose their learning methods, resources, and pacing (Mynard & Shelton-Strong, 2022; Stolk, 2024; Zhou & Ahmad, 2025). Amid the digital transformation of higher education, students are confronted with diverse learning formats, flexible technological

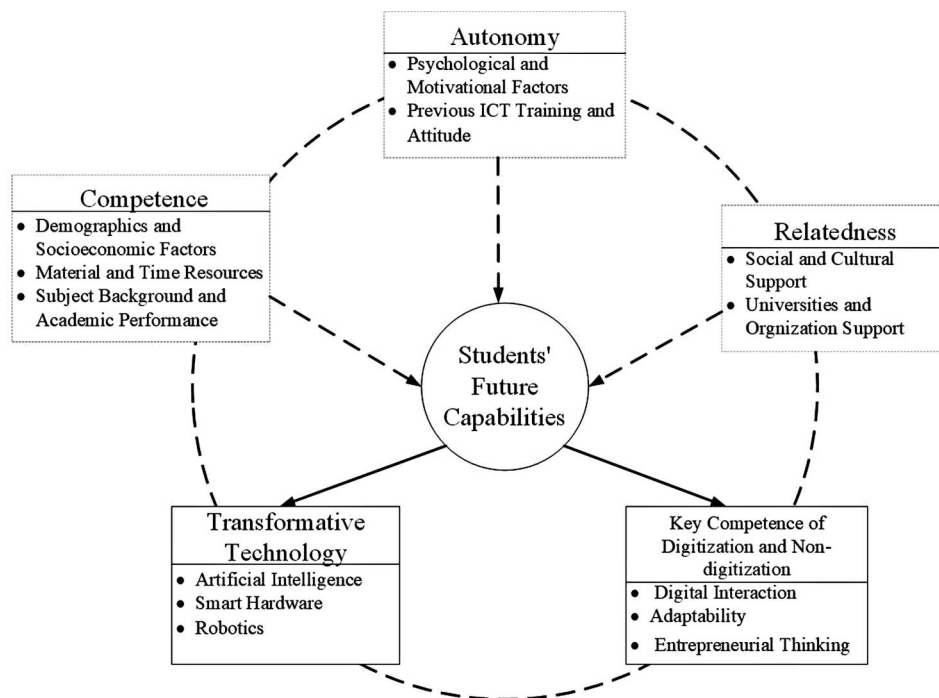


Figure 1. Generation framework for the future capabilities based on SDT in the context of digital transformation of higher education.

pathways, and optional resource structures – their autonomy is often manifested through interest-driven engagement and self-regulation. Therefore, “psychological and motivational factors” (closely associated with learners’ intrinsic motivation) and “prior ICT training and attitudes” (reflecting their technological readiness, technological attitudes, and self-regulatory tendencies) can be regarded as key conditions for satisfying the need for autonomy. These factors collectively determine whether students are willing and able to take the initiative to make learning choices among a wealth of digital resources, thereby stimulating self-directed learning behaviors. Secondly, Competence refers to the sense of effectiveness, control, and capacity improvement that individuals experience in the learning process (Dunn & Zimmer, 2020). In digital learning contexts, competence often depends on learners’ ability to use technical tools smoothly, understand digital resources, and gain achievement experiences and feedback in technology-driven environments. Therefore, resource-based factors such as “demographic and socioeconomic factors”, “material and time resources”, and “disciplinary background and academic performance” are highly aligned with the need for competence. These factors directly determine whether students can gain a sense of control and technological confidence in digital learning activities by influencing their access to devices and the Internet, the possibility of learning engagement, and their academic foundational level. Finally, relatedness emphasizes the critical role of social connection and support in sustaining learning motivation (Chiang, 2025). Relatedness stems not only from teacher-student interaction and peer collaboration but also from the learning spaces and institutional teaching support provided by schools. Therefore, two categories of factors – “social and cultural support” and “school organizational support” – can be regarded as the core sources to meet the need for relatedness. Whether it is online learning communities, collaborative platforms, or the organized arrangements of physical learning spaces and smart classrooms, they are all important conditions that influence students’ emotional connections, participation experiences, and sense of community belonging.

Under the framework of self-determination theory, when the three basic psychological needs are met, students’ intrinsic motivation will be stimulated, that is, the motivation to spontaneously engage in learning driven by interest, curiosity, or intrinsic value (Ryan & Deci, 2000). In the context of digital transformation of higher education, intrinsic motivation is mainly manifested in students actively selecting and switching learning resources on multimodal platforms, using adaptive feedback systems and instant evaluation, virtual reality and recurrence functions of smart classrooms, students repeatedly practicing and constantly adjusting strategies to gain achievement experience, and in online learning communities and blended classrooms, students spontaneously discuss, participate in peer reviews, share experiences and resources, and jointly construct knowledge. Driven by intrinsic motivation, students can sustainably engage in self-directed inquiry, deep practical application and collaborative learning, thereby progressively mastering transformative technologies and acquiring both digital and non-digital key competences to enhance their future capability levels. High-quality motivation not only fosters students’ deep learning engagement but also propels their sustained use and exploration of digital technologies, enabling continuous development in future core capabilities such as digital literacy, data literacy, critical thinking, communication and collaboration. Consequently, this study proposes a pathway mechanism comprising “technological condition support→psychological need fulfillment→motivation enhancement→proactive learning behavior→competency development”, termed the “technology–motivation–competency” cycle. This provides a robust theoretical foundation for explaining the generation mechanism of students’ future competencies within the context of higher education’s digital transformation.

2.3. Machine learning and digital transformation of higher education

In the field of digital transformation of higher education, scholars mainly use methods such as literature research, questionnaire survey and quantitative analysis, case study and qualitative interview to study the implementation status, influencing factors and effect evaluation of digital transformation of higher education. Existing studies have revealed the application trends of technologies such as blended learning, augmented reality/virtual reality (AR/VR), and adaptive learning in campus environment, teaching methods, and learning experience through systematic reviews (Bui & Nguyen, 2023; Romero & Ventura, 2020). There are also studies that combine structural equation models, regression analysis and other methods to empirically measure the expectations and satisfaction of teachers and students in learning

analysis, intelligent recommendations and online collaboration tools, in order to examine the key factors affecting the adoption of digital platforms (Fritz et al., 2024; Yulin & Danso, 2025). In addition, some scholars have focused on the organizational coordination mechanism, technical implementation path and obstacles in the process of introducing machine learning-driven predictive analysis or intelligent tutoring systems in typical institutions, providing practical experience for other colleges and universities to learn from (Antonopoulou et al., 2023). In terms of qualitative interview research, some scholars have conducted semi-structured interviews with teaching managers, informatization managers, and front-line teachers to deeply explore the cultural identity, training needs, and data ethics considerations behind technology adoption, revealing the deep challenges in digital transformation (Gorrell, 2023). The above studies summarize the application status and main findings of various research methods in the field of digital transformation of higher education.

