A Multi-Level Examination of Performance in Innovation Ecosystems: Board, Asset Scale, Technology, and Government Support

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Abstract

We investigate how the firm's board structure (i.e. CEO duality or independence) and its asset scale at the micro level, the industry's technological intensity at the meso level, and the government's initiatives at the macro level influence firms' digital innovation performance in the innovation ecosystem of the Chinese manufacturing industry. Drawing on a longitudinal study of 1,098 firms sourced from the CSMAR database, we utilise a co-evolutionary multi-level model for the exploration. Our findings reveal that firms led by independent board members with largescale assets and that have received government subsidies are more likely to achieve superior digital innovation performance. Furthermore, the impact of micro-level factors varies with technological intensity, with medium and high-tech firms showing more significant innovation performance improvements. We suggest that firms maintain a board composition with a balanced mix of independents with objective oversight and non-independents with strategic influence and allocate their resources to capitalise on emerging technological trends to perform better in innovation ecosystems. Firms should not solely depend on government support but align their resource basis and governance structures to leverage technology and incentives effectively. Policymakers should craft targeted initiatives depending on the innovation ecosystems' technological intensity and the firms' resource endowments.

Index – Terms: Innovation ecosystems, multi-level analysis, CEO duality, government support, technological intensity, digital innovation performance, manufacturing industry, China.

Managerial Relevance Statement

We find that firms led by independent boards outperform those under CEO duality in high-tech innovation ecosystems. Thus, objectivity and technical oversight outweigh hierarchical command. For engineering managers, this implies that board restructuring to incorporate independent, digitally fluent directors can accelerate innovation performance. Technological intensity acts as a catalytic moderator in high-tech subsectors to enhance innovation. Therefore, engineering managers should adopt agile resource orchestration and iterative capability development, while in medium- or low-tech firms, gradual digital maturation and absorptive capacity building are essential. The insights offer a foundation for formulating decision-support tools that integrate board composition analytics, sectoral tech-readiness indexes, and government incentive mapping. Engineering managers and policy architects can thus co-develop feedbackrich innovation governance infrastructures that continuously realign firm-level resource configurations with the evolving dynamics of national innovation ecosystems.

I. INTRODUCTION

Innovations are not isolated novelties; they emerge from various actors' interactive and collective efforts within a broader ecosystem [1], [2]. A firm's sole practices can only partially influence its innovation performance since it relies on the other elements and dynamics of the broader external network [3], [4]. The innovation ecosystem highlights the complementary roles occupied by different actors for achieving superior performance [5]. Research has traditionally resorted to impersonal analyses of social, structural, political, economic, and historical factors, neglecting the importance of firms and individuals or focusing on individuals and firms, overlooking the effects of environmental or contextual factors on the performance of innovation ecosystem [6], [7]. This concentration was partially a necessity that emerged from the limited availability of specific micro-level firm or meso-level data that can be used for innovation ecosystem studies. Previous studies [8], [9] have often relied on case studies and other qualitative methods or quantitative studies using macro-level data to assess performance in the innovation ecosystems. Some studies [10], [11] have used big data analytics, which provided researchers with immense data revealing macro trends and searches about innovation in ecosystems. All these studies offered invaluable insights into the innovation research stream. Despite the scholarly efforts to scrutinise innovation systems and policies, research exploring the interactive effects of actors at different levels of the ecosystems, particularly at the meso-level, on innovation success is limited [12], [13]. Understanding the impact of dynamic multi-level factors is crucial because their interactions and interdependencies can vary and make the boundaries of innovation ecosystems fluid over time [14], [15].

We draw on a co-evolutionary multi-level perspective [16], [17] and fill this gap by investigating the interactive effects of the macro-level factors, i.e. government subsidies and the meso-level factor, i.e. technological intensity, concurrently with micro-level factors, i.e., the firm's board structure and asset scale in the innovation ecosystem of the Chinese manufacturing industry. In management literature, evolution is closely associated with innovation and change [18]. We suggest that our multi-level factors are not static; they evolve together within the innovation ecosystem dynamically and influence each other's development and, ultimately, innovation performance. This co-evolution is marked by their complementary nature, wherein changes or advancements in a factor impact and trigger adaptations in others, resulting in improved innovation performance. For example, increasing technological intensity at the mesolevel may prompt firms to adjust their board structures and resource allocation at the micro-level, while government subsidies at the macro level support firms to invest in technological innovations. Each factor at a different contextual level responds to the environment created by the others and promotes an ongoing cycle of digital innovations.

We thus describe our broad innovation ecosystem as a dynamic multi-layered network of dependent and interdependent elements, i.e., firms, suppliers, customers, incubators, technology developers, start-ups, finance institutions, investors and government that interact with each other and/or integrate specialised but complementary assets and skills to deliver unique and creative outputs [19], [5]. In line with this, we identify our ecosystems' value proposition as enabling firms to achieve digital innovation performance that ultimately determines the overall success within the innovation ecosystem in which they operate. Our study focuses on listed firms that are primarily large-sized manufacturing companies. While we cannot repudiate the importance of micro firms and start-ups' innovation performance, the substantial contribution of large firms' performance to the innovation ecosystem of the Chinese manufacturing industry, along with data availability, led us to select listed firms for our sample. This approach directs us to investigate listed firms' interactions with the most relevant and critical innovation ecosystem actors and exclude less central participants such as incubators and venture capitalists. Therefore, in addition to firms' strategic behaviours, which we examine through their board structures and resource bases, our study examines key structural factors that act as game changers across all industries, such as government support and technological intensity. We consider Adner's [19] ecosystemsas-structure approach, which encompasses a heterogeneous set of actors that are firms, technology level and government in our study that contribute directly or indirectly to innovation and value-creation processes involving the innovation ecosystem.

Our paper contributes to the literature in four ways. First, we examine the individual, interactive, and comparative effects of critical factors at different layers of the innovation ecosystem and present a holistic picture to better understand the improvement of digital innovations driven by the multi-level factor co-evolution that appears to be inconclusive in the literature [20], [21]. The results can help managers and policymakers alter their innovation ecosystem strategies uniquely and meaningfully and make informed decisions over time. Second, the paper empirically shows the driving role of technology in digital innovations. It explores how digital innovation performance varies with the meso-level technological intensity within the ecosystem. The meso-level is positioned somehow between the micro and macro layers but has been largely overlooked as a significant dimension in organisational studies [13], [22]. However, digital innovation performance is contingent upon meso-level factors such as the technological diffusion level and requirements of the innovation ecosystem [23], [24]. Thus, our findings can offer evidence regarding the role of technological intensity in achieving the ecosystem's fullest digital innovation potential for Chinese manufacturing firms.

Third, we create a unique dataset based on a multi-faceted performance indicator comprising firms' propensity for digital transformation and innovation output. Digital transformation significantly contributes to firms aligning with technological advancements in the ecosystem and boosting their digital innovation performance [25], [26]. It involves infusing digital technology into all business functions and fundamentally changes how businesses innovate and deliver customer value [27], [28]. Furthermore, the propensity for digital transformation can strongly indicate potential digital innovation performance over time, consistent with the study's adopted co-evolutionary model. Employing propensity-based scales in addition to the objective measures may reduce the findings' dependency on a single point in time [29]. Therefore, we choose firms' digital transformation propensity along with innovation output as proxies of their digital innovation performance. Our approach provides a more nuanced measurement of firms' innovation performance outcomes compared to studies that rely on a single performance criterion.

