

PATHWAYS ANALYSIS OF DIFFERENT TYPES PLATFORM ENTERPRISES' DIGITAL INNOVATION: FROM THE PERSPECTIVE OF DIGITAL CAPABILITY AND AMBIDEXTROUS LEARNING

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Annotation. Digital innovation is crucial for platform enterprises to gain a competitive advantage in their digital transformation. In order to identify the necessary factors and differentiated paths for platform enterprises to achieve high-level digital innovation, this study employs organisational learning theory and digital capability theory, utilises Necessary Condition Analysis (NCA) and Fuzzy-Set Qualitative Comparative Analysis (FsQCA) to examine the impact of platform type, digital capability, ambidextrous learning approaches, and their matching mechanisms on digital innovation among 139 enterprises. The NCA results showed that neither a single learning style nor digital capability alone constituted a necessary condition for achieving high-level digital innovation. The FsQCA results identified five paths to achieving high-level digital innovation. Specifically, for producer-led platforms, their digital infrastructure and platform capability are generally strong. If executives also have strong digital leadership capabilities, they can collaborate with low-level exploratory learning. If the digital leadership capabilities of executives are weak, it can be combined with low-level exploratory learning and high-level exploitative learning. For buyer-led platforms, the digital platform capability of enterprises and the digital leadership capabilities of executives are generally strong, but the digital infrastructure is weak and needs to be combined with high-level exploratory learning and high-level exploitative learning. For bidirectional platforms, high-level digital innovation requires high level of executive digital leadership capabilities and the adoption of both high-level exploratory learning and high-level exploitative learning. When different types of platform enterprises pursue high-level digital innovation, they must base themselves on their digital capabilities and choose appropriate ambidextrous learning methods.

Keywords: platform type, digital capability, ambidextrous learning, digital innovation, FsQCA.

JEL classification: O31, O32, M10, L26, B40.

Introduction

Platform enterprises actively use digital infrastructure, recombine digital resources, and perform digital innovation to produce new products and services, processes, and business models (Weihong et al., 2019). Although the value of enterprise digital innovation is self-evident, the results of digital innovation are quite different. For instance, Jingdong uses AI logistics and IoT to realise intelligent logistics but LeTV's blind digital transformation eventually led to their collapse, ignoring their own characteristics and instinctively following the trend. Such differentiated outcomes have triggered the researchers to explore the factors affecting the digital innovation. Different types of platform enterprises have different paths to undertake digital innovation. The needs of users, service providers, and other stakeholders are a valuable source for purchaser-led platforms such as Taobao to perform digital innovation while producer-led platforms such as Apple leverage innovation's digital capability. The differentiated digital capability foundation of platform enterprises puts forward different requirements on the path of digital innovation. Therefore, actively exploring the impact of differentiated digital capability of different platform types on digital innovation is a necessary measure to improve the success rate of enterprise digital transformation. Presently, platform enterprises must learn to optimally use digital technology. However, the key knowledge for platform enterprises' innovation has changed from traditional data to digital big data (Dawei, 2023). Digital capabilities broaden learning channels and improve learning efficiency, affecting the digital innovation development. Thus, organisational learning and the synergy between organisational learning and digital capability are notable factors affecting the digital innovation.

In order to neutralise competitive pressure, platform enterprises utilise digital technologies to leverage business strategies (Li et al., 2017). Such enterprises use digital technologies to edit, homogenise, and disseminate data on an unprecedented level (Yoo et al., 2010). For example, new software, devices, and network standards assist novel features to emerge, thereby, transforming the manner enterprises develop a competitive edge (Parker et al., 2016). According to Cenamor et al. (2017), platform enterprises play a pivotal role in value preposition by leveraging information management. In particular, AI, machine learning, and big data have become top priorities for numerous enterprises that compete in the digital ecosystems (Subramaniam et al., 2018). Thus, digital innovation constitutes an emerging domain by challenging the fundamentals of enterprise performance (Cenamor et al., 2019). Innovation strategy constitutes the process of planning the execution of innovative activities.

Exploration and exploitation present two opposing innovation modes based on diverges in the innovation magnitude (Zhang et al., 2022). On the one hand, exploitative learning is market-oriented and adapts innovation activities based on the current knowledge and learning to respond to user needs (Wang et al., 2015). However, explorative learning is technology-focused and breaks down old technological hurdles to achieve a competitive edge by experimenting with novel fields and knowledge (Morgan and Berthon, 2008). These two innovation modes complement each other despite the existence of logical differences between them. From an ambidextrous viewpoint, innovation strategy can be categorised into combined dimension and balanced dimension of ambidextrous innovation strategies (Cao et al., 2017). The former focuses on the synergy's theory which elucidates how strengthening the complementarity between the two broadens the width and depth of digital innovation, in a manner that realises the high-level digital innovation while the latter seeks to lower the risk associated with imbalance of resource allocation and innovation by narrowing the gap between the two and achieving innovation by avoiding drawbacks (Cao et al., 2009).

As a dynamic capability, digital ambidextrous capabilities are also strongly associated with business model innovation. It is imperative to elucidate the effect of platform enterprises on enterprise digital

innovation from the standpoint of explorative and exploitative learnings (Jing et al., 2023). The insights on the relationship between the digital ambidextrous capabilities and transformation process are scarce, especially related to the enterprise digital innovation. Previous studies have extensively scrutinised the advantages of embracing digital innovation (Parida and Ortgyist, 2015). Explicitly, digital innovation may optimise operational efficiency by upgrading market orientation and task management through advanced market information (Melville et al., 2004). The comprehension of the influence of platform enterprises on digital innovation is still limited, with a substantial number of enterprises failing to integrate such platforms. Consequently, examining the role of enterprise platforms in the digital innovation is of vital relevance to the digital economy development (Zott et al., 2011).

The extant literature ignores the impact of platform type on digital innovation and pays less emphasis on the impact of ambidextrous learning, digital capability, and the synergetic effect of ambidextrous learning and digital capability on digital innovation. In terms of the influencing factors of digital innovation, researchers emphasise market uncertainty, entrepreneurship (Natsuki, Xinger, 2023), and digital orientation (Ling and Houyong, 2023), neglecting ambidextrous learning and digital capability. Previous studies also ignore the deep impact of the platform type on digital innovation. Different types of platforms have different resource base and path required for enterprise value creation, resulting in platform heterogeneity of their ambidextrous learning and digital capability. Moreover, studies also analyse the driving factors of enterprise digital innovation from a single viewpoint, lacking to explore the linkage effect of ambidextrous learning and digital capability (Yuan et al., 2021). Thus, there is a need to explore the linkage effect of ambidextrous learning and digital capability.