In recent years, machine learning technology has been increasingly used in the field of education, and has shown important value in learning behavior prediction, personalized recommendation, and automated evaluation. For example, Torres-Cruz et al. (2025) used random forest model to predict the risk of university students dropping out, with an overall accuracy of 85.9%. It was found that “semester” and “enrollment year” were the most critical predictive features, which can effectively identify the differences between low-risk and high-risk students. Some scholars also used K – means clustering to group students’ learning performance, and then implemented personalized interventions for different groups, which increased learning participation by about 15% (Maguate, 2024). In addition, Roslan and Chen (2022) found in a systematic review of educational data mining that decision trees are one of the most commonly used classification algorithms and are widely used in student performance prediction, course recommendation, and the design of early warning systems. Based on the C4.5 decision tree, early studies such as Hamsa et al. (2016) modeled the learning data of undergraduate and master students in computer science and electronic engineering. The model accuracy exceeded 82%, and the decision order and split threshold of each feature were clearly displayed through a visualized tree structure. In addition, Escolano-Perez and Losada (2024) used decision tree regression model to reveal the relationship between executive function and learning outcomes. This study not only verified the excellent predictive performance of the decision tree model in the field of education, but also provided a practical logical basis for personalized teaching design and intervention strategies with its intuitive and interpretable tree structure.

Reviewing the existing literature, existing studies often pay more attention to the overall prediction effect of the model or the verification of macro-influencing factors, but few studies use machine learning methods to deeply explore the dynamic evolution and mechanism of the digital transformation of education. Although existing studies have achieved remarkable results in static prediction of transformation effects and macro-influencing factor testing, they rarely explore how technical factors, organizational factors and policy factors are intertwined, synergistic and jointly shape the evolution mechanism of digital transformation practices.

Against this backdrop, this study adopts an integrated approach of Self-Determination Theory (SDT) and machine learning to address the dual deficiencies of existing research in theoretical explanation and mechanism identification. Specifically, Self-Determination Theory provides a solid theoretical perspective for understanding the intrinsic mechanisms between learners’ motivation, the satisfaction of psychological needs, and learning outcomes. However, it has been rarely applied in digital transformation research to explain how technological, environmental, and individual factors jointly influence students’ competence development. Meanwhile, existing machine learning research mostly focuses on predictive accuracy or feature importance. Despite its advantage in handling complex, non-linear relationships, it lacks theoretical underpinnings and thus struggles to reveal the psychological pathways and structural logic underlying competence development. By integrating the psychological need framework of Self-Determination Theory with the feature identification and model interpretability of machine learning, this study can not only characterize the impact intensity of various digital factors on students’ future capability development but also clarify how these factors function by satisfying the three basic psychological needs – autonomy, competence, and relatedness – thereby providing a theoretically driven and methodologically complementary comprehensive perspective for understanding the capability generation mechanism in the digital transformation of higher education.

3. Methodology

3.1. Data source and sample

This study employs survey data collected from current students at German higher education institutions by the “Higher Education Forum for the Digital Age (HFD)” between November 2023 and March 2024. The selection of German students as the research subjects is mainly based on the following considerations. First, the German government and key industry organizations – such as the Federal Ministry of Education and Research and Stifterverband – attach great importance to the digital transformation of higher education institutions and have issued multiple action plans, making it a policy model. Second, most German higher education institutions have established relatively complete digital infrastructure, including online teaching platforms, digital learning spaces, and university-enterprise collaborative laboratories, which provide ideal research conditions for exploring the relationship between digital elements and students’ future capabilities development. Third, the HFD survey was jointly designed by Stifterverband, Centrum für Hochschulentwicklung (CHE), and Hochschulrektorenkonferenz (HRK). Its items have undergone multiple rounds of demonstration and pilot testing by an official expert team, ensuring high content validity in terms of content design; its variable settings can also be structurally classified according to the theoretical division of autonomy, competence, and relatedness in Self-Determination Theory, which enhances the construct validity of the indicator system. In addition, the HFD data used in this study consists of multiple independent structured indicators, making it unsuitable for traditional scale reliability and validity tests such as Cronbach’s α or KMO. Instead, this study examines the predictive validity of the variables through the classification performance of machine learning models – including accuracy, Kappa value, and AUC – and verifies their explanatory power and robustness with respect to future capabilities development. The survey ultimately yields 1,083 valid samples covering different types of German higher education institutions, laying a solid foundation for the external validity of the research conclusions. A list of all independent variables and control variables used in the study is presented in Table 1.

Table 1. Variable list.

Variable Number	Variable Name	Variable Description
Dependent Variable		
Y	Future Capabilities	Binary coding: 0 = low; 1 = high
Competence		
X1	Students’ evaluation of AI activities in university	The original scale range is 1–5. Ternary coding: 1 = low satisfaction (original score 1–2), 2 = medium satisfaction (original score 3), 3 = high satisfaction (original score 4–5)
X2	Number of digital devices used by students for revision	The original scale range is 0–6. Ternary coding: 1 = low (original score 0–2), 2 = medium (original score 3–4), 3 = high (original score 5–6)
X3	Number of digital devices used by students during class	The original scale range is 0–7. Ternary coding: 1 = low (original score 0–2), 2 = medium (original score 3–4), 3 = high (original score 5–7)
X4	Number of digital media or tools used by students for study	The original scale range is 0–13. Ternary coding: 1 = low (original score 0–4), 2 = medium (original score 5–8), 3 = high (original score 9–13)
X5	Number of digital test forms in school	The original scale range is 0–5. Ternary coding: 1 = low (original score 0–1), 2 = medium (original score 2–3), 3 = high (original score 4–5)
Autonomy		
X6	Types of learning forms	The original scale range is 0–9. Ternary coding: 1 = low (original score 0–3), 2 = medium (original score 4–6), 3 = high (original score 7–9)
X7	Frequency of use of each learning form	The original scale range is 0–17. Ternary coding: 1 = low (original score 0–5), 2 = medium (original score 6–11), 3 = high (original score 12–17)
X8	Whether the school provides opportunities to participate in the development of strategies on generative AI	Nominal, coding: 1 = cannot be judged, 2 = no, 3 = yes
X9	The purpose of students using AI	The original scale range is 0–14. Ternary coding: 1 = low (original score 0–4), 2 = medium (original score 5–9), 3 = high (original score 10–14)
Relatedness		
X10	The allocation of school learning space	The original scale range is 0–16. Ternary coding: 1 = low (original score 0–5), 2 = medium (original score 6–10), 3 = high (original score 11–16)
X11	Frequency of students’ use of learning space	The original scale range is 0–19. Ternary coding: 1 = low (original score 0–6), 2 = medium (original score 6–12), 3 = high (original score 13–19)
X12	Students’ willingness to use learning space	The original scale range is 0–5. Ternary coding: 1 = low (original score 0–1), 2 = medium (original score 2–3), 3 = high (original score 4–5)

N = 1083.