Finally, we provide empirical evidence on digital performance in the innovation ecosystem within an emerging economy, which has yet to be sufficiently covered in the literature. Emerging economies have become crucial contributors to the global economy and popular innovation hubs [30]. The 2020 China Enterprise Digital Transformation Index Research report indicated that only 11% of firms' digital investments result in excellent innovation and business performance. Only 22% of firms effectively adjust and optimise production using real-time data [31]. China released a national strategic plan, "2035 Vision Outline", aiming to enhance the proportion of innovations in the manufacturing industry as an essential task of China's economic development [32]. In line with this vision, Chinese manufacturing firms and the government have invested considerably in digitalisation and technology transfer [33], making China an ideal context for this study. Therefore, the implications might help decision-makers in other emerging economies that share similarities with China.

II. LITERATURE REVIEW

A. Conceptual Framework: Co-evolutionary Multi-Level Model

In dynamic business landscapes, actors' roles and effects can shift, making their positions within or outside their ecosystem uncertain. These shifts in roles reflect the interdependencies among the actors. Similar co-evolution can render the interactions and interdependencies among actors the most critical determinants of success within the innovation ecosystem [34]. Thus, we must understand the co-evolutionary dynamics of the key actors within the Chinese manufacturing innovation ecosystem to identify new strategies and design new systemic policies for nurturing digital innovations. The Chinese government, as a macro-level actor, plays a pivotal role in developing the innovation ecosystem of its manufacturing industry through policies emphasising industrial upgrading (shifting the industry from a low-cost, labour-intensive to an advanced innovation-driven, high-tech digital structure), digital transformation, and the integration of artificial intelligence (AI) and robotics. Our research focuses exclusively on innovation-specific government support, such as patent and talent training subsidies, i.e., Yantai City patent subsidy funds, and research grants like the 131 Talent Subsidy from the Hangzhou Shangcheng District Finance Bureau and the Technology Innovation Park grants from the Bao'an District Finance Bureau in Shenzhen. This differs from previous studies that include broader variables such as GDP growth, per capita income, and general incentives for specific industries and allows our research to more directly measure the government's impact on innovation ecosystems. Consequently, government influence within an innovation ecosystem is crucial and cannot be overlooked.

The primary focus of China's innovation ecosystems is technology, as evidenced by China's leading position in global spending and investment in inward technology transfer. This emphasis is further reinforced by the Chinese government's policy initiatives and strategic vision. As a meso-level factor, technological intensity drives innovation, fosters collaboration, and enhances competitiveness while shaping policy and investment in the manufacturing industry. Given its critical role in shaping the innovation landscape, technological intensity is essential for inclusion in our analysis. Finally, firms like original equipment manufacturers (OEMs), chemical and material producers and equipment and machinery manufacturers are at the core of Chinese manufacturing and lead innovation processes to improve production efficiency, product quality, and technological integration. Thus, they evolve from traditional manufacturers to digital innovators, implementing advanced manufacturing solutions like AI-driven production lines. As key players in the innovation ecosystem of Chinese manufacturing, their firm-level strategies for enhancing their innovation capacity are crucial. However, due to its dynamic and evolutionary nature, navigating the innovation ecosystem of the Chinese manufacturing industry presents several challenges. These challenges include understanding the differences in industrial contexts, making prudent strategic decisions about investments to address the innovation ecosystems' resource requirements and with whom to collaborate or compete, aligning internal innovation activities with technological advancements, and enhancing the firm's role within the ecosystem [14], [35].

For example, government regulations and policies evolve in response to technological advancements within the innovation ecosystem. The government, initially a financial supporter of the ecosystem, may shift toward enforcing stricter environmental standards or promoting green technologies, pushing the firms to respond quickly and reallocate their resources toward more innovative, sustainable practices. These heavy resource allocations make technological intensity, initially driven by government investment, a self-reinforcing force that shapes both firm strategies and government policies. As the ecosystem matures, the government becomes a facilitator and regulator. This dynamic creates a feedback loop where technological advancements shape both firm strategies and government policies. Firms evolve from adopters of government-supported technologies to drivers of innovation whose actions set new benchmarks for policy and industry practices. Therefore, the co-evolution of the government, technological intensity, and firms within the innovation ecosystem of Chinese manufacturing follows dynamic and interconnected processes where each actor adapts and evolves, thus creating a continuous cycle of digital innovations.

Since ecosystems are influenced by systemic evolutions [36], we grounded our study in a coevolutionary multi-level model [37], [38] to investigate how digital innovations result and evolve from the interactions between the actors in three pillars: government initiatives (macro), technological diffusion and practices, namely technological intensity (meso), and firm behaviour (micro), namely, firm governance and resource base, within the innovation ecosystem of the Chinese manufacturing industry. In our study, co-evolutionary multi-level refers to multi-layered gradual change mechanisms, i.e., firm behaviour, technology level and government actions [36]. We aim to offer adaptive (evolutionary) policies for innovation ecosystems, considering the dynamics of this variation. Specifically, we suggest that a firm's board structure strongly influences the reconfiguration of its resource base, which is connected to the ecosystem's technological requirements, resulting in superior innovation performance. The firm's strategic vision and objectives direct its investment choices, resource deployment, and skill enhancement, which in turn influence its technology development and utilisation efforts [39]. These efforts contribute to the overall level of technological intensity in the ecosystem. Simultaneously, the prevailing standards and requirements of technological intensity in the ecosystem can compel the firm to adapt its strategies and actions, including technology investments, accordingly.

Moreover, government support at the macro level interacts with firms' innovation processes and technological development, impacting firms' digital innovation performance. Consequently, we suggest that the continuous interplay of multi-level factors, i.e., firms, technology, and government, where each evolves in response to changes in the others, drives the digital innovation performance of the firms and the broader ecosystem.

B. Development of Hypotheses

Digitalisation and innovation are crucial strategic directions [40], [41] to cope effectively with the reconstruction of the global value chain, reverse the trend of entities sliding into the virtual economy, and promote firm development in an innovation ecosystem [42], [43]. They exert a broad transformative influence on optimising and reorganising production factors and have farreaching effects on processes, products and services, and new business models [44], [45].

Innovation and digital transformation include ongoing extended processes and necessitate a pertinent leadership vision and mindset for allocating resources per the competition requirements of the ecosystem, as well as providing continuous executive support [42]. Corporate governance theories, such as the upper echelons and stakeholder theories, provide insightful frameworks to examine firm decision-making, resource allocation, and strategic outcomes. However, while upper echelons theory [46] primarily concerns top managers' personality traits and cognitive biases, stakeholder theory [47] mainly focuses on sustainability and social responsibility related to firm behaviours, yet the structural governance insights they offer are relatively limited. The complex nature of digital innovations involves long R&D cycles and sunk costs along with shortterm financial returns to nurture technological improvements leading to better innovation performance. These two opposing yet complementary objectives and requirements highlight the importance of governance structures that effectively balance control and autonomy within an organisation. As digitalisation and innovation unfold over time, they require ongoing strategic adaptations driven by evolving governance and leadership visions. The board composition controls a firm's strategic direction and power centralisation. Thus, different board governance structures, such as the choice of independent members and CEO duality [48], [49] can impact a firm’s propensity for digital transformation and innovation output as the boards adapt their approach to lead the firm’s short and long-term strategic directions [50], [51].