The significance of this study lies in the following marginal contributions. By exploring the effect of digital capability of platform enterprises on digital innovation, this study not only expands the research scope of digital capability theory, but also extends the logical chain of digital capability theory. Additionally, based on the configuration effect between organisational learning and digital capability, this paper reveals the mechanism black box affecting enterprise digital innovation, which establishes the foundation for improving the path mechanism of platform enterprises to support digital innovation. Furthermore, this study reinterprets the organisational learning theory in digital context, reflecting that enterprise's ambidextrous learning utility must be subject to its digital capability. This offers a novel idea for development of ambidextrous learning theory under enterprise digital economy.

Based on the digital competence and organisational learning theories, this study aims to examine the impact of platform enterprises' digital capability on digital innovation. Accordingly, this paper studies the digital competence (digital infrastructure, executive digital leadership, and digital platform capability), ambidextrous learning (exploitative learning and exploratory learning) types of platform enterprises (producer-driven, purchaser-driven, and bidirectional driven), and the effect of their relationship on digital innovation. Thus, the NCA and FsQCA are combined to identify the necessary conditions and configuration paths that reveal the focus of digital innovation of different types of platform enterprises and the path to realise high-level digital innovation.

1. Literature Review and Theoretical Framework

1.1 Enterprise Platform Types and Digital Innovation

Due to their distinct business models and value creation paths, different types of digital platforms have been observed to follow different paths of digital innovation. The digital platforms can be classified into purchaser-driven, producer-driven and bidirectional-driven platforms. Producer-driven platforms (e.g. Apple and Google) emphasise technology and product innovation (Jiang *et al.*, 2023). Purchaser-driven

platforms (e-commerce/service sector) focus on the efficient matching between supply and demand, utilising algorithm optimisation and data analytics. Common in social media and content sharing platforms, the value-added model of the bidirectional-driven platform comes from the value co-creation of digital products, which is a process in which enterprises interact with consumers to co-create consumer experience to meet their customised needs.

1.2 Ambidextrous Learning Strategy and Digital Innovation

Ambidextrous learning is defined as a simultaneous performance of exploratory learning and exploitative learning by enterprises to cope with external environment changes (Guo *et al.*, 2021). Enterprises with high learning tendency actively develop and utilise abundant knowledge resources for digital innovation. Exploratory learning means that enterprises continuously acquire new knowledge and actively respond to environmental changes to expand their knowledge base (March, 1991), exploring new opportunities and solutions, establishing novel knowledge structure, and promoting digital innovation. Exploitative learning means that enterprises continuously tap existing resources to cope with environmental changes from existing practices and solutions (March, 1991), expanding their existing knowledge (Chaoying *et al.*, 2019), constantly strengthening the knowledge absorption, exploring the application value of current knowledge, and creating new perspectives.

1.3 Digital Capability and Digital Innovation

Digital capabilities are divided into three dimensions: digital infrastructure, digital platform capability, and digital leadership (Caili, Yuanxun, 2019). Digital infrastructure refers to the basic skills of enterprises in using digital technologies and tools to create new products, improve production processes, optimise service processes, etc. Digital platform capability refers to the integration and reconstruction capability of internal and external data resources of enterprises, which plays an enabling role in digital innovation. Executive digital leadership implies that senior executives support the

1.3.1 Digital Infrastructure and Digital Innovation

Digital technology has gradually become the core driving force for enterprises to improve the efficiency of operation and production, identify consumer demand, and promote digital innovation. Specifically, enterprises promote digital innovation (e.g. AI and IoT) for a high degree of automation, replacement of repetitive operations, and elimination of standardised work, enhancing production and operational efficiency. Similarly, enterprises use digital platforms for internal and external collaboration. The use of advanced collaboration platforms allows team members to easily share information, coordinate tasks, and accelerate the innovation projects. These technologies are also used to analyse sophisticated data, offering insights for digital innovation. In the supply chain, real-time data analytics accurately predict demand. Enterprises also drive digital innovation by leveraging digital technology to identify consumer demand. Primarily, enterprises extract information from massive user data, including user search behaviour and social media interaction (Gong *et al.*, 2023). For example, e-commerce sites push related products based on users' browsing and purchase history. Enterprises also leverage digital technologies to create more intuitive interface to attract more users (Gong *et al.*, 2023), identifying market trends and consumer needs. Innovation decisions are more precise and forward-looking, improving innovation efficiency (Jiang, Jiang, 2020).

1.3.2 Digital Platform Capability and Digital Innovation

Digital platform capability is a second-order concept that includes platform reconstruction and integration capability. It reflects both integration capability and capability of enterprises to reconstruct

resources based on digital technologies such as platform modularisation (Ogink, Dong, 2019) to integrate massive user data into valuable data resources. Enterprises also use digital platform capability to improve the efficiency of resource reconstruction and integration, accurately identifying innovation needs (Wang *et al.*, 2022). Prominently, the standardised interfaces of digital platforms significantly improve the resource restructuring capability, help enterprises achieve differentiated innovation with minimal additional work, and provide users scalable innovative services. The existing transparent modules provide references to develop new products/services, shortening the time and cost of digital innovation (Junzheng *et al.*, 2020). Conversely, without integration, the ‘explosive’ user data of the platform is difficult to create a direct effect (Ogink, Dong, 2019). Only by using platform technology to play the role of resource integration, enterprises efficiently integrate massive information at a lower cost, predict the market trend and customer preference trend, and introduce new products/services (Junzheng *et al.*, 2020).

1.3.3 Digital Leadership Capability and Digital Innovation

As corporate leaders, executives have the strategic vision to identify the opportunities and challenges brought by digital technologies, as well as the corresponding executive capability (Hambrick, Mason, 1984). Executive digital leadership promotes the formulation and implementation of enterprise digital strategy (Hogna *et al.*, 2023). Strong digital leadership identifies the prospects and threats brought by digitalisation, elucidate the future direction, and devise a clear and feasible digital strategy (El Sawy *et al.*, 2020). Senior executives use advanced data analysis tools to accurately assess market demand, consumer behaviour, and the cost/benefit of innovative projects (Peng *et al.*, 2023). In terms of culture building, executives encourage innovation to motivate employees to participate more actively in digital innovation; strong digital leadership attracts and retains technical digital talents and provides human support to analyse complex user data to realise high-value innovation (Yangping, Li, 2019). Senior executives promote digital innovation through cross-departmental collaboration and resource integration. They also break barriers between teams or departments by building collaboration platforms (Zahoor *et al.*, 2023).