The dependent variable, “Future Capabilities” is designed to measure students’ comprehensive competence in career development and social participation over the next five years, and it is jointly composed of two dimensions: the curriculum/extracurricular activity dimension and the competence dimension. The curriculum/extracurricular activity dimension uses a three-point coding system (0 = No, 1 = Uncertain, 2 = Yes) to record whether the curriculum includes content related to future capabilities. The competence dimension adopts a three-point coding system (0 = Not reflected, 1 = Reflected only in extracurricular activities, 2 = Reflected in the curriculum) to assess the manifestation of key competence elements, including digital literacy, data literacy, AI literacy, core interdisciplinary competencies, entrepreneurial spirit, resilience, and academic writing. To facilitate model learning and maintain classification balance, this study binarizes the composite score based on the full sample distribution: samples with scores in the top 50% are classified as having a high future capabilities level (= 1), while the rest are categorized as having a low level (= 0).

The independent variables, centered on the mechanism for generating future capabilities within the context of educational digitalization, are categorized into three types based on the SDT construct: competence, autonomy, and relatedness. Competence-related variables reflect resource availability and feedback experiences, such as AI activity evaluations, number of digital devices, number of digital media tools, and digital examination formats, while autonomy-related variables embody freedom of choice in learning methods and AI usage purposes. Relatedness-related variables encompass learning space configuration, usage frequency, willingness to use, and usage intensity.

All independent variables are count-type indicators within finite intervals, exhibiting highly skewed original distributions that are unsuitable for quantile-based partitioning. To enhance model stability while preserving the behavioral significance of variables, this study employs a three-tier coding system—“low–medium–high”—based on the original intervals and educational practice logic. For instance, the nine types of learning formats are categorized as follows: 0–3 formats indicate low engagement, 4–6 formats represent moderate engagement, and 7–9 formats reflect high engagement. This three-tier classification avoids the sparse category samples resulting from five-level coding while preventing decision tree structures from becoming excessively deep, thereby ensuring model interpretability. Meanwhile, Self-Determination Theory emphasizes differential thresholds for need fulfillment – such as insufficient, moderate, and sufficient autonomy – where the three-tier classification aligns logically with this theoretical framework. This facilitates identifying how varying degrees of need fulfillment differentially impact future capabilities. Consequently, the three-tier approach achieves a favorable equilibrium between theoretical fit, statistical robustness, and model interpretability. Descriptive statistics for each variable are presented in [Table 2](#).

3.2. Variable preprocessing

In data mining, research results are sometimes not pre-determined but rather potential patterns are inferred from the data between variables through a series of logically designed processes. Data mining generally includes three steps: instance selection, attribute selection and classifier evaluation. Instance selection describes how to select the data samples most relevant to the prediction of future capabilities levels from the original questionnaire to reduce noise and eliminate irrelevant or redundant records. Attribute selection evaluates the correlation between each feature and the achievement of future capabilities levels on the screened samples, and proposes low-correlation or redundant attributes to obtain the most predictive variable subsets. Classifier evaluation uses different classification algorithms to train and test the above selected data and features, evaluate model performance, and predict students’ future capabilities levels based on the optimal model. This study used Weka 3.8.6 software for data mining.

3.2.1. Sample selection and classification

Considering that the dependent variable “future capabilities level” is a binary indicator, in the sample preprocessing stage, the 1083 questionnaire samples were first randomly shuffled by the Randomize filter in Weka to eliminate potential bias caused by the order of issuance or entry. Subsequently, the RemoveWithValues filter was used to delete all records marked as “uncertain” or “cannot be judged” (such as X8 = 1) in all independent variables to eliminate noise. At the same time, the dependent variable Y and independent variables X1–X12 were converted from numerical to categorical (Nominal) for subsequent classifier. Finally, a

Table 2. Descriptive statistics of variables.

Grouping	Variable Number	Categories	Frequency(n)	Percentage(/Mean)
Future Capabilities	Y	0 = low	584	53.92
		1 = High	499	46.08
Competence	X1	1 = Low satisfaction	589	72.63
		2 = Medium satisfaction	142	17.51
		3 = High satisfaction	80	9.86
	X2	1 = Low	454	41.92
		2 = Medium	546	50.42
		3 = High	83	7.66
	X3	1 = Low	820	75.72
		2 = Medium	227	20.96
		3 = High	36	3.32
	X4	1 = Low	332	30.66
		2 = Medium	622	57.43
		3 = High	129	11.91
	X5	1 = Low	531	49.03
		2 = Medium	420	38.78
		3 = High	132	12.19
Autonomy	X6	1 = Low	294	27.15
		2 = Medium	25	2.31
		3 = High	764	70.54
	X7	1 = Low	700	64.63
		2 = Medium	239	22.07
		3 = High	144	13.30
	X8	1 = cannot be judged	94	11.51
		2 = No	173	21.17
		3 = Yes	550	67.32
	X9	1 = Low	570	52.63
		2 = Medium	274	25.30
		3 = High	239	22.07
Relatedness	X10	1 = Low	288	26.59
		2 = Medium	496	45.80
		3 = High	299	27.61
	X11	1 = Low	455	42.01
		2 = Medium	263	24.29
		3 = High	365	33.70
	X12	1 = Low	910	84.03
		2 = Medium	139	12.83
		3 = High	34	3.14

N = 1083.

complete data set containing binary dependent variables and cleaned independent variables was obtained, which laid a solid foundation for subsequent feature selection and model training.

3.2.2. Attribute selection

This study employs Weka 3.8.6 to conduct systematic feature selection on variables, successively applying both filter-based and wrapper-based methods to ensure selected features possessed both statistical robustness and model interpretability (Table 3). Within the filter approach, both InfoGainAttributeEval and GainRatioAttributeEval (with thresholds set at 0.01) are applied to conduct an initial screening of all 12 variables. Results indicated that X7 (frequency of use of each learning form) achieved the highest InfoGain score

Table 3. The joint screening results of the filter and the wrapper.