We use agency and stewardship theories, which provide compelling yet contrasting explanations for how control and autonomy shaped by governance structures, i.e. board oversight and CEO-led, influence firms’ innovation trajectories. Moreover, agency and stewardship theories offer insights into how firms adapt their governance structures in response to evolving technological and governmental forces [52], [53]. This co-evolutionary dynamic between governance structures and digital innovation performance reflects how firms continuously adapt their internal governance to maintain alignment with the innovation ecosystem's external pressures. Agency theory posits that chief executive officers (CEO) (agents) have self-serving motivations and prioritise greater economic rewards [54]. On the other hand, stewardship theory considers CEOs to be diligent stewards intrinsically motivated to pursue the company's organisational goals. CEOs align themselves with the company's mission; thus, possessing more than typical power, i.e. CEO duality, known as the possession of the board chairperson and CEO positions by the same individual, will better serve the firm's and its shareholders' interests [55], [56]. According to stewardship theory, a CEO duality leadership structure eliminates ambiguity in the decision-making process [57], which is vital in dynamic innovation ecosystems. However, agency theory believes in a separate board leadership structure, encourages independent board members and objects to CEO duality because it weakens board control and promotes CEO entrenchment [58], [59]. Traditional Confucian Chinese culture promotes paternalistic and collectivistic values [60]. It encourages individuals to embrace collectivism instead of selfserving and individualistic behaviours, thereby endorsing stewardship in making decisions. Moreover, the dual role of the CEO in management and governance can facilitate the alignment of the firm’s innovation strategies with overall business objectives, ensuring that innovation efforts are cohesive and well-supported in the innovation ecosystem. Therefore, we hypothesise: H1:

Compared to independent boards, CEO duality is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.

Innovation ecosystem dynamics such as competition and rivalry, technological intensity, knowledge flows, regulatory environment, and collaborative partners require firms to possess specific resources and skills [61]. The asset scale constitutes a firm's resource base, strategically influenced by the boards' decisions. Research [62], [63] shows that the availability of firm-level resources influences how a firm addresses the challenges, dynamics and demands of its innovation ecosystem, ultimately affecting its performance.

Therefore, a firm-centric perspective is needed to explore how firms' internal resources and capabilities contribute to digital innovation performance. Given that digital innovations are highly dependent on financial, organisational and technological assets, the resource-based view of the firm (RBV) is particularly relevant and has the strongest explanatory power for understanding how firms can achieve superior innovation performance through internal asset accumulation [64], [65]. RBV theorises that firms with larger asset bases typically possess greater financial resources [66], [67]. Moreover, the speed and outcomes of the innovation process are a function of the firm's resource availability [68], deployment and reconfiguration. Having substantial financial resources enables firms with a digitalisation vision to invest in advanced technologies, hire skilled personnel and fund extensive research and development (R&D) initiatives, all essential for digital innovation performance [69]. Thus, the greater the firm's asset scale, the more likely the firm's digital transformation continuity and better digital innovation output. Namely, we suggest that large firms with greater asset scales can create more digital innovations at the firm level, thus driving better ecosystem performance. Based on the explanations, we hypothesise:

> H2: Asset scale is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.

The influence of external environment and pressures on firms' performance are examined by several theories such as industrial organisation theory (IDT), resource-dependency theory (RDT) or technology-organization-environment (TOE) framework in the literature. While industrial organisation [70] focuses on market-driven pressures, RDT [71] highlights how firms actively manage dependencies from a more strategic perspective. The TOE framework [72] explores why firms adopt digital technologies and offers a more structured view of technological and organisational adaptation, making it more firm-centric. However, institutional theory, which deals with all regulatory, normative and cultural forces, provides a more holistic macro-level perspective and is one of the most suitable theories for analysing policy-driven digital transformation and innovation.

Moreover, the institutional theory supports the co-evolutionary perspective, suggesting that macro-level social structures, i.e., governments, can shape innovation ecosystems by providing authoritative guidelines for firm behaviour [73]. This co-evolution between government initiatives and firm strategies ensures that firms can leverage government support to maximise their innovation output while adapting to new regulatory frameworks. Indeed, government initiatives can provide the necessary resources and support to stimulate firms' innovation capacity and foster a dynamic innovation ecosystem [74]. Governments play a crucial role in encouraging and even compelling firms to adopt digital innovations to control financial transactions within markets, detect money laundering and other grey operations, provide intelligence, security, and data protection, improve efficiency and cost reduction in public and private services, and promote environmental sustainability [75], [76]. Furthermore, the rapid improvement in data information processing and digital transformation generates new jobs. The government dominates firms' economic activities in China through regulations, policies and even more direct control mechanisms [77]. Due to the reasons mentioned above, governments can significantly impact ecosystems' innovation performance through tax incentives, project support, and direct financial premiums for the R&D expenditures of firms [78].

H3: Government support is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.

Technology has long served as the primary driver of innovation. Industry 4.0 and 5.0 advancements compel actors to understand the complex interconnections between technology and innovation processes [79]. Technological intensity refers to the degree to which an industry relies on advanced technologies to drive digital innovations. Technological intensity is particularly significant in the manufacturing industry due to intense global competition and the continuous push to optimise production and innovate products. For example, digital technologies can create new production functions [80], resulting in unique outputs that vary according to the degree of technological intensity, such as high, medium, or low. Our study examines the Chinese manufacturing industry, which consists of various sub-sectors, each characterised by different levels of technological intensity. For instance, consumer electronics manufacturing often employs high-tech processes, whereas chemical manufacturing uses medium-tech solutions. Based on the OECD's classification of manufacturing technologies [81], we group these subsectors into three categories: low- and medium-tech manufacturing, medium- and high-tech manufacturing, and high-tech manufacturing. Each firm is classified within one of these categories. Consequently, we consider the technological intensity of each categorised sub-sector as a meso-level factor in the broader innovation ecosystem. Studies [82], [83] find that high-tech industries are more likely to embrace digital technologies. In high-tech industries' innovation ecosystems, firms capitalise on resources for digital technologies such as AI and IoT, swiftly navigate technological changes and enable aggressive investment in R&D and innovation. This underscores how firms' resource basis and technological intensity co-evolve, each pushing the other to higher levels of innovation. Thus, a firm's strategic behaviour regarding resource allocations aligns with its sub-sector's technological intensity in the ecosystem, leading to higher digital innovation performance. Based on the explanations, we hypothesise:

H4a: The level of technological intensity within the ecosystem moderates the relationship between a firm's asset scale and digital innovation performance.

Technology may be an even more influential meso-level factor affecting the ecosystems' macro-level institutional forces, translating their impact into higher digital innovation performance. Nelson and Winter [34] highlight the importance of technology and institutional congruity: "In a regime in which technical advance is occurring and organisational structure is evolving in response to changing patterns of [the market] … the problem of evolutionary theory is the generation by new technologies of benefits and costs that old institutional structures ignore” (p. 368). Understanding these dynamics is crucial for policymakers to design effective initiatives that cater to different industrial sectors' specific needs and capacities, ultimately fostering a more robust and dynamic innovation ecosystem.

Firms from high-tech industries, with their inherent focus on innovation, are more likely to respond vigorously to government initiatives [84], [45]. With their advanced digital infrastructure and a higher absorptive capacity—the ability to recognise, assimilate, and apply external knowledge—firms in high-tech industries might be better positioned to leverage government support for digital innovations. While firms from medium-tech industries benefit from similar initiatives, they may adopt a more measured approach, focusing on incremental improvements and practical applications. With their conservative stance towards innovation, firms that operate in low-tech industries require targeted government interventions demonstrating clear and immediate benefits to drive technological adoption. Firms in medium- and low-tech industries may struggle to utilise government support effectively due to a lack of technological capabilities and absorptive capacity, and its effect on those firms’ digital innovation performance might be less pronounced than that of firms from high-tech sub-sectors [10]. Therefore, the impact of government support on digital innovation performance may vary depending on the technological intensity of the manufacturing firms’ subsector in the ecosystem. Considering this, we hypothesise:

> H4b: The level of technological intensity within the ecosystem moderates the relationship between government support and firms’ digital innovation performance.

Figure 1 below represents the theoretical basis and hypotheses of the study.