1.4 Digital Capability and Ambidextrous Learning

1.4.1 The Supporting and Empowering Effect of Digital Capability on Ambidextrous Learning

The resources required for innovation have changed from traditional resources to complex data resources. Therefore, enterprises cannot capture key information by solely relying on traditional learning methods. Digital infrastructure broadens the learning channels of enterprises, digital platform capability can improve the learning efficiency of enterprises, and digital leadership of executives can guide the learning direction of enterprises, thus ensuring a smooth development of digital innovation activities. First, enterprises use AI and other technologies to overcome the dilemma of insufficient exploration caused by the data analysis limitation (Ying *et al.*, 2022). Conversely, enterprises also use platform technology to reduce the cost of knowledge interpretation and sharing within the organisation. Second, the resources acquired by enterprises through exploitative and exploratory learning are heterogeneous. If enterprises lack effective integration and reconstruction due to the limitations of the digital platform capability, it is difficult to form a resource base that meets their innovation needs. Third, although digital technology offers instrumental support for enterprise learning, if the grasp of the learning direction is ignored, it will lead to the wrong direction of ‘opposite direction’. Consequently, executive digital leadership is pivotal in guiding the learning direction and the allocation of innovation resources in the ambidextrous learning.

these industries include three platform types and their development is relatively complete. In these industries, digital innovation is more frequent and obvious, offering sufficient data for analysis (*Table 1*).

Table 1. Basic Information of Sample Enterprises

Indicators	Categories	Number of businesses	Percentage (%)
Time of establishment	Within 5 years	4	2.9
	5 to 10 years	72	51.8
	10 + years	63	45.3
Ownership	State-owned enterprise	3	2.2
	Collectively-owned firms	2	1.4
	Foreign-funded firms	0	0
	Joint venture	2	1.4
	Private business	132	95
Enterprise size (person)	≤10	36	25.9
	10 ~ 50	51	36.7
	50 ~ 100	30	21.6
	100 ~ 300	16	11.5
	300 ~ 500	4	2.9
	500 ~ 1000	1	0.7
	>1000	1	0.7
Listed company or not	Listed company	3	2.2
	Unlisted companies	136	97.8

Source: created by the authors.

In this paper, online and offline questionnaire surveys are used to collect data. Online respondents were mainly contacted by means of government, industry associations, and business relations while offline questionnaires were sent and received onsite through industry annual meetings and forums. In order to ensure the validity and reliability of the responses, the respondents should meet one of the following three conditions: they should be senior executives, middle managers, or technical personnel who are familiar with the digital innovation practices of the enterprise. A total of 200 questionnaires were sent out in the early stage of the investigation, and 169 completed questionnaires were received, excluding the following: the response time was less than or equal to 60 seconds; the marked items in the same category of the questionnaire were illogical; and numerous identical items were selected in the questionnaire. A total of 139 valid questionnaires (82%) were obtained.

2.2 Measurement of Variables

The questionnaire is divided into two parts (*Table 2*). The first part includes the basic information of the enterprise, including the name, scale, and equity nature. The second part covers the type of enterprise platform, digital capability, ambidextrous learning mode, and digital innovation level. To ensure the scientificity of the questionnaire survey, the measurement of some related variables is based on the existing mature scale. The original scale is adjusted according to the expert suggestions. The measurement of platform types divides digital platforms into producer-driven platforms, purchaser-driven platforms, and bidirectional-driven platforms (Ying *et al.*, 2022). Digital capability theory states that it is divided into three dimensions: digital infrastructure, digital platform capability, and digital leadership capability (Xuexin *et al.*, 2022; Zhenning *et al.*, 2011). The measurement of digital infrastructure is based on the measurement of digital technology level and digital application range (Fichman *et al.*, 2014; Yoo *et al.*, 2010). Referring to Rai and Tang (2010) and Javier *et al.* (2019), digital

platform capability is measured. The scale compiled and used measurements by Zeike *et al.* (2019) and Peng *et al.* (2023) to gauge digital leadership. The measurement of ambidextrous learning draws on the measurement methods proposed by Chung *et al.* (2019). Digital innovation learns from Paladino's (2007) estimation of digital innovation. The item for scaling platform type was a single choice with three platform types. With the exception of the platform type, the remaining variables were scaled using a 7-point Likert scale, ranging from 1 to 7, thus indicating the increasing degree of respondents' agreement with the description of the item.

Table 2. Measures of the Basic Situation of Variables

Variable name	Variable dimension	Variable Metrics	References
Digital Innovation	\	'The quality of digital solutions is better than competitors' and 6 other questions	Paladino, 2007
Type of platform	Producer driven	'The value-added links of the platform mainly include open code writing, software development such as operating systems, technical standard formulation and digital content production' and other characteristics	Qiu Ying <i>et al.</i> , 2022
	Purchaser-driven	'The platform takes consumer demand as the core driving force of the value chain' and other characteristics	
	Bidirectional drive type	'Producer and consumer value co-creation' and other characteristics	
Digital capability	Digital infrastructure	'The adoption of big data technologies (such as big databases, data analysis technologies, etc.)' and 7 other questions	Yang Zhenning <i>et al.</i> , 2021; Yoo <i>et al.</i> , 2010; Fichman <i>et al.</i> , 2014
	Digital Platform Capability	'Our platform has a strong capability to share information' and 8 other items	Rai and Tang, 2010; Javier Cennamor <i>et al.</i>
	Executive digital leadership	8 items including 'Senior executives will actively plan digital strategy for the company'	Zeik <i>et al.</i> , 2019; Xie Peng <i>et al.</i> , 2023
Organisational learning	Exploratory learning	'Our goal is to acquire knowledge and develop a product/service that will lead us into new areas of learning, such as new markets and technological experiences' and 5 other questions	Chung <i>et al.</i> , 2015
	Exploitative learning	5 questions such as 'Our goal is to find information to improve common methods and ideas for solving problems in the development of new products/services'	

Source: created by the authors.