Variable Number	InfoGain	GainRatio	InfoGain $\geq$ 0.01	GainRatio $\geq$ 0.01	Wrapper Selection
X1	0.0440598	0.0545171	Yes	Yes	No
X2	0.0202049	0.0155301	Yes	Yes	Yes
X3	0.0000475	0.0000506	No	No	Yes
X4	0.0130195	0.0097576	Yes	No	No
X5	0.0299219	0.0217854	Yes	Yes	No
X6	0.0740159	0.0737130	Yes	Yes	Yes
X7	0.1934753	0.1528071	Yes	Yes	Yes
X8	0.0061837	0.0092453	No	No	No
X9	0.1053579	0.0728974	Yes	Yes	Yes
X10	0.1616674	0.1045260	Yes	Yes	Yes
X11	0.0024390	0.0015781	No	No	No
X12	0.0294277	0.0392858	Yes	Yes	No

(0.193), significantly surpassing other variables, demonstrating its strongest discriminatory power in explaining the dependent variable; followed by X10 (the allocation of school learning space, 0.162) and X9 (the purpose of students using AI, 0.105). In contrast, X3 (number of digital devices used by students during class) and X11 (frequency of students' use of learning space) yields the lowest InfoGain scores (both below 0.003), failing to meet the screening threshold and thus excluded from the filter method's candidate set. It is noteworthy that although X4's GainRatio is marginally below 0.01, its high InfoGain score retain it within the candidate set. To further validate variable importance, this study also calculates the χ^2 value from ChiSquaredAttributeEval. However, this metric serves only as an auxiliary judgement and is not adopted as a mandatory criterion for feature inclusion.

Subsequently, this study employs WrapperSubsetEval based on J48 ($C = 0.25$, $M = 2$) alongside the Best-First search strategy to evaluate the filter results using the wrapper method. This ultimately yields six variables: X2, X3, X6, X7, X9, and X10. Integrating the outcomes from both approaches, the intersection yields X2, X6, X7, X9, and X10 as the final feature subset. These variables demonstrate outstanding performance across all three evaluation metrics, representing key factors with stable contributions to future capabilities classification. As shown in Table 3, the five variables exhibit consistent performance in both the filter and wrapper methods, indicating that the selected features possess clear informational advantages and robustness, thereby providing a reliable foundation for subsequent model training.

3.2.3. Training set/test set partition and category balance

This study first used 70%:30% stratified random sampling to divide the cleaned data into training set and test set to ensure that the distribution of "future capabilities level (high/low)" in both sets was consistent with the full sample, and then the "high level" samples in the training set were oversampled using the SMOTE algorithm to balance the sample sizes of the two types.

3.3. The construction of decision tree model

In the model construction stage, this study selected the J48 algorithm in Weka 3.8.6 as the classifier and conducted grid search for its hyperparameters on the balanced training set (70% of data, including five features X2, X6, X7, X9, and X10), that is, the pruning confidence C was taken in {0.05, 0.15, 0.25, 0.35}, and the minimum sample leaf M was taken in {1, 2, 5, 10}. First, the average accuracy of each parameter combination was evaluated using 10-fold cross validation, and finally $C = 0.25$ and $M = 2$ were determined to be the optimal configuration. Subsequently, the model is trained with the selected parameters using the same 10-fold cross-validation framework, and its generalization performance is then validated on an independent 30% test set. After the training, the derived decision tree takes "frequency of use of each learning form (X7)" as the root and splits into each leaf in turn. Its clear splitting logic and leaf sample distribution provide a solid basis for subsequent rule extraction and visualization analysis.

3.4. Model evaluation

The training set was evaluated by 10-fold cross validation, and the average accuracy of the J48 model was 79.59%, Cohen's Kappa was 0.5787, Precision was 0.805, Recall was 0.796, F1 Score was 0.791, and ROC AUC was 0.806. When verified on an independent test set, the model had an accuracy of 81.16%, Cohen's Kappa of 0.6172, Precision of 0.845, Recall of 0.812, F1 Score of 0.805, and ROC AUC of 0.809, and showed good recognition balance on both low-level and high-level samples. The above results show that the constructed decision tree maintained stable, balanced and excellent classification performance in both the training and testing stages.

3.5. Interpretation and visualization

During the visualization phase, this study first employs Weka Explorer's Visualize Tree tool to present the structure of the trained J48 model (Figure 2), illustrating the split rules for each node and the sample distribution within leaf nodes. To further enhance model interpretability, this study extracts key decision paths based on tree structures, with their rules, support, and confidence summarized in Table 4. An analysis of

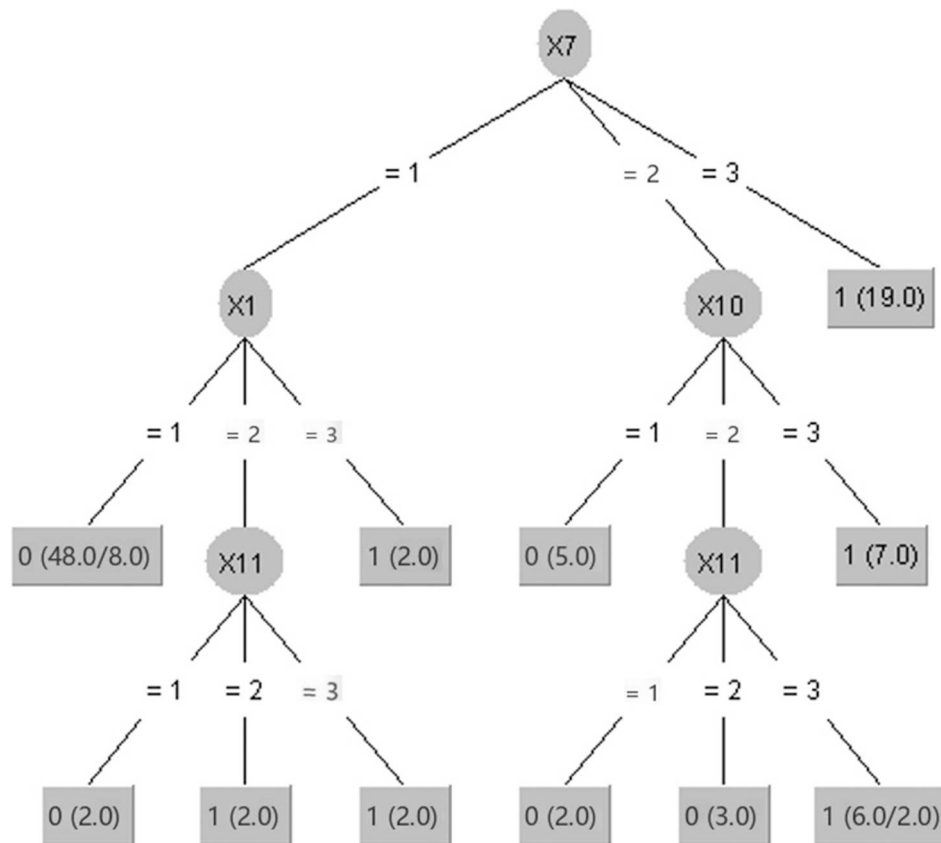


Figure 2. Decision tree for predicting students' future capabilities based on the J48 algorithm.