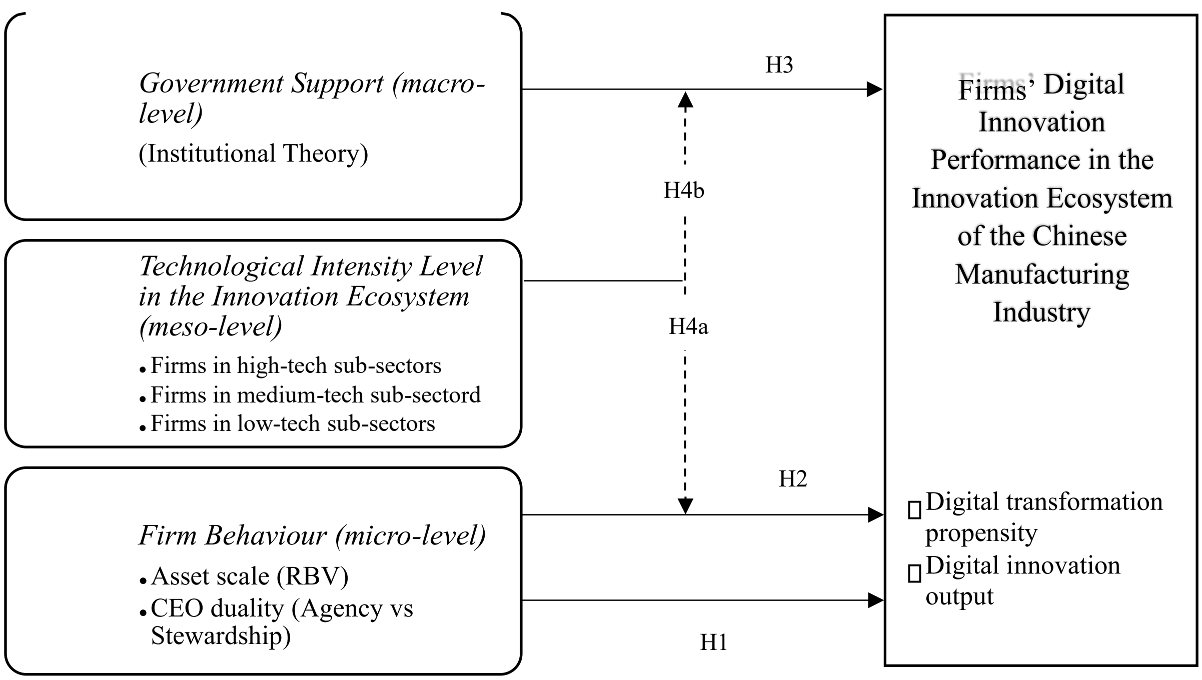


Figure 1: The theoretical framework and hypotheses of the study

III. METHODOLOGY

A. Data Selection

We conducted our research on listed Chinese manufacturing firms. We selected a sample of listed manufacturing firms classified as digital and core industries between 2008 and 2019 from the China Stock Market & Accounting Research (CSMAR) database, the country's pioneering domestic economic and financial database. The CSMAR database covers China's core digital industries, such as the information and communication cluster with telecommunications, internet services, software development, and data services; the e-commerce cluster with online retail, marketplaces, and B2B platforms; semiconductors and electronics cluster, including manufacturing of integrated circuits, microchips, and other digital components; smart logistics and digital supply chain cluster and healthcare technology (telemedicine) with digital platforms in medical services, diagnostics, and remote healthcare solutions. The CSMAR database includes objective firm-level data, such as basic information, financial statistics, and corporate governance metrics, for manufacturing firms from a diverse range of sub-industries in 31 provinces of China. Hong Kong, Macao, and Taiwan were excluded owing to their specific institutional systems, which function differently from other regions of China. Our rationale for selecting data from 2008 and 2019 is twofold: China's digital economy's significant expansion and rapid development occurred after 2008, and the relevant data were found afterwards [85]. China's national economic industry classification (GB/T 4754–2017) categorises listed firms into sectors, with the manufacturing industry split into 30 sectors out of 81 divisions. Then, we collected the patent data from China National Intellectual Property. We combined the International Patent Classification (IPC) and National Economic Industry Classification (NEQ, GB/T 4754–2017) with Python text data mining and information matching methods. We extracted the digital technology patents according to the NEQ code of patents and the 2021 Chinese Statistical Classification of Digital Economy and Core Industries [86]. We also used input-output tables from 2012 and 2017, which serve as a critical foundation and offer detailed inter-industry flows and economic linkages [87]. The year 2012 marked a significant period in China's economic development as the country embarked on the implementation of its 12th FiveYear Plan (2011–2015), which emphasised industrial upgrading and innovation [88]. Similarly, 2017 was chosen as it reflects the progress achieved under the 13th Five-Year Plan (2016–2020), which prioritised digital economy development and the integration of traditional manufacturing with digital technologies [89]. Any discrepancies between the two years due to methodological differences, classification updates, or evolving economic conditions might introduce inaccuracies in the data.

Therefore, the interval between 2012 and 2017 was particularly relevant for tracking the impact of digital technology integration and sectoral innovation over a reasonable duration without excessive data sparsity or missing trends. Although the input-output tables were not directly included in our quantitative analyses, we examined these tables to identify and exclude any biased or inconsistent data that might have arisen during the Five-Year Plan transition periods. This approach supported the robustness and reliability of the data used in our study [90].

We removed ST, *ST and delisted companies and samples with missing and invalid data by utilising winsorising. Our final dataset comprised 11,379 observations from 1098 firms. We aimed to track the same firms over the entire period; however, due to missing data for some variables, we could not use panel data and instead used a longitudinal approach.

B. Model Specifications

To investigate the impact of the predictors, i.e. government support, firm asset scale, and board structure, including CEO duality and independent board, on digital transformation propensity and innovation output, we set a binary variable for Logit models as follows:

$$logit(DInnov_{irkt} = 1) = \varphi(\beta_0 + \beta_1 Support_{irkt} + \beta_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt}) \quad (1)$$

$$logit(DInnov_{irkt} = 1) = \varphi(\beta_0 + \beta_1 Asset_{irkt} + \beta_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt}) \quad (2)$$

$$logit(DInnov_{irkt} = 1) = \varphi(\beta_0 + \beta_1 Board_{irkt} + \beta_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt}) \quad (3)$$

$logit(DInnov)_{irkt}$ represents the digital transformation propensity of firm i, which operates in the industry k of urban agglomeration r in year t. $Support_{irkt}$ stands for government support firm i obtained for digital innovation. $Asset_{irkt}$ represents the asset size of firm i, respectively. Finally, $Board_{irkt}$ consists of $independence_{irkt}$ and $duality_{irkt}$ and represents the interdependency of the board and the combined title of board chair and CEO in firm i, respectively. We also constructed models to measure the exploratory variables' impact on the digital innovation outputs of the firm – $DigInnov_{irkt}$, below:

$$DigInnov_{irkt} = \alpha_0 + \alpha_1 Support_{irkt} + \alpha_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt} \quad (4)$$

$$DigInnov_{irkt} = \alpha_0 + \alpha_1 Asset_{irkt} + \alpha_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt} \quad (5)$$

$$DigInnov_{irkt} = \alpha_0 + \alpha_1 Board_{irkt} + \alpha_2 X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt} \quad (6)$$

C. Measures Dependent variables

We measured the dependent variable, the digital innovation performance of firms in the ecosystem, using two proxies: (1) firms' digital transformation propensity and (2) digital innovation output. *Digital transformation propensity* is assessed by firms' sustainable digital technology patent output (1 yes, 0 no). *Digital innovation output* is measured at the firm level by the natural logarithm of the number of a firm's applications or authorisations of digital technology innovation patents.

Independent variables

Government support: We collected data from the profit and loss items of "government support" in the notes in the financial statements of listed companies in the CSMAR database. We identified 164 keywords related to digitalisation, such as 5G, AI, digital technology, intelligence, machine learning, information technology, deep learning, robots, blockchain, and the Internet of Things. We considered each firm's government support regarding digital innovations, such as patent subsidies, enterprise talent training subsidies, chemical raw material technology awards, funds for postdoctoral workstation researchers, rewards for particular research and special funds for intellectual property. We extracted and summarised the number of related subsidies annually.