The scores for each sample were derived by summation of each item, with the items themselves relating to digital infrastructure, digital platform capability, digital leadership capability, exploratory learning, exploitative learning, and digital innovation.

2.3 Common Method Bias Analysis

In order to reduce the common method bias, the questionnaire was processed by referring to Peiyu *et al.* (2023). The questionnaire is pre-investigated and modified according to the feedback received. Furthermore, the questionnaire structure underwent modification, with the objective of mitigating potential deviations. This modification entailed the integration of face-to-face completion with remote completion, thereby ensuring a more comprehensive and accurate data collection process. The present study employs the Harman single-factor test. The total variance interpretation ratio of the extracted single factor is 43%, indicating an absence of significant bias.

2.4 Reliability and Validity Test

The Cronbach's α coefficient of both the single variable and the questionnaire was greater than 0.8, indicating that the questionnaire was reliable. With regard to the validity analysis, the KMO value was greater than 0.700, and the significance of the approximate Chi-square statistic value of Bartlett sphere test was less than 0.001, confirming test validity (Du *et al.*, 2022).

2.5 Data Analysis Methods

The present paper employs a methodological approach that integrates the NCA and FsQCA frameworks. The NCA can evaluate whether a certain kind of ambidextrous learning styles or digital capabilities is a necessary condition for enterprises to attain high-level digital innovation and if so, at what level (Jianqing *et al.*, 2023; Yunzhuo *et al.*, 2019; Dul *et al.*, 2020; Dul, 2019). This paper employs FsQCA to explore the multiple and complex paths for enterprises with different platforms to attain high-level digital innovation (Ting-Wei *et al.*, 2023; Hong *et al.*, 2021). Hence, this paper first adopts NCA to analyse the necessary conditions and necessity levels of whether each conditional variable is a result variable, and then uses FsQCA to test the robustness of NCA's results and analyse the path to achieve high-level result variables.

3. Analysis of Results

3.1 Descriptive Statistical Analysis

Among the 139 enterprises, 11 are producer-driven, 89 are purchaser-driven, and 39 are bidirectional-driven platform enterprises (Table 3). The sample enterprises differ greatly in terms of digital infrastructure, but most have higher than mean digital infrastructure. These enterprises also have large variances in digital platform capability, executive digital leadership capability, exploratory learning, exploitative learning, and digital innovation, but most are above relevant means.

Table 3. Descriptive Statistics of the Main Variables

Variables	Variable dimensions	Mean value	SD	Min.	Max.	Median
Number capability	Digital infrastructure	69.04	16.08	25	91	73
	Digital platform capability	41.22	9.01	14	54	44
	Digital Leadership	39.74	9.98	10	53	42
Ambidextrous Learning	Exploratory learning	35.93	8.86	11	49	38
	Exploitative learning	34.41	9.11	9	47	37
Digital Innovation	\	24.75	6.30	6	35	26

Source: created by the authors.

3.2 Necessary Condition Analysis and Fuzzy Set Qualitative Comparative Analysis

Drawing on the determining anchor points in the existing literatures (Lidong *et al.*, 2023; Xuemei *et al.*, 2018), this paper adopts Digital Technology Infrastructure (DTI) and Digital Platform Capability (DPC). Executive Digital Leadership Skills (DLS), Exploratory Learning (TS), Exploitative Learning (LY), and Digital Innovation (DI) are the lower, median, and upper quartiles of the data as full membership points, intersections, and total non-membership points (*Table 4*).

Table 4. Anchor Points of Variables

Variable	Full membership points	Crossing points	Completely unaffiliated points
Digital infrastructure	77	73	70
Digital platform capability	46	44	40.5
Executive digital leadership	45	42	39.5
Exploratory learning	41	38	36
Exploitative learning	39	37	34
Digital innovation	29	26	24

Source: created by the authors.

3.2.1 Necessity analysis (NCA)

Table 5. NCA Method Necessary Condition Analysis Results

Conditions	Methods	Precision	Upper limit area	Range	Effect size d value	P value
Producer-driven	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Purchaser-driven	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Bidirectional-driven	CR	100%	0.000	1	0.000	1.000
	CE	100%	0.000	1	0.000	1.000
Digital infrastructure	CR	98.6%	0.001	1	0.001	0.164
	CE	100%	0.002	1	0.002	0.164
Digital platform capability	CR	97.8%	0.000	1	0.000	0.239
	CE	100%	0.000	1	0.000	0.310
Executive digital leadership	CR	100%	0.000	1	0.000	0.313
	CE	100%	0.000	1	0.000	0.313
Exploratory learning	CR	100%	0.000	1	0.000	0.404
	CE	100%	0.000	1	0.000	0.404
Exploitative learning	CR	99.3%	0.008	1	0.008	0.000
	CE	100%	0.011	1	0.011	0.001

Notes: 1) membership value of calibrated fuzzy set; (2) $0.0 \leq d < 0.1$: "low level"; $0.1 \leq d < 0.3$: 'medium level'; (3) permutation test in NCA analysis (number of redraws = 10000).

Source: created by the authors.

The NCA analysis is performed employing both CR and CE methods to compare the reliability of the results (*Table 5*).

The necessary conditions must concurrently meet the following three conditions: (1) rationality; (2) the effect size d is not less than 0.1 (Dul, 2016); and (3) the result of Monte Carlo simulation replacement test is significant. Reportedly, platform type, digital platform capability, executive digital leadership, and

exploratory learning do not show any effect size level. Thus, no antecedent conditions constitute the necessary conditions for digital innovation.

The bottleneck analysis results show that platform type is not necessary for digital innovation (*Table 6*). To achieve 90% level of digital innovation within the observation range, all eight condition variables are non-essential; although to attain the 100% level of digital innovation, digital infrastructure, digital platform capability, executive digital leadership, exploratory learning, and exploitative learning must reach 4.7-, 2.7-, 8.0-, 1.0-, and 92% of the observed range, respectively.