Table 4. Main decision rules and their support and confidence.

Rule Number	Rule Condition	Support (Number of Covered Samples)	Confidence (Correctness)
R1	If X7 = High(3) → Predict Y = High(1)	19	100%
R2	If X7 = Medium(2) and X10 = High(3) → Predict Y = High(1)	7	100%
R3	If X7 = Low(1) and X1 = Low(1) → Predict Y = Low(0)	56	85.7%
R4	If X7 = Medium(2), X10 = Medium(2) and X11 = High(3) → Predict Y = High(1)	8	75.0%
R5	If X7 = Low(1) and X1 = High(3) → Predict Y = High(1)	2	100%
R6	If X7 = Low(1), X1 = Medium(2) and X11 = High(3) → Predict Y = High(1)	2	100%
R7	If X7 = Medium(2) and X10 = Low(1) → Predict Y = Low(0)	5	100%
R8	If X7 = Medium(2), X10 = Medium(2) and X11 ≠ High(3) → Predict Y = Low(0)	5	100%
R9	If X7 = Low(1), X1 = Medium(2) and X11 = Low(1) → Predict Y = Low(0)	2	100%

the primary rules reveals that the frequency of learning modes employed (X7) serves as the most discriminative splitting variable: when X7 is at a high level (R1), the model predicts with 100% confidence that the student's future capabilities will be high, indicating that learning engagement is the strongest positive driver.

When X7 is at an intermediate level, variations in learning space conditions yield distinct differentiation outcomes. Should a school possess well-equipped learning spaces (X10 = high), the model consistently classifies it as high capability with 100% confidence (R2); However, when spaces are inadequately equipped (X10 = low) or moderately equipped but underutilized (X11 ≠ high), they are more likely to be predicted as low capability (R7, R8). This finding indicates that in moderate engagement scenarios, the physical and usage dimensions of learning spaces play a crucial compensatory role in capability development.

At lower levels of X7, students' evaluations of school AI activities emerge as a significant differentiating factor. If students exhibit low satisfaction with AI activities ($X1 = \text{low}$), their capability levels are significantly lower (R3), indicating the negative effect of insufficient competence. However, if satisfaction is high ($X1 = \text{high}$), the model predicts high capability (R5) even with lower learning engagement, demonstrating the compensatory effect of positive experiences on enhancing ability. Furthermore, moderate evaluations coupled with high space usage frequency ($X11 = \text{high}$) also predict high competency (R6), indicating the facilitating role of spatial belonging. Conversely, when space usage frequency is also low ($X11 = \text{low}$), future competency levels are predicted to be low (R9).

3.6. Robustness check

To assess the robustness of the J48 decision tree model, we compare it against several mainstream classifiers, evaluating metrics including accuracy, precision, recall, F1-score, AUC (area under the ROC curve), and Cohen's Kappa.

The results indicate that the Random Forest model performs best, achieving an accuracy of 84.76% with high precision (0.855) and recall (0.853). However, it exhibits high model complexity and requires extended training time. The accuracy of KNN is 83.84%, with its AUC (0.897) outperforming J48 (0.806). However, it incurs higher computational costs and exhibits sensitivity to the K value and distance metric. In contrast, while J48 yields slightly lower accuracy, it features a simpler architecture and faster training speed, alongside advantages in interpretability.

Logistic Regression (75.44% accuracy) and Naive Bayes (71.19% accuracy) underperform J48, particularly in precision and recall. Whilst AdaBoost demonstrates strong robustness when handling imbalanced data, its accuracy (74.05%) and AUC (0.797) remain below J48's.

In summary, although certain models such as Random Forest and KNN outperform in accuracy and AUC, J48 demonstrates balanced performance across all evaluation metrics. It exhibits distinct advantages in structural simplicity, rapid training speed, and interpretability, thereby showcasing its robustness in classification tasks [Table 5](#).

4. Results

4.1. Dominant factors influencing students' future capabilities

This study employs the J48 decision tree model to identify dominant factors influencing students' future capabilities. Through joint filter-wrapper feature selection, five key variables are ultimately determined as model input features: number of digital devices used during revision (X2), variety of learning formats (X6), frequency of use of each learning format (X7), purpose of students using AI(X9), and allocation of school learning space (X10).

Specifically, frequency of use of each learning format (X7) emerges as the most discriminative variable within the model, exerting the strongest influence. When the frequency of learning format usage is high, the model predicts higher future capability levels among students, indicating that learning engagement serves as the most potent positive driver. This finding aligns with Self-Determination Theory principles concerning autonomy, wherein students typically enhance their competency levels when afforded freedom to select learning approaches.

Table 5. Comparison of robustness across different classification models.

Models	Accuracy	Precision	Recall	F1-Score	AUC (area under the ROC curve)	Kappa
J48 Decision Tree Model	79.59%	0.805	0.796	0.791	0.806	0.5787
Logistic Regression	75.44%	0.756	0.754	0.753	0.807	0.5055
Naive Bayes	71.19%	0.713	0.712	0.712	0.784	0.4241
Random Forest	84.76%	0.855	0.853	0.854	0.932	0.6947
Linear SVM	74.98%	0.754	0.747	0.747	0.746	0.4957
KNN	83.84%	0.839	0.838	0.838	0.897	0.6757
AdaBoost	74.05%	0.743	0.741	0.739	0.797	0.4773

The allocation of school learning space (X10) also plays a crucial role. High-quality learning space provision effectively supports students' future capability development, particularly when learning mode usage frequency is moderate, as the physical conditions of learning spaces offer additional support.

Students' evaluations of school AI activities (X1) also demonstrates significant influence within the model. Where students rate AI activities poorly, the model predicts lower future capabilities, indicating a negative impact stemming from a lack of competence. Conversely, where students rate AI activities highly, the model still predicts higher future capability even with lower learning engagement, suggesting that positive experiences with AI activities can partially offset the negative effects of low learning engagement.

These findings reveal that the aforementioned characteristics exhibit distinct patterns of differentiation with future capability categories at the statistical association level: the frequency and diversity of learning formats employed (X7, X6), learning space conditions (X10), and the purpose of students using AI (X9) all demonstrate strong predictive signals within the model, while the number of digital devices utilized during revision (X2) also possess a certain degree of discriminatory efficacy. In alignment with Self-Determination Theory, these variables correspond respectively to autonomy (X7, X6), relatedness (X10), and competence (X2, X9), further validating the central role of these psychological needs in students' capability development.