Technological intensity: We classified the national sectors into three categories per the OECD manufacturing technology classification standards [81] and coded them: low- and medium-tech manufacturing (1), medium- and high-tech manufacturing (2), and high-tech manufacturing (3).

Firm asset scale: We used total net asset size (log value of the total amount of a firm's assets in CNY).

Board structure: We have two indicators: Independence and CEO duality. We reached the firms' board size, which refers to the total number of members on the board. We calculated the proportion of independent directors to the board size, which defines independence, while the possession of Board Chair and CEO positions refers to duality. We coded (1) for duality and (0) otherwise. Table 1 presents all variables' denominations, descriptions, means, standard deviations, and other statistical information.

TABLE 1

Control variables

Studies [91], [92] show that employee numbers (Employee), average wage level (Wage), the nature of ownership, i.e. state-owned enterprise (SOE), less financial risk (Leverage), and high market value (Market) create more business and performance. Therefore, we controlled the mentioned variables to remove whatever effect they might generate on firm performance. We also controlled the dummy variables of years, industries, and regions (CityGroup) in all regressions to assess the pure influences of the independent variables in the ecosystem. While (X) represents the control variables in the model specifications, λ_r, δ_k, and $_t$ stand for the area, industry sector and year fixed effect, respectively, and $_{irkt}$ indicates the error term.

IV. ANALYSES AND RESULTS

A. Multicollinearity

Multicollinearity occurs when explanatory variables are highly correlated, which can compromise a regression model's statistical significance and precision. To address this, we conducted a bivariate correlation analysis to examine the relationships between all variables. The results revealed that none of the correlations exceeded 0.80, indicating an acceptable level of correlation [93]. Moreover, the variance inflation factor (VIF) scores were under the threshold value of 5 [94]. Table 2 provides the inter-item correlations and VIF scores.

TABLE 2

B. Regression Analyses

We analysed the impact of independent variables on digital innovation performance by hierarchical OLS regression. In this method, we enter each set of independent variables into separate blocks and analyse the incremental changes in beta coefficients and the R^2 statistic, assessing the impact and fraction of the variance explained by these variables [95]. Table 3 presents the results of the regression analyses.

TABLE 3

First, we entered the control variables in Model 1. Model 1 shows the benchmark specifications with a constant. In Model 2, we added independent variables, independence and CEO duality. Although both variables were significantly associated with digital innovation performance ($\beta_{independence}$= 0.575, $p< 0.05$; $\beta_{duality}$= 0.134, $p< 0.01$), we observe higher beta coefficients favouring independence, indicating a more significant influence than CEO duality on innovation performance. Thus, in contrast to our proposition, we reject H1.

In Model 3, we enter firms' total asset scale and find a significant relationship with digital innovation performance ($\beta_{asset\ scale}$= 0.094, $p< 0.01$), confirming H2. Similarly, Model 4 shows a significant association between government support and digital transformation performance ($\beta_{support}$= 1.890, $p< 0.01$), confirming H3.

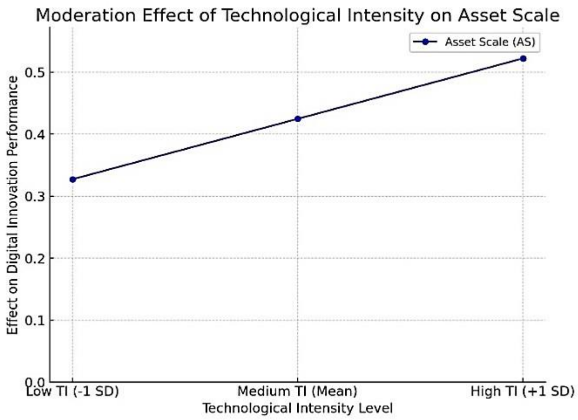
As a precondition for testing the moderation effect of technological intensity between independent and dependent variables, we assess the association of technological intensity with digital innovation performance and find it significant ($\beta_{technology}$= 0.209, $p< 0.1$) in Model 5. This finding allows us to continue our analyses. Model 6 and Model 7 display the results of the interactions between asset scale and technological intensity (β_{ASxTI}= 0.138, $p< 0.01$) and between government support and technological intensity (β_{GSxTI}= 3.591, $p< 0.01$), both significant.

Compared to the individual impact of asset scale on digital innovation performance, its interaction with technological intensity increases the β value from 0.094 to 0.138. Additionally, the R^2 value, which represents the explanatory power of asset scale alone on innovation performance, rises from 20.4% to 21.8% after the interaction of technological intensity, providing an additional significant explanatory power of 1.4% ($\Delta R^2 = 0.014$). These results prove that technological intensity moderates the relationship between asset scale and innovation performance. Thus, we support H4a.

Similarly, the interaction between government support and technological intensity increases the β value from 1.890 to 3.591, compared to the individual impact of government support on innovation performance. Moreover, the R^2 value rises from 21.8% to 23.4% after accounting for the interaction with technological intensity, providing an additional significant explanatory power of 1.6% ($\Delta R^2 = 0.016$). These findings confirm that technological intensity moderates the relationship between government support and innovation performance, supporting H4b.

TABLE 4

Table 4 summarises the study's hypotheses along with the findings regarding their support or rejection. Figures 2 and 3 illustrate how different levels of technological intensity moderate the impact of asset scale and government support on digital innovation performance. As technological intensity increases, asset scale and government support positively affect digital innovation performance.



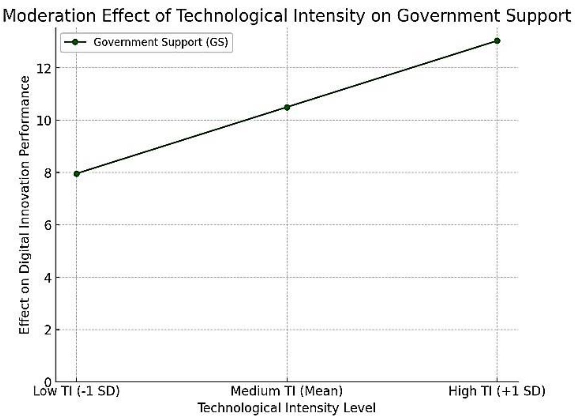


Figure 2: Moderation effect of TI on AS

Figure 3: Moderation effect of TI on GS

In our models, R^2 values are relatively low, i.e. 21–22% of explanatory power. Dikova et al. [96] consider this typical when working with longitudinal or large panel datasets. Therefore, we do not consider this a negative aspect of our study. Most control variables are significantly associated with digital innovation performance. In some findings, the coefficients of a few control variables appear negative, likely due to high correlations with other variables, causing coefficient instability and unexpected signs. For example, the coefficient of employee (log) becomes negative after the inclusion of the asset scale variable, which is highly correlated with it (0.661). However, the VIF score of 4.38 indicates a moderate level of multicollinearity. Moreover, robustness checks where the employee (log) was removed confirmed that multicollinearity did not impact the results, supporting the robustness and reliability of the predictions.

C. Endogeneity

The Chinese government considers digital transformation so critical that it will likely become a policy experiment or a natural market behaviour rather than a strategic choice for innovation ecosystems. Thus, the dominant policy effects of the Chinese government and presupposed market efficiency, which may not always represent reality, can cloud the unobserved timevarying productivity effects of digital innovation performance [52], [53]. This situation may create an endogeneity issue when a firm's propensity to continue digital transformation is included in measuring digital innovation performance. The degree of transformation among the firms is also uneven. To address a possible endogeneity problem, we employed Propensity Score Matching (PSM) and Difference-in-Difference (DID) methods to carry out one-to-one nearest matching with return for the treatment and control groups and then estimate the successfully matched samples.