Table 6. Analysis Results of NCA Method Bottleneck Level (%)

Digital Innovation	Producer-driven	Purchaser-driven	Bidirectional-driven	Digital infrastructure	Digital platform capability	Executive digital leadership	Exploratory learning	Exploitative learning
0	NN	NN	NN	NN	NN	NN	NN	NN
10	NN	NN	NN	NN	NN	NN	NN	NN
20	NN	NN	NN	NN	NN	NN	NN	NN
30	NN	NN	NN	NN	NN	NN	NN	NN
40	NN	NN	NN	NN	NN	NN	NN	NN
50	NN	NN	NN	NN	NN	NN	NN	NN
60	NN	NN	NN	NN	NN	NN	NN	NN
70	NN	NN	NN	NN	NN	NN	NN	NN
80	NN	NN	NN	NN	NN	NN	NN	NN
90	NN	NN	NN	NN	NN	NN	NN	NN
100	NN	NN	NN	4.7	2.7	8.0	1.0	92.0

Notes: (1) CR method, NN= unnecessary.

Source: own calculations.

3.2.2 Qualitative Comparative Analysis of Fuzzy Sets (FsQCA)

(1) Single factor necessity analysis

FsQCA 3.0 software is used to analyse whether each condition variable meets the necessary condition for the result variable (*Table 7*).

Table 7. Analysis Results of Single Factor Necessary Conditions

Variables	Consistency	Coverage
Producer-driven platform	0.10	0.64
Purchaser-driven platform	0.53	0.41
Bidirectional-driven platform	0.37	0.66
Digital infrastructure	0.67	0.65
Digital platform capability	0.68	0.67
Executive digital leadership	0.69	0.64
Exploratory learning	0.67	0.64
Exploitative learning	0.68	0.68

Source: own calculations.

Generally, when the consistency is greater than 0.9, the variable is a necessary condition for the result variable's realisation (Yunzhou *et al.*, 2019). Reportedly, the consistency of each condition variable is

lower than 0.7. Each condition variable is not a necessary condition for the result variable's realisation. Alternatively, any of the producer-driven platform, purchaser-driven platform, bidirectional-driven platform, digital infrastructure, digital platform capability, executive digital leadership, exploratory learning, and exploitative learning are not sufficient for enterprises. Therefore, each condition variable must collaborate with the others to achieve a high-level digital innovation, confirming the robustness of the results.

(2) Configuration analysis

The consistency threshold was set to 0.8 and the case number threshold was set to 1. The derived five configurations represent the matching of digital capability and ambidextrous learning capability of enterprises belonging to different platform types when they carry out digital innovation (*Table 8*). According to platform type, the following five configurations can be divided into three groups, with each group representing a path for a platform type to achieve a high-level digital innovation.

Table 8. Configurations That Enable High Levels of Digital Innovation

Variables	Conf. 1	Conf. 2	Conf. 3	Conf. 4	Conf. 5
Producer-driven	•	⊗	⊗	•	⊗
Purchaser-driven	⊗	⊗	⊗	⊗	•
Bidirectional-driven	⊗	•	•	⊗	⊗
Digital infrastructure	•	⊗		•	⊗
Digital platform capability	•		•	•	•
Executive digital leadership	•	•	•	⊗	•
Exploratory learning		⊗	•	⊗	•
Exploitative learning	⊗	•	•	•	•
Raw coverage	0.039	0.070	0.205	0.015	0.068
Unique coverage	0.036	0.034	0.169	0.011	0.068
Consistency	0.884	0.914	0.963	0.898	0.840
Overall coverage			0.357		
Overall consistency			0.917		

Notes: ⊗ indicates that the condition does not occur, • indicates that the condition occurs; Empty indicates that the condition does not affect the result. The large • is the core condition, and the small • is the edge condition.

Source: own calculations.

Configurations 1 and 4 indicate the path for producer-driven platform enterprises.

Configuration 1 (PD * ~BD * ~BiD * DTI * DPC * DLS * ~LY) indicates that if the producer-driven platform exhibits a high level of digital capability (combined with a high level of digital infrastructure, digital platform capability, and executive digital leadership), only a low level of exploitative learning is required to achieve a high-level digital innovation. Since a high level of digital capability means that the enterprise already has superior resources and capability conditions, and can reduce the investment in learning and adopt the low level of exploitative learning. Configuration 4 (PD * ~BD * ~BiD * DTI * DPC * ~DLS * ~TS * LY) demonstrates that when the producer-driven platform has a high level of digital infrastructure and digital platform capability but lacks a high level of executive digital leadership, ambidextrous learning approach with low exploration and high utilisation is required to attain a high-level digital innovation. The

lack of high-level executive digital leadership limits the vision of digital innovation. Exploitative learning should be chosen first while exploratory learning with high cost should be carefully adopted.

Configuration 5 indicates the path for purchaser-driven platform enterprises.

Configuration 5 ($\sim PD * BD * \sim BiD * \sim DTI * DPC * DLS * TS * LY$) reveals that when the purchaser-driven platform exhibits a high level of digital platform capability and executive digital leadership but a low level of digital infrastructure, ambidextrous learning with high exploration and utilisation is required to attain a high-level digital innovation. Given the difference in the value-added mode, the digital infrastructure of purchaser-driven platform is limited. The digital innovation focuses on improving the user experience (Jiang *et al.*, 2023). Therefore, high-level digital platform capability and executive digital leadership capability are more valuable. High-level executive digital leadership capability determines the learning strategy and digital strategic orientation of the enterprise, with high-level digital platform capability improving the ambidextrous learning efficiency.

Configurations 2 and 3 indicate the path for bidirectional-driven platform enterprises.

Configuration 2 ($\sim PD * \sim BD * BiD * \sim DTI * DLS * TS * LY$) indicates that when the digital infrastructure of the bidirectional-driven platform is found to be deficient but the executive has a high level of digital leadership, a high level of digital innovation can be achieved by adopting ambidextrous learning approach of high exploration and -utilisation. Although the digital infrastructure of the bidirectional-driven platform is weak, executives with high level of digital leadership choose appropriate digital and learning strategies, and offer guidance for exploratory and exploitative learning to improve the digital innovation. Configuration 3 ($\sim PD * \sim BD * BiD * DPC * DLS * TS * LY$) demonstrates that a high-level digital innovation can be achieved by adopting a high-exploration, high-utilisation binary learning approach when a bidirectional-driven platform has both a high level of digital platform capability and executive digital leadership. The high-level digital platform capability improves the capability of bidirectional-driven platform to restructure and integrate resources, supports digital innovation strategy of executives. In addition, it enhances the efficiency of exploratory learning and utilisation learning, connecting the digital leadership of executives and ambidextrous learning to achieve a high-level digital innovation.