4.2. Combinations of factors influencing and inhibiting students' future capability development

This study employs decision tree modeling to identify combinations of factors influencing students' future capability development, revealing that the interaction of these factors across different contexts significantly impacts students' capability growth. Firstly, the frequency of use of each learning form (X7) is a core factor in predicting students' future capabilities. When students utilize learning formats frequently, the model can predict their future capabilities with near 100% accuracy. Even with moderate participation frequency, if the school's learning spaces are well-equipped (X10 = high), students' future capabilities can still be effectively enhanced. This indicates a synergistic effect between learning engagement and learning space quality in capability development. Conversely, for students with lower learning engagement, their evaluation of AI activities (X1) becomes the decisive factor. Should students hold a favorable view of AI activities, the model can still predict higher future capability even with low learning format participation frequency. This indicates that positive experiences with AI activities can partially offset the negative effects of low engagement. Furthermore, in scenarios of moderate engagement, if students hold moderate to high evaluations of AI activities and exhibit high frequency of learning space usage (X11 = High), the model similarly predicts higher future capability. This demonstrates that when students utilize learning spaces frequently, positive evaluations of AI activities and a sense of belonging can foster capability development, even amidst lower engagement levels.

However, certain combinations of factors may inhibit the enhancement of students' future capabilities. For instance, when the frequency of learning format usage is low and students' evaluations of AI activities are unfavorable, the model predicts a low future capability level, indicating that insufficient learning engagement and negative assessments of AI activities lead to capability suppression. Another combination of inhibiting factors arises when learning formats are employed with moderate frequency, yet learning spaces are inadequately equipped or underutilized (X10 = low, X11 $\neq$ high), similarly constraining students' capacity development. This indicates that while students may exhibit a degree of engagement, suboptimal learning environments lacking sufficient support and interactive opportunities will stifle their skill development.

Moreover, when the frequency of learning formats is low and students' evaluations of both learning spaces and AI activities are suboptimal, the model similarly predicts lower future capacity. This indicates that a lack of active learning engagement and recognition of learning spaces and AI activities severely constrains capability development. In summary, the enhancement of students' future capabilities depends not on a single factor but on the interplay of multiple elements. An effective combination of factors such as learning engagement, the provision and frequency of use of learning spaces, and students' evaluations of AI activities can significantly promote the development of their future capabilities. Conversely, in unfavorable contexts, the absence of these factors may inhibit students' capability development.

5. Discussion

5.1. Interpretation of the results

5.1.1. Dominant factors affecting students' future capabilities

The first research question focuses on which single factors are both dominant and necessary conditions for improving and inhibiting students' future capabilities levels in the context of digital transformation of education. According to the results of the joint screening of the filter and the wrapper, the frequency of use of each learning form becomes the most weighted predictor variable. When the participation frequency is high, it is the key driver to promote students' future capabilities, while when the participation frequency is below a certain critical value, it is also the most important factor to inhibit the development of future capabilities.

This finding highlights the core position of autonomy in the self-determination theory in the digital learning environment, that is, giving students the freedom to frequently switch and initiatively choose a variety of learning methods is necessary and sufficient to determine their future capabilities level. The conclusion of this study consistent with the results of Chiu et al. (2024), both verifying the key role of demand satisfaction in ability generation in the digital educational environment. Meanwhile, Chiu (2022) also show that relatedness support has a significant impact on student participation and capabilities improvement. Existing studies have further pointed out that learners with high autonomy are better at setting learning goals, monitoring learning progress and flexibly adjusting strategies (Salikhova et al., 2020; Shen et al., 2024), while Faza and Lestari (2025) and Mohammadi Zenouzagh et al. (2023) also showed that the use of self-regulated learning strategies can help students cope with challenges in complex situations more effectively and ultimately improve their future capabilities. In addition, the results of this study found that the configuration of school learning spaces reflects the supportive role of relatedness, that is, high-quality digital learning spaces can not only enhance students' sense of community identity, but also provide a field for collaborative learning and resource sharing, thereby further promoting the generation of future capabilities based on a sense of autonomy. This echoes the conclusion of Penrod (2021) in the study of future learning spaces, that is, flexible and diverse digital learning space design can promote collaboration and community construction among students, and strengthen learners' sense of relatedness and collective goal awareness. Dulfer et al. (2025) pointed out that when learning spaces provide collaborative tools, clear guide, and opportunities for interaction with teachers or peers, they can effectively build community identity and enhance students' sense of relatedness and willingness to cooperate. Finally, the purpose of students using AI reflects the dimension of competence. When AI applications have clear learning goals and personalized feedback mechanisms, they can significantly enhance students' technical confidence and sense of task control, providing strong support for their application of what they have learned in complex situations.

It is worth noting that the number of digital devices used by students in class (X3), the frequency of students' use of learning spaces (X11), whether the school provides opportunities to participate in the development of strategies on generative AI (X8), and the number of digital media or tools used by students for study (X4) are relatively low in importance. However, there are still differences in the existing research conclusions on the impact of these factors on students' abilities or learning outcomes. Li and Zhu (2023) found that the frequency of students' use of ICT inside and outside the school indirectly promotes academic performance by satisfying their sense of autonomy, competence and relatedness, reflecting the role of ICT use in enhancing autonomous motivation. Peng et al. (2022) shows that active learning classrooms, with their flexible, comfortable spatial layout and humanized facilities, not only improve students' informal learning satisfaction, but also enhance their social interaction and related experience. At the same time, personalized technology-enhanced learning (TEL) has a medium effect size in improving university students' cognitive skills and non-cognitive traits, such as motivation and self-confidence (Hooshyar et al., 2024). The possible reasons are: first, these variables are distributed more concentratedly in the sample and lack sufficient differentiation, resulting in limited information gain. Second, their impact on students' capabilities is more through regulating or mediating other key factors, such as the frequency of use of various learning forms and the allocation of learning space, so they are weakened in the direct prediction model. Finally, in the context of digital transformation in which the research is located, the diversity of learning forms and the richness of application scenarios may better reflect the real learning experience and motivation differences of students than the simple use of equipment, making indicators that focus on "quality" rather than "quantity" have more predictive value.

5.1.2. *Combinations of factors that enhance and inhibit students' future capabilities levels*

The second and third research questions focus on the heterogeneity of the influencing factor combinations, aiming to reveal which factor combinations are most likely to promote or inhibit students' future capabilities. With the help of the visual structure of the decision tree, this study not only confirmed the role of the frequency of use of each learning form as a core influencing factor, but also revealed the significant differences in the combination of different factors in improving and inhibiting students' future capabilities.