While doing so, we use total factor productivity (TFP) as the firm's economic efficiency indicator since it includes financial data that conveys historical firm performance and can offer realistic and objective results. We calculate TFP with the return of net assets – equity (ROE), return on assets (ROA), and Tobin's Q, where$DInnov_{irkt}$ is the key explanatory variable, ${Y_{irkt}}^{PSM}$

is the TFP of the enterprise, and X are the control variables. The corresponding regression model is as follows:

$$Y_{irktPSM} = \alpha + \beta DInnov_{irkt} + \gamma X_{irkt} + \lambda_r + \delta_k + {}_t + {}_{irkt}$$

We tested the TFP differences between firms which implement digital transformation initiatives and those that do not adequately engage in digital transformation by Olley–Pakes (OP) and Levinsohn–Petrin (LP) estimates [97], [98]. The growth in TFP is called "intensive growth", which refers to high-quality economic performance [99]. We consider firms implementing digital transformation as the treatment group and less implementing ones as the control group. We use our exploratory variables to calculate both groups' propensity scores by the nearest neighbour matching method and compare the mean scores of the treatment and control groups. The comparison based on the t-values verifies the parallel trend hypothesis, which indicates no significant difference between the groups in terms of TFP, as shown in Table 5.

TABLE 5

Therefore, the estimation results confirm that digital transformation significantly and positively affects the TFP of different group enterprises.

V. DISCUSSION

Innovation ecosystems are multifaceted and interdependent environments where value creation emerges from interactions among diverse actors, including firms, governments, and technological infrastructures [100]. Accordingly, we examined how the interactions of these actors across multiple levels provoke co-evolutionary dynamics of digital innovation performance within the innovation ecosystem of the Chinese manufacturing industry. Our study shows that each level significantly impacts digital innovation by co-evolving in the ecosystem, often in interdependent ways. The findings resonate with broader discussions of GramaVigouroux et al. [101], who emphasise systemic drivers' interconnected and interactive impact in shaping performance outcomes within national innovation ecosystems. Furthermore, the alignment with findings from studies employing alternative theoretical perspectives, such as the value-based theory [102] or technology-organisation-environment (TOE) framework and configurational theory [103], in examining collaborative innovation driven by diverse relational elements demonstrates that consistent results across different theoretical lenses provide a robust foundation for our recommendations.

A key contribution to understanding the micro-level impact on innovation trajectories within the ecosystem was the role of firm governance, specifically, CEO duality versus independent board structures, in shaping a firm's digital innovation performance. The findings which did not support our first hypothesis may be surprising within the context of the Chinese manufacturing industry's innovation ecosystem. In contrast to our initial hypothesis, which was grounded in the prevailing cultural values of Chinese society and the centralised governance style and concentrated decision-making power in China [104], independent boards seem more conducive to driving digital innovation than CEO duality. The positive effect of board independence on digital innovation performance might be explained by providing unbiased oversight, mitigating the risks of entrenchment associated with CEO duality, or curbing the hegemony of a limited number of executives, which impedes participation and creativity in decision-making. This finding is interesting because many Chinese firms have government-appointed independent directors who ensure accountability and risk management and follow innovation strategies, aligning them with national policies and government incentives [105]. Given that these independent directors have limited autonomy in influencing firm decisions and shaping firms' behaviour and policies and are generally constrained as they adhere closely to national and government directives, another factor might be driving digital innovation performance. In this context, board members' digital expertise and technology orientation could serve as the primary determinant of innovation performance disparities rather than the structure of the board and traditional agency-stewardship dynamics, which primarily revolve around autonomy and risk perception. Recent empirical research increasingly supports this perspective. For example, Liu et al. [106] present the increasing importance of board members' digital expertise, an issue often overlooked in traditional board composition research. The study finds that Chinese firms with board members specialising in digital technologies outperform competitors in digital innovations, i.e., AI, Fintech, and Blockchain. Therefore, the board-level technological capabilities might play a more critical role than the structure and composition of the board in explaining digital innovation performance in the context of our study.

Another micro-level factor, asset scale, aligns with the co-evolutionary model's emphasis on resource endowment. We find that larger firm asset scales are associated with enhanced digital innovation performance. Firms with larger asset bases are better equipped to navigate challenges, such as market saturation, regulatory compliance, supply chain complexity, integration of digital transformation and sustainability pressures, by leveraging their financial strength to invest in cutting-edge technologies, attract specialised talent, and support extensive R&D initiatives in a competitive ecosystem [107]. This finding aligns with the resource-based view (RBV), which underscores the critical role of allocating resources toward innovation to adapt to changes [68] in technologically intensive and dynamic innovation ecosystems.

However, it is not merely the size of a firm's assets that determines its innovation performance but rather the nature and strategic utilisation of those assets. Prior studies [108], [109] indicate that to maximise their effectiveness in fostering innovation and creativity, firms must allocate, mobilise, and circulate tangible and intangible assets both within and beyond their ecosystems. For instance, networking skills and corporate political activities can play a more significant role by enhancing the firm's ability to interact with the government and leverage more support within the innovation ecosystem or foster synergies and facilitate collaboration among diverse ecosystem components. The research [110] highlights the importance of flexible mechanisms for firms to swiftly reallocate and deploy resources in response to dynamic demands and technological changes in ever-evolving innovation ecosystems. Thus, in our context, a firm's diversified governance structure influences decisions regarding optimising, investing, and deploying innovation resources, approaching government initiatives, and forming regional innovation networks to thrive [111]. Together, these elements highlight the intricate interdependencies that underpin the co-evolutionary nature of innovation performance.

Our evidence shows that government support at the macro level is a crucial determinant of digital innovations in the ecosystem. This finding is particularly relevant in China, where the government is central in directing economic and industrial policy. Government support, delivered through subsidies, tax incentives, and direct financial assistance, is instrumental in helping firms navigate the significant financial barriers inherent in transferring advanced technologies and achieving digital innovations [112]. The strong response from firms to these incentives underscores the powerful institutional influence on innovation outcomes, reflecting the government's ability to guide and accelerate digital innovation within this complex and dynamic ecosystem. In this context, government support serves as a catalyst and accelerates firms' digital innovations by offering the financial and institutional frameworks essential for success. This process is further reinforced by effective firm governance and substantial asset scale, which ensure strategic resource allocation and alignment with the dynamic demands of the evolving ecosystem.

The technological intensity at the meso-layer of the ecosystem moderates the relationships between the micro-layered firm's asset scale, macro-layered government support, and digital innovation performance. The interaction between a firm's asset scale and technological intensity, as well as between government support and technological intensity, highlights the importance of aligning firm-level strategies and government policies with the industry's technological demands. High-tech industries, characterised by rapid innovation cycles and significant R&D investments, exhibit the most pronounced improvements in innovation performance when these factors are well-aligned. The interplay between technological intensity and firm-level and macro-level factors reflects the co-evolutionary dynamics of the ecosystem, where the firm's internal capabilities and external supports must adapt to the evolving technological landscape. Technological intensity can amplify the effects of well-aligned resources and policies, driving significant improvements in innovation performance. Thus, we highlight that the technological intensity of the ecosystem in which firms operate can either amplify or attenuate the effects of firm-level resources and government policies.

We identified significant relationships between control variables and digital innovation. Average wage level, state-owned enterprise (SOE) status, and market value are strongly associated with digital innovation performance. Higher wage levels often correlate with a more skilled workforce, which can enhance innovative output. This positive impact on digital innovation may also reflect executive leadership's focus on efficiency and the increased digital awareness among employees. The positive relationship between SOEs and digital innovation performance likely stems from government policy enforcement and additional support from government institutions, such as improved borrowing opportunities from public banks and streamlined processes for obtaining patents or trademarks. Additionally, higher market value naturally drives the need for continuous digital innovation to maintain a competitive edge, with variations in digital innovation output often reflecting the degree of digital transformation implementation. In contrast to these positive relationships, financial risk (Leverage) demonstrated an inverse relationship with digital innovation performance, particularly in models where the asset scale variable was included. With financial leverage coded inversely, this finding suggests that as a firm's financial risk increases, executive leadership may reduce investments in digitalisation, decreasing the firm's innovation output.