Configurations 2 and 3 demonstrate that bidirectional-driven platform adopts the ambidextrous learning mode of high exploration and high utilisation to attain high-level digital innovation while the digital leadership of executives is essential in this process. In short, there is no path in which digital infrastructure, digital platform capability and executive digital leadership capability are weak at the same time. For the producer-driven platform, digital infrastructure and digital platform capability, and the ambidextrous learning mode with low exploration and high utilisation, are more frequent. For purchaser-driven platforms, digital platform capability and ambidextrous learning styles with high exploration and high utilisation are more frequent. For bidirectional-driven platforms, executive digital leadership and high-exploration and high-utilisation ambidextrous learning styles are frequent.

3.3 Robustness Analysis

QCA is a set theory method that is assumed robust (Lidong *et al.*, 2023; Du *et al.*, 2022; Ming and Yunzhou *et al.*, 2019) when a slight change in operation produces a subset relationship between the results that does not change the substantial interpretation of the findings. Referring to Lidong *et al.* (2023), the present study tests the reliability of the results by adjusting the calibration anchor points. After adjusting the full membership, crossing points and no membership to the 80th, 50th and 20th percentiles, the results are consistent with the original configuration. The method of raising the case frequency

threshold from 1 to 2 is also adopted, reducing the consistency from 0.8 to 0.75, and increasing the PRI consistency from 0.75 to 0.8, confirming that the derived configuration is stable.

4. Discussion

4.1 Identical Types of Platform Enterprises and Path of Digital Innovation

The digital innovation paths of the same type of platform enterprises are also distinct. Specifically, digital capability affects the option of ambidextrous learning mode and the degree of digital innovation. Following this, enterprises may opt for the ambidextrous learning strategy in line with their resources and capability. A high-utilisation learning strategy is used when the digital leadership level of executives is low, since at this point, firms must rely on learning to boost their digital capability. However, a low-level digital leadership restricts their innovation prospect, asserting the usage of less risky and relatively cheap exploitative learning. Conversely, producer-driven platforms with a high level of digital capability and infrastructure incorporate low-utilisation learning when their executives exhibit a high-level digital leadership, as the firm not only shows a high-level digital capability, but also effectively lessens the learning cost when attaining high-level digital innovation.

4.2 Different Types of Platform Enterprises and Paths of Digital Innovation

Since the emphasis of digital innovation of different platform types is distinct, different types of platform enterprises have diverse paths of digital innovation. The requirements for digital capability and ambidextrous learning are also different. For the purchaser-driven platform, digital platform capability is comparatively more prominent, since digital innovation of these enterprises primarily stresses the integration of data resources, the optimisation of algorithms and the upgrade of user experience. In the context of ambidextrous learning, the new needs of users in the present data should be uncovered through exploitative learning while devising novel solutions by exploratory learning. In terms of the bidirectional-driven platform, the pursuit of product and technological innovation characterises its digital innovation, which requires firms to concurrently perform a high-level ambidextrous and exploratory learning, supported by a high-level digital platform capability and a sound digital infrastructure. However, the digital leadership of senior executives is useful, for a small number of firms can fulfil such requirements. In the development process of enterprises, the senior executives with high-level digital leadership explicitly recognise the related shortcomings while setting out a rational ambidextrous learning strategy for digital innovation. In the context of producer-driven platforms, digital capability, digital infrastructure, and exploitative learning are more significant for realising a high-level digital innovation. Based on the higher utilisation of innovation, the digital innovation of producer-driven platform upgrades the existing products.

Conclusions

The study employs NCA and FsQCA methodologies on 139 platform enterprises. The NCA shows that a single conditional variable does not constitute a necessary condition for digital innovation. However, when a high level of digital innovation is pursued, attention should be paid to improving digital capability and ambidextrous learning level, especially exploitative learning level. This is also aligned with the path derived in the FsQCA: out of the five paths to high-level digital innovation, exploitative learning occurs four times. Exploitative learning emphasises the expansion and extension of current knowledge and taps its application value in different fields.

This study also proposes several implications. High-level digital innovation cannot be attained regardless of any ambidextrous learning strategy when the enterprise exhibits low level of digital platform capability,

digital infrastructure, and digital leadership capability as the resource base of ambidextrous learning and digital innovation. Hence, in the digital context, the theory of organisational learning should be reinterpreted, whereas the effectiveness of ambidextrous learning must be subjected to the enterprise digital capabilities.

Previous studies emphasise the impact of a single factor on corporate digital innovation, refusing to study the synergic influence between organisational learning and capability. Extant literature also shows that enterprise digital innovation is an outcome of a co-evolution of capability and learning factors. However, there is still a scarcity of rigorous data support. Therefore, the development of ambidextrous learning and digital capability can assist the practitioners in recognising the antecedents of digital innovation. With the active roles of learning and capability, the ‘multiple possible concurrent causal relationships’ can be explored by identified configuration.

There are certain limitations associated with this paper. Firstly, given the limitation of three types of platforms to realise high-level digital innovation paths in terms of their sample size, these platforms may not fully cover all scenarios. The sample indicates that the three types of platform enterprises are significantly different in terms of quantity. Furthermore, the proportion of platforms driven by producers is comparatively limited. It is recommended that future studies gather a greater number of samples of platform enterprises in order to examine the possibility of the existence of other types of paths to attain high-level digital innovation. Further studies may apply alternative objective approaches to gather data, given the inherent defects of the questionnaires. Finally, in the majority of cases, the degree of digital capability, ambidextrous learning, and digital innovation exceeds the overall mean value. Consequently, the derived configuration may not be appropriate for firms with a limited level of digital capability. In consideration of the constraints imposed by the selection of methodologies employed in this study, it is not possible to determine the precise degree of digital capability that would be appropriate for each individual pathway. This underscores the necessity for further analysis in this area.