The results of this study confirm the heterogeneity of multiple dimensions, that is, no single factor can improve students' future capabilities alone, but a combination of multiple factors is needed. Combined with the rule results of this study, the following five types of factor combinations can effectively stimulate a sense of autonomy, competence and relatedness, thereby improving future capabilities: First, when the frequency of use of various learning forms is at the highest level, they have more choices and a sense of control, which directly satisfies the sense of autonomy, stimulates intrinsic motivation, and makes learning activities more endogenously driven, thus laying a solid foundation for capabilities improvement. This is consistent with Pham (2023)'s research findings. By allowing students to choose learning materials and modes independently, teachers' cognitive autonomy support strategies significantly improve students' learning autonomy and intrinsic motivation. Second, when the frequency of use of various learning forms is moderate, high-quality learning spaces, such as flexible layouts and sufficient equipment, significantly satisfy students' sense of competence by providing timely feedback and practice opportunities. As Dou et al. (2018) pointed out, in classrooms with interactive facilities, students' self-efficacy and problem-solving abilities are improved above average through peer discussions and instant teacher comments. Third, when both learning frequency and space allocation are at a medium level, but the learning space is used frequently, students' sense of relatedness is fully satisfied. Yuerong et al. (2024) also found that the high utilization rate of learning space enhances students' social presence and meets the need for relatedness, thereby promoting them to participate more actively in collaborative learning and obtain emotional support. Fourth, even if the learning form is used less frequently, students' high recognition of AI activities can still play a role through the competence compensation mechanism. Baum and Trzcińska-Król (2024) pointed out that students' positive cognitive and sentiment attitudes towards AI tools are significantly positively correlated with their digital capabilities and AI self-efficacy, indicating that positive AI attitudes can make up for the lack of form use to a certain extent and stimulate their ability perception and exploration motivation. Fifth, in the case of lack of both autonomy and AI interest, high-frequency use of high-quality learning spaces can partially satisfy competence and relatedness through dual paths. The above mechanism shows that the use of high-frequency learning forms is the core lever to stimulate autonomy, while high-quality space design and positive attitudes compensate or amplify the effects of autonomy through competence and relatedness respectively. Only when the three basic psychological needs are met in coordination can students' intrinsic motivation be fully stimulated and their future capabilities improvement can be optimal.

Similarly, there are three types of factor combinations that inhibit students' future capabilities: First, when the frequency of use of various learning forms is extremely low, that is, autonomy is hindered. And the evaluation of school AI activities is low, that is, competence is hindered. Therefore, students lack both choice and sense of control, and lack the experience of achievement, and their intrinsic motivation drops sharply, leading to reduced future capabilities. Johansen et al. (2023) also confirmed that when students perceive a situation of "lack of choice", their participation and willingness to learn independently will be significantly reduced. Second, when the frequency of use of different learning forms is at a medium level but the learning space is insufficiently allocated, or the utilization rate is low despite the medium allocation, students find it difficult to obtain timely feedback and achievement experience in practice, which makes the sense of competence hindered. At the same time, they lack effective peer interaction and social support, which makes the sense of relatedness hindered, resulting in a decrease in learning engagement and collaboration willingness. Related studies have pointed out that when students' relatedness and competence needs cannot be met in the classroom, it will significantly inhibit their behavioral and cognitive participation (Bizimana, 2025). Third, when the frequency of use of various learning forms is low, the evaluation of AI activities is moderate, and the use rate of learning space is also low, that is, a lack of choice, social support and team belonging. Even if there is a slight recognition of AI activities, it is difficult to convert it into continuous engagement, which

ultimately inhibits the growth of capabilities. In summary, when any of the basic needs of students are hindered during the learning process, intrinsic motivation will be weakened and the development of future capabilities will be inhibited.

The findings of this study provide new empirical evidence for the methodological and technical research on the asymmetry and complex relationship among variables, further enriching the theoretical and practical results in this field.

5.2. Theoretical contributions and implications

Extensive research indicates that Self-Determination Theory identifies autonomy, competence, and relatedness as the three fundamental psychological needs that foster intrinsic motivation (Deci & Ryan, 2000; Ryan & Deci, 2000). Traditional theories typically assume that the effects of these three needs are independent and cumulative. This study further reveals the differentiated manifestations of this mechanism within digital learning environments. The configuration results based on decision trees reveal that the fulfillment of these three psychological needs does not exhibit linear addition, but rather demonstrates distinct threshold effects and compensatory structures: When behavioral characteristics associated with autonomy, such as high-frequency participation in learning formats, reach elevated levels, the high future capability category exhibits the most pronounced predictive pattern within the model. Conversely, when autonomy is at moderate-to-low levels, variables corresponding to competence and relatedness – such as high-quality learning spaces, positive AI usage experiences, and high learning space utilization frequency – can collectively correlate with the high capability category through distinct feature combinations. This asymmetrical, condition-dependent configuration pattern indicates that within digital environments, the three fundamental needs not only exhibit complementary relationships but also demonstrate context-dependent dynamic substitution effects. This extends the original understanding of how basic needs operate within SDT.

This finding holds significant implications for extending SDT within technology-supported learning contexts. Research reveals that technological-environmental elements – such as digital resources, AI tools, and learning spaces – are not merely external conditions supporting psychological needs. Rather, through varied combinations, they can reshape the structure of need fulfillment, thereby altering the relative weightings and causal pathways between needs. This discovery offers fresh empirical insights into SDT's theoretical boundaries, operational conditions, and structural mechanisms within digital learning ecosystems. It propels SDT beyond traditional classroom settings into highly technology-dependent learning environments, providing more adaptable theoretical support for explaining motivational variations and behavioral outcomes in digital learning.

To enhance the practical applicability of theoretical contributions, this study further proposes an institutional implementation framework based on the three-dimensional structure of “autonomy – competence – relatedness” to guide universities' practical pathways in digital transformation. Within the autonomy dimension, universities may enhance students' perception of choice and control over learning methods by diversifying learning formats, offering flexible course structures, and providing digital tools that support self-directed planning. Within the competence dimension, systematic AI usage training, instant feedback mechanisms, and digital competence support services can foster students' competence. Regarding the relatedness dimension, reconfiguring collaborative learning spaces, improving spatial accessibility, and enhancing offline-online interaction scenarios can further consolidate social cohesion within learning communities. Concurrently, the framework's effective implementation is constrained by several conditions, including the level of digital infrastructure, teachers' technological adoption capabilities, variations in students' digital literacy, and governance rules and ethical norms governing AI applications. Only when these conditions are fully met can higher education institutions effectively operationalize support strategies for these three psychological needs, thereby enhancing learning motivation and developing capabilities within the digital environment.

5.3. Practical and policy implications

This study, drawing upon the associative patterns revealed by Self-Determination Theory's psychological needs structure and decision tree model, uncovers an asymmetrical configuration of autonomy,

competence, and relatedness within digital learning environments. Consequently, the crux of policy and practice lies not in the isolated promotion of specific technologies or spatial developments, but in establishing a learning ecosystem that sustainably supports these three psychological needs, thereby aligning the structure of need fulfillment with the digital context.