VI. THEORETICAL CONTRIBUTIONS

Grounded in a co-evolutionary, multi-level framework, this study advances the understanding of innovation ecosystems by exploring the dynamic interplay between firm-level governance, resource endowments, macro-level government support, and meso-level technological intensity within the Chinese manufacturing industry. With this study, we shed light on the co-evolutionary nature of innovation ecosystems, where changes at one level can have ripple effects throughout the ecosystem. For example, a shift in government policy (macro-level) can lead to changes in the technological landscape (meso-level), which in turn can influence firm behaviour and resource allocation (micro-level). Our findings corroborate Jütting [113] and Chen et al. [114], who demonstrate how co-evolutionary interactions among ecosystem actors enhance the performance of regional innovation ecosystems. We empirically validate the moderating role of technological intensity in shaping the effectiveness of government subsidies while also amplifying the impact of firm-level governance and asset mobilisation, thereby bridging macro and micro-level perspectives. This dynamic interplay reveals the importance of considering the entire ecosystem when developing strategies to enhance firms' digital innovation performance.

As another theoretical contribution, we extend the traditional corporate governance literature that has been split between agency and stewardship theories, focusing on control versus autonomy and risk. We position governance structures as co-evolving with the ecosystems' conditions, which become a dynamic enabler of innovation rather than a static mechanism executing an internal check and balance function.

VII. IMPLICATIONS

We provide actionable insights for ecosystem stakeholders, from managers to policymakers, to design adaptive strategies that enhance firms' digital innovation performance and foster sustainable growth. Independent and autonomous perspectives play a pivotal role in enhancing digital innovation performance. A board composition with balanced governance between oversight, creativity and strategic decision-making can stimulate collaborative thinking with all stakeholders in the innovation ecosystems, which is essential for adapting to rapid technological changes in the manufacturing sector. Thus, manufacturing firms should move away from centralised decision-making models, embrace governance structures that harmonise foresight, creativity and collaboration, and encourage strategic innovations. While larger firm asset bases correlate with improved digital innovation, it is the firms' capabilities for strategic allocation and utilisation of these resources that maximise their impact.

Government subsidies can catalyse initial adoption, but sustained innovation and performance depend on robust internal resources, effective governance, and advanced technological capabilities [115]. Consequently, firms should focus on strengthening their internal competencies and governance frameworks to maximise the benefits of these subsidies rather than relying solely on government initiatives. Technological intensity serves as a critical moderator that amplifies or attenuates the interactions between firm governance, asset base, and government support. In high-tech environments, rapid innovation cycles necessitate robust governance structures, strategic asset mobilisation, and adaptive policy measures. Conversely, medium- and low-tech ecosystems may require foundational investments and targeted support to enhance technological capacity and foster gradual innovation.

Despite their potential, many manufacturing firms have yet to realise the full benefits of digital technologies for sustainable innovation. While high-tech innovation ecosystems demonstrate enhanced agility in their wide range of operations, medium to low-tech ecosystems use lower technological intensity and face challenges in innovation and operation-related outcomes [116]. Per PwC's 2024 Digital Trends in Operations Survey [117], 69% of manufacturing firms' digital transformation investments have not delivered the expected results. Similarly, the World Manufacturing Foundation's recent survey [118] shows that only 9% of manufacturing organisations leverage artificial intelligence, indicating a vast untapped potential. This understanding empowers managers and policymakers to make informed decisions within the ecosystems. Engineering managers must bridge the gap between technical expertise and strategic decision-making, ensuring that manufacturing firms can harness their innovative capabilities to remain competitive.

Analytics and reporting systems enable the tracking of the impact of government policies and technological trends on firms' innovation performance while facilitating reciprocal adaptations and iterative feedback loops across the micro-, meso-, and macro-level elements of the ecosystem. Policymakers should consider the co-evolutionary nature of innovation ecosystems and create adaptive frameworks that support ecosystem-wide collaboration and innovation when designing policies. The impact of government initiatives may vary depending on the industry's technological intensity and the firms' resource endowments. Therefore, government support policies should be tailored to the specific needs of evolving innovation ecosystems and strengthen their technological infrastructure.

VIII. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has several limitations. The data's timeframe, from 2008 to 2019, may not fully reflect the most recent developments and trends in digital innovations, especially given the rapid pace of technological change in the last few years. The research focuses specifically on manufacturing firms in China. Thus, the findings may not directly apply to other industries or countries. Different sectors and countries may have unique challenges and drivers of digital innovation, which might not be captured in this study. We used patent counts and financial data as digital innovation and performance proxies. While these are commonly used indicators, they may not fully encompass the breadth of digital transformation activities or the qualitative aspects of innovation, such as process improvements or customer satisfaction. The measure of government subsidies is based on financial statements, which might not comprise all forms of government support, such as indirect incentives or regulatory advantages. Missing data for some variables prevented us from employing an entire panel data approach, so we used a longitudinal approach, which may impact the consistency of observations across all years. The explanatory power of the variables in R^2 values was relatively low, which could be attributed to numerous ecosystem-related factors impacting firm-level digital innovation performance. Despite this, the findings provide insights into understanding these influences on digital innovation performance. Since our control variables demonstrated significant associations with innovation performance, we do not view low R^2 values as a significant limitation [89] but emphasise that the findings should be interpreted cautiously. Finally, using Logit models to analyse digital innovation performance assumes that the relationships between variables are linear and additive. This may oversimplify the complex and potentially non-linear interactions between different factors influencing the digital innovation performance of the ecosystems.

Future research should address these limitations by incorporating other ecosystem actors, i.e. suppliers, customers or strategic partners, with more comprehensive and up-to-date data, exploring other sectors and regions, and employing more sophisticated analytical methods such as machine learning algorithms, network analysis, and predictive analytics to uncover hidden patterns and capture ecosystem innovation performance's complex and dynamic nature. Additionally, qualitative studies could provide deeper insights into the decision–making processes within firms and ecosystems, complementing this study's quantitative findings. Finally, the examination of the background of board members, whether independent or executive, could provide deeper insights into whether digital innovation disparities arise from board structure or from board members' specialised digital expertise that aligns with the ecosystem's requirements.

REFERENCES

[1] D. Cetindamar, C. Renando, M. Bliemel, and S. De Klerk, "The evolution of the Australian start-up and innovation ecosystem: Mapping policy developments, key actors, activities, and artefacts," *Science, Technology and Society*, 2023.

[2] T. Lammers, D. Cetindamar, and M. Borkert, "A digital tale of two cities – Exploring the dynamics of the artificial intelligence ecosystems in Berlin and Sydney," *Sustainability*, 2021. https://doi.org/10.3390/su131910564

[3] A. Ates, S. Paton, H. Sminia, and M. Smith, "Crafting strategic responses to ecosystem dynamics in manufacturing," *Technological Forecasting and Social Change*, vol. 194, p. 122727, 2023.

[4] E. Gifford, M. McKelvey, and R. Saemundsson, "The evolution of knowledge-intensive innovation ecosystems: Co-evolving entrepreneurial activity and innovation policy in the West Swedish maritime system," *Industry and Innovation*, vol. 28, no. 5, pp. 651–676, 2021.

[5] R. Adner, *The Wide Lens: A New Strategy for Innovation*. New York, NY, USA: Portfolio/Penguin, 2012.

[6] M. Smit, S. S. Grobbelaar, and N. Sacks, "Measuring innovation system functions: A survey of additive manufacturing in South Africa," *IEEE Transactions on Engineering Management*, 2024.

[7] P. Muñoz, E. Kibler, V. Mandakovic, and J. Amoros, "Local entrepreneurial ecosystems as configural narratives," *Research Policy*, 2020. https://doi.org/10.1016/j.respol.2020.104065

[8] G. Piantoni, M. Arena, and G. Azzone, "Exploring how different innovation ecosystems create shared value: Insights from a multiple case study analysis," *European Journal of Innovation Management*, vol. 26, no. 7, pp. 206–232, 2023.

[9] D. Xu and B. Yu, "How can regional innovation ecosystems affect innovation level? An FsQCA analysis," *Technology Analysis & Strategic Management*, pp. 1–17, 2023.

[10] R. Kamasak, A. D. Palalar, and B. Yalcinkaya, "Emerging trends of Industry 4.0 in equality, diversity, and implementations," in *Contemporary Approaches in Equality, Diversity, and Inclusion: Strategic and Technological Perspectives*, B. Kucukaltan, Ed., Emerald Publishing, 2023, pp. 129–148.

[11] A. Kar, R. Kamasak, and B. Yalcinkaya, "The role of consumption in the identity formation of conservative women: A web analytics and netnographic exploration," in *Analytics Enabled Decision Making,* V. Sharma, C. Maheshkar, and J. Poulose, Eds. Singapore: Palgrave Macmillan, 2023, pp. 245–264.

[12] N. Stojcic, "Innovation failure, training for innovative activities, and public support for innovation: Multi-annual evidence from emerging European innovation systems," *Research Policy*, vol. 53, no. 8, p. 105059, 2024.

[13] B. Zhang, X. Yin, J. Xiong and Z. Yuan, "The evolution of complex Global Innovation Collaboration Network: A multilevel analysis of a CoPS Industry 2001–2020," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 1039-1051, 2025, doi: 10.1109/TEM.2025.3548857.

[14] K. Shahzad, S. Hafeez, T. Heimo, A. Mäenpää, M. F. Mubarak and R. Evans, "Developing the Innovation Capabilities of SMEs: The Role of Intermediary Firms in Knowledge Ecosystems," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 604-618, 2025, doi: 10.1109/TEM.2025.3543779

[15] R. Kamasak, U. Yozgat, and M. Yavuz, "Knowledge process capabilities and innovation: Testing the moderating effects of environmental dynamism and strategic flexibility," *Knowledge Management Research & Practice*, vol. 15, no. 3, pp. 356–368, 2017.

[16] Q. Wu, G. Chen and K. Cormican, K. “The Wisdom of the Collective: An Integrated Multi-

Level Framework of Shared Leadership in Engineering Management Project Teams," *Engineering Management Journal*, vol. 37, no. 1, pp. 114–132, 2024. https://doi.org/10.1080/10429247.2024.2370185

[17] F. W. Geels, "Ontologies, socio-technical transitions (to sustainability), and the multi-level perspective," *Research Policy*, vol. 39, no. 4, pp. 495–510, 2010.

[18] G. Dosi, "Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change," *Research Policy*, vol. 11, no. 3, pp. 147– 162, 1982.

[19] R. Adner, "Ecosystem as structure: An actionable construct for strategy," *Journal of Management*, vol. 43, no. 1, pp. 39–58, 2017.

[20] S. Noviaristanti, N. Acur, and K. Mendibil, "The different roles of innovation intermediaries to generate value," *Management Review Quarterly*, 2023. https://doi.org/10.1007/s11301-02300364-2

[21] E. Autio, E., and L. Thomas, "Researching ecosystems in innovation contexts," *Innovation & Management Review,* vol. 19, no. 1, pp. 12–25, 2022.

[22] M. Hodson, F. W. Geels, and A. McMeekin, "Reconfiguring urban sustainability transitions, analyzing multiplicity," *Sustainability*, vol. 9, p. 299, 2017.

[23] J. A. Porfírio, J. A. Felício, and T. Carrilho, "Factors affecting digital transformation in banking," *Journal of Business Research*, vol. 171, p. 114393, 2024.

[24] A. G. Frank, L. S. Dalenogare, and N. F. Ayala, "Industry 4.0 technologies: Implementation patterns in manufacturing companies," *International Journal of Production Economics*, vol. 210, no. 1, pp. 15–26, 2019. https://doi.org/10.1016/j.ijpe.2019.01.004

[25] N. Wijegunawardhana, M. Hassanabadi, R. Hassani, and R. Kamasak, "Digital transformation as a source of competitive advantage and sustainability: The digital transformation challenges faced by the container shipping industry in Sri Lanka," in *Global Cargo Industry: Resilience of Asia-Pacific Shipping Industries,* B. Datta and H. Satghare, Eds. Hershey, USA: IGI Global Publications, 2024, pp. 109–135.

[26] G. F. Davis and T. DeWitt, "Organization theory and the resource-based view of the firm: The great divide," *Journal of Management*, vol. 47, no. 7, pp. 1684–1697, 2021. https://doi.org/10.1177/0149206320982650

[27] C. Cubillas-Para, J. G. Cegarra-Navarro, and E. M. Vătămănescu, "Gliding from regenerative unlearning toward digital transformation via collaboration with customers and organisational agility," *Journal of Business Research*, vol. 177, p. 114637, 2024.

[28] X. Jiang and Y. Jiang, "The Impact of Digital Transformation on Employee Protection," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 202-209, 2025, doi: 10.1109/TEM.2024.3510401.

[29] V. M. de Jong, J. Hoogland, K. G. Moons, R. D. Riley, T. L. Nguyen, and T. P. Debray, "Propensity-based standardization to enhance the validation and interpretation of prediction model discrimination for a target population," *Statistics in Medicine*, vol. 42, no. 19, pp. 3508– 3528, 2023.

[30] M. Gong, W. Wang and X. Jiang, "Performance Surplus Inconsistency and Firm Innovation: Evidence From China," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 512526, 2025, doi: 10.1109/TEM.2025.3532700.

[31] Accenture, "China Enterprise Digital Transformation Index 2020," *Accenture Insights,* 2020. [Online]. Available: https://www.accenture.com/cn-en/insights/consulting/china-digitalmaturity-index-report. [Accessed: Dec. 1, 2024].

[32] China Briefing, "China's Vision 2035: From Beijing's Forbidden City to Interconnected Eurasian Megacity," *China Briefing News,* 2021. [Online]. Available: https://www.chinabriefing.com/news/chinas-vision-2035-from-beijings-forbidden-city-to-interconnected-eurasianmegacity. [Accessed: Dec. 1, 2024].

[33] S. Chen, J. Sun, and Y. Liang, "The impact on knowledge transfer to scientific and technological innovation efficiency of talents: Analysis based on institutional environment in China," *Technology Analysis & Strategic Management*, vol. 36, no. 7, pp. 1398–1413, 2024.

[34] R. R. Nelson and S. G. Winter, "The Schumpeterian tradeoff revisited," *The American Economic Review,* vol. 72, no. 1, pp. 114–132, 1982.

[35] E. Autio and L. D. W. Thomas, "Innovation ecosystems: Implications for innovation management," in *Oxford Handbook of Innovation Management*, M. Dogson, D. Gann, and N. Philips, Eds., Oxford, U.K.: Oxford University Press, 2014, pp. 204–228.

[36] J. Nill and R. Kemp, "Evolutionary approaches for sustainable innovation policies: From niche to paradigm?" *Research Policy*, vol. 38, no. 4, pp. 668–680, 2009.

[37] F. W. Geels, "Regime resistance against low-carbon transitions: Introducing politics and power into the multi-level perspective," *Theory, Culture & Society