Literature

- Cei, L., Du, X., Yang, H. (2022), “Operation research in the management practices”, *Journal of Operations Management*, Vol. 31, No 12, pp.220-226.
- Cenamor, J., Parida, V., Wincent, J. (2019), “How entrepreneurial SMEs compete through digital platforms: The roles of digital platform capability, network capability and ambidexterity”, *Journal of Business Research*, Vol. 100, July, pp.196-206, <https://doi.org/10.1016/j.jbusres.2019.03.035>.
- Chen, H., Liu, X., Liu Dongxia, L. Guangrong. (2021), “Ambidextrous Strategy, complementary assets and innovation performance: Qualitative comparative analysis based on fuzzy sets”, *China Science and Technology Forum*, No 04, pp.102-109.
- Cheng, J., Liu, Q., Du, Y. (2023), “Entrepreneurial ecosystem and national entrepreneurial growth aspiration: a hybrid study based on NCA and fsQCA methods”, *Science of Science and Management of Science and Technology*, Vol. 44, No 03, pp.80-97.
- Chung, H.F.L., Yang, Z., Huang, P.H. (2015), “How does organizational learning matter in strategic business performance? The contingency role of guanxi networking”, *Journal of business research*, Vol. 68, No 6, pp.1216-1224.
- Ding, D. (2023), “Scientific Knowledge Production in the era of Big Data from STS perspective”, *Research in Science of Science*, pp.1-11, <https://doi.org/10.16192/j.cnki.1003-2053.20230504.002>.
- Du, X., Xue, P., Song, S. (2018), “Research on the effectiveness of online word-of-mouth communication based on lens model”, *Management Science*, Vol. 31, No 06, pp.74-91.

- Du, Y., Liu, Q., Chen, K., Xiao, R., Li, S. (2022), "Multiple models of business environment ecology, total factor productivity and high-quality urban development: a configuration analysis based on complex system view", *Management World*, Vol. 38, No 09, pp.127-145.
- Du, Y., Liu, Q., Cheng, J. (2019), "What kind of business environment ecology produces high entrepreneurial activity in cities? -- Analysis based on institutional configuration", *Management World*, Vol. 36, No 09, pp.141-155, [in Chinese].
- Duan, C., Gu, Y. (2021), "New product architecture innovation Mechanism based on ambidextrous learning and organization forgetting the old: A case study of small and micro enterprises' management cloud platform work circle", *Journal of Management*, Vol. 18, No 11, pp.1589-1599.
- Dul, J., van der Laan E., Kuik, R. (2020), "A statistical significance test for necessary condition analysis", *Organizational Research Methods*, Vol. 23, No 2, pp.385-395.
- Dul, J. (2016), "Necessary condition analysis (NCA): Logic and methodology of "necessary but not sufficient" causality", *Organizational Research Methods*, Vol. 19, No 1, pp.10-52.
- Dul, J. (2019), *Conducting Necessary Condition Analysis for Business and Management Students*, London: Sage.
- EL Sawy, O., Kræmmergaard, P., Amsinck, H., Vinther, A.L. (2016), "How LEGO built the foundations and enterprise capability for digital leadership", *MIS Quarterly Executive*, Vol. 15, No 2, pp.141-166.
- Feng, J., Wang, H., Zhou, D., Liu, Q., Chen, J. (2022), "Research on value creation mechanism of digital platform architecture and integration capability", *Studies in Science of Science*, Vol. 40, No 07, pp.1244-1253.
- Fichman, R.G., Santos, D.B., Zheng, Z.Z.E. (2014), "Digital Innovation as a Fundamental and Powerful Concept in the Information Systems Curriculum", *MIS Quarterly*, Vol. 38, pp.329-353, [in Chinese].
- Gong, Y., Yao, Y.H., Zan, A. (2023), "The Too-much-of-a-good-thing Effect of Digitalization Capability on Radical Innovation: The Role of Knowledge Accumulation and Knowledge Integration Capability", *Journal of Knowledge Management*, Vol. 27, No 6, pp.1680-1701.
- Guo, J.J., Zhou, S., Chen, J., Chen, Q. (2021), "How Information Technology Capability and Knowledge Integration Capability Interact to Affect Business Model Design: A Polynomial Regression with Response Surface Analysis", *Technological Forecasting & Social Change*, Vol. 170, September, 120935, <https://doi.org/10.1016/j.techfore.2021.120935>.
- Hambrick, D.C., Mason, P.A. (1984), "Upper Echelons: The Organization as a Reflection of Its Top Managers", *Academy of Management Journal*, 6: pp.9-37, <https://doi.org/10.5465/amr.1984.4277628>.
- Jiang, H., Yang, J.X., Gai, J.L. (2023), "How Digital Platform Capability Affects the Innovation Performance of SMEs—Evidence from China", *Technology in Society*, Vol. 72, No 1, 102187, <https://doi.org/10.1016/j.techsoc.2022.102187>.
- Li, L., Tao, H. (2023), "Research on the relationship between digitalization orientation and enterprise digital innovation", *Studies in Science of Science*, Vol. 41, No 08, pp.1507-1516.
- Li, Y., Miao, L. (2019), "The structural dimension and influence of enterprise digital leadership: a grounded theory study based on Chinese context", *Journal of Wuhan University (Philosophy and Social Sciences Edition)*, Vol. 73, No 06, pp.125-136.
- Liu, X., Yang, Y., Sun, Z. (2022), "Construction and Evolution of enterprise digital capability -- Based on multi-case exploration of leading digital enterprises", *Reform*, No 10, pp.45-64.
- Luo, W., Chen, W. (2023), "Farmers' e-commerce entrepreneurial decision-making: a configuration effect analysis based on institutional environment, social network and entrepreneurial learning",

Science of Science and Management of Science and Technology, pp.1-21, <http://kns.cnki.net/kcms/detail/12.1117.g3.20230922.1616.002.html>.

March, J.G. (1991), "Exploration and exploitation in organizational learning", *Organization Science*, Vol. 2, No 1, pp.71-87.

Ogink, T., Dong, J.Q. (2019), "Stimulating Innovation by User Feedback on Social-media: The Case of an Online User Innovation Community", *Technological Forecasting and Social Change*, Vol. 144, July, pp.295-302, <https://doi.org/10.1016/j.techfore.2017.07.029>.

Paladino, A. (2007), "Investigating the drivers of innovation and new product success: a comparison of strategic orientations", *Product Innovation Management*, Vol. 24, No 6, pp.534-553.

Qiu, Y., Guo, Z., Rao, Q. (2022), "Theoretical mechanism and policy suggestion of unimpeded double cycle of Chinese digital platform from RCEP perspective", *Reform*, No 11, pp.70-83.

Rai, A., Tang, X. (2010), "Leveraging IT capability and competitive process capability for the management of interorganizational relationship portfolios", *Information Systems Research*, Vol. 21, No 3, pp.516-542.

Tang, C., Liu, L., Li, M. (2019), "Internal and external knowledge distribution and ambidextrous learning balance: An empirical study of innovation-oriented enterprises in China", *Management Review*, Vol. 32, No 06, pp.82-92.

Tanzawa, N., Guan, X. (2023), "The influence of multi-dimensional driver linkage effect on enterprise digital innovation: an empirical analysis from SEM and fsQCA", *Science and Technology Progress and Countermeasures*, pp.1-11, <http://kns.cnki.net/kcms/detail/42.1224.G3.20230625.0952.002.html>.

Tian, H., Sun, M., Wang, L. (2023), "How digital leadership promotes enterprise green innovation: SEM and fsQCA methods", *Science and Technology Progress and Countermeasures*, Vol. 40, No 08, pp.54-65.

Wang, T.-W., Su, F., Li, J.-Z. (2023), "Research on dynamic mechanism and driving path of high-quality development of manufacturing industry from the perspective of configuration -- Based on qualitative comparative analysis of fuzzy sets", *Soft Science*, pp.1-13.

Wang, Y.G., Tian, Q.H., Li, X., Xiao, X.H. (2022), "Different Roles, Different Strokes: How to Leverage Two Types of Digital Platform Capability to Fuel Service Innovation", *Journal of Business Research*, Vol. 144, May, pp.1121-1128.

Wei, J., Wei, Y., Li, X. (2020), *Digital Innovation*, Beijing: China Machine Press.

Wu, L., Li, S., Wang, H., Su, Z., Li, J. (2023), "Research on advanced mechanism of digital transformation of manufacturing enterprises based on "corporate governance-organizational capability" configuration model", *Nankai Management Review*, pp.1-27, <http://kns.cnki.net/kcms/detail/51.1268.G3.20230811.1333.002.html>.

Wu, X., Xiao, J., Wu, J. (2022), "A new type of organizational learning based on human-AI collaboration: a multi-case study based on scene perspective", *China Industrial Economy*, No 02, pp.175-192.

Xie, P., Ma, L., Wei, Y., He, X.A., Du, Y. (2023), "Digital leadership and organizational innovation: The role of digital platform competence and environmental competitiveness", *Economics and Management Research*, Vol. 44, No 01, pp.129-144.

Xie, W., Li, Z., Li, X. Sun, M., Zhu, P. (2019), "Knowledge structure and development direction of digital Innovation Research", *Economic Management*, Vol. 42, No 12, pp.184-202.

Yang, Z.N., Hou, Y.F., Wu, C. (2022), "The balancing effect of open innovation networks in the dual circulation of Chinese enterprises: An investigation based on digital empowerment and organizational flexibility", *Journal of Management World*, Vol. 37, No 11, pp.194-205.

Yoo, Y., Henfridsson, O., Lyytinen, K. (2010), "Research Commentary-the New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research", *Information Systems Research*, No 21, pp.724-735.

Yuan, C., Xue, D., He, X.A. (2021), balancing strategy for ambidextrous learning, dynamic capability, and business model design, the opposite moderating effects of environmental dynamism[J]. *Technovation*, Vol. 103, May, 102225, <https://doi.org/10.1016/j.technovation.2021.102225>.

Zahoor, N., Zopiatitis, A., Adomako, S., Lamprinakos, G. (2023), "The micro-foundations of digitally transforming SMEs: How digital literacy and technology interact with managerial attributes", *Journal of Business Research*, Vol. 159, April, 113755, <https://doi.org/10.1016/j.jbusres.2023.113755>.

Zeike, S., Bradbury, K., Lindert, L., Pfaff, H. (2019), "Digital leadership skills and associations with psychological well-being", *International Journal of Environmental Research and Public Health*, Vol. 16, No 14, pp.26-28.

Zhang, M., Du, Y. (2019), "The application of QCA method in organization and management research: Orientation, strategy and direction", *Journal of Management*, Vol. 16, No 09, pp.1312-1323.

Zhu, P., Miao, X., Jin, S. (2023), "Cross-border search, resource coordination and enterprise business model innovation: the moderating role of shared cognition", *Journal of Management Engineering*, pp.1-15, <https://doi.org/10.13587/j.cnki.jjeem.2024.02.005>.

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SKIRTINGŲ TIPŲ SKAITMENINIŲ PLATFORMŲ ĮMONIŲ SKAITMENINIŲ INOVACIJŲ STRATEGIJŲ TYRIMAS: SKAITMENINIŲ GEBĖJIMŲ IR DVIPUSIO MOKYMOSI PERSPEKTYVA**Yuan Cheng, Xia Liu, Jinyu Chen, Yaqi Wang**

Santrauka. Skaitmeninės inovacijos yra būtinos, kad skaitmeninių platformų įmonės įgytų konkurencinį pranašumą skaitmeninės transformacijos metu. Siekiant atskleisti būtinus veiksnius ir diferencijuotas strategijas, kuriomis platformų įmonės gali pasiekti aukšto lygio skaitmeninės inovacijos, šiame tyrime, remiantis organizacinio mokymosi teorija ir skaitmeninių gebėjimų teorija, naudojama būtinųjų sąlygų analizė (NCA) ir neapibrėžtų duomenų kokybinė lyginamoji analizė (FsQCA). Siekiama ištirti platformos tipo, skaitmeninių gebėjimų, dvipusio mokymosi metodų ir jų derinimo mechanizmų įtaką 139 įmonių skaitmeninėms inovacijoms. NCA rezultatai atskleidė, kad mokymosi stilius ir skaitmeniniai gebėjimai nėra būtina sąlyga siekiant aukšto lygio skaitmeninių inovacijų. FsQCA rezultatuose nustatytos penkios strategijos, padedančios pasiekti aukšto lygio skaitmeninės inovacijos. Gamintojo platformos atveju jos skaitmeninė infrastruktūra ir platformos pajėgumas paprastai yra stiprūs. Kai skirtingų tipų platformų įmonės siekia aukšto lygio skaitmeninių inovacijų, jos turi remtis savo skaitmeniniais gebėjimais ir pasirinkti tinkamus dvipusio mokymosi metodus.

Reikšminiai žodžiai: platformos tipas; skaitmeniniai gebėjimai; dvipusis mokymasis; skaitmeninės inovacijos; FsQCA.