Firstly, the model results indicate that characteristics associated with autonomy, particularly the frequency of learning mode usage, constitute the strongest predictive signals for distinguishing future capability categories. This aligns closely with Self-Determination Theory's emphasis that "autonomy is the core source of motivational quality". Consequently, from a theoretical perspective, higher education digital policies should prioritize supporting learners' self-regulation and learning choices. For instance, institutional-level course flexibility, configurable learning pathways, and safeguarding learners' choice of learning methods all represent core structural conditions for sustaining a sense of autonomy (Han et al., 2022; Ruiz Viruel et al., 2025).

Secondly, the pronounced role of space-related characteristics in moderately autonomous contexts indicates that the effects of relatedness in digital learning exhibit strong situational sensitivity. This finding extends Self-Determination Theory's understanding of relatedness within technology-mediated settings, suggesting that schools should theoretically conceptualize learning spaces as "mediating fields for psychological needs" when formulating digital campus development plans. This approach necessitates attention to students' social connection experiences, collaborative structures, and mechanisms for forming learning communities, rather than focusing solely on hardware upgrades (Christou et al., 2023).

Moreover, empirical findings reveal that competence-related variables – such as evaluations of AI activities and learning objectives – co-occur with high-ability categories in low-autonomy contexts, providing fresh digital evidence for the "need compensation mechanism" within Self-Determination Theory. This structural finding implies that, at the policy level, technology deployment should adopt "enhancing competence" as its theoretical core, which ensures AI tools enhance learners' sense of mastery through their purpose, feedback mechanisms, and comprehensibility, rather than merely pursuing technological coverage (Wang et al., 2023).

Finally, the multidimensional interactions and asymmetrical configuration structures revealed by the decision tree collectively demonstrate that psychological needs are not satisfied in isolation within digital learning environments. Rather, their fulfillment relies upon the systematic synergy of three types of resources: technological, spatial, and institutional. Therefore, from a theory-driven perspective, policy formulation should focus on constructing a digitally-enabled learning ecosystem characterized by "needs coherence". This entails ensuring logical complementarity and coordination among technological infrastructure, learning space planning, teachers' professional development, and academic support systems, thereby providing learners with a stable environment for psychological needs support (Sajja et al., 2023; Staring et al., 2022).

5.3. Limitations and future research

While this study provides important empirical findings, several limitations remain that warrant further exploration in future research.

Firstly, the data for this study derives from a single cross-sectional survey of German higher education institutions. Although the sample size is substantial, its cultural and institutional context exhibits considerable homogeneity, lacking cross-cultural comparison. Consequently, the external validity of the research conclusions requires further validation within the educational contexts of other countries or regions. Differences in educational policies, cultural backgrounds, and technological implementation across nations may influence the mechanisms shaping students' future capabilities. Cross-cultural research would therefore help broaden the applicability of these findings.

Secondly, this study employs supervised learning methods such as the J48 decision tree, which primarily reveal statistical associations between variables rather than causal relationships. Owing to the absence of longitudinal data or experimental design, potential confounding factors could not be fully excluded, thereby limiting the model's explanatory power and capacity for causal inference. To better understand how these factors interact and influence students' future capabilities, future research may employ longitudinal data or experimental designs to validate causal chains linking core needs fulfillment to student capability enhancement.

Thirdly, to enhance model interpretability, this study simplifies several original count variables by categorizing them into low, medium, and high tiers. Whilst this approach enhances model stability, it may diminish

subtle variations in variables such as learning behavior and spatial utilization, particularly concerning specific learning activity types and the precise levels of AI tool usage. Refined variable measurements, such as employing five-level coding, behavioral log data, or detailed records of specific learning activity types, may more effectively reveal complex patterns within learning behavior. Therefore, future research should consider employing more refined measurement approaches, such as granular variable segmentation, to capture students' diverse experiences within digital learning environments with greater precision. This approach would preserve the distinctiveness of variables while enhancing the interpretability of the model.

Finally, this study primarily focuses on the influence of digital technologies and learning space factors, yet does not account for other potentially significant variables such as teachers' digital literacy, the quality of curriculum design, students' digital anxiety, or their level of technology acceptance. These factors may play crucial roles in the development of students' capabilities. Consequently, future research could expand the variable framework to incorporate additional factors likely to impact students' abilities, thereby constructing a more comprehensive digital learning ecosystem model.

6. Conclusion

This study systematically identifies key factors influencing the development of students' future capabilities and their underlying mechanisms within the context of digital transformation in higher education, by integrating Self-Determination Theory with machine learning methodologies. By analysing questionnaire data from 1,083 students enrolled at German higher education institutions, this study not only confirms the frequency of use of each learning form (X7) as a core driver for enhancing students' future capabilities, but also reveals the compensatory effects of factors such as the allocation of school learning space (X10) and students' evaluations of artificial intelligence activities (X1) on capability generation under varying circumstances.

Research findings indicate that the enhancement of students' future capabilities is influenced by the interplay of multiple factors. Particularly when autonomy is insufficient, high-quality learning spaces and positive AI activity evaluations can effectively compensate for students' intrinsic motivation, thereby promoting capability development. Concurrently, the frequent utilization of learning formats, well-equipped learning spaces, and positive AI activity evaluations constitute key pathways for fostering students' capability advancement. Conversely, infrequent use of learning formats, negative AI activity evaluations, and inadequate provision of learning spaces may inhibit students' capability development.

The theoretical contribution of this study lies in further validating the operational mechanisms of the three fundamental psychological needs within the Self-Determination Theory in a digital learning environment. It reveals that the fulfillment of these needs does not follow a linear additive pattern, but rather exhibits threshold effects and compensatory structures, indicating that the interactions between these needs are asymmetrical. Building upon the foundation of autonomy, the compensatory effects of competence and relatedness can effectively enhance students' intrinsic motivation and future capabilities.

Moreover, the findings of this study offer significant insights for educational practice and policy formulation within digital learning environments. Higher education institutions should place greater emphasis on diversifying learning formats, developing learning spaces, and applying artificial intelligence tools to enhance students' intrinsic motivation and foster their interdisciplinary capabilities, innovative capacities, and lifelong learning skills. The research findings also provide data-driven support for strategic decision-making in higher education concerning digital infrastructure development, staff training, and pedagogical innovation.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data collected in this study are part of the Monitor Digitalisierung 360° survey on the current status and trends of digital teaching at German higher education institutions and are publicly available in the GESIS data repository at https://search.gesis.org/research_data/SDN-10.7802-2822.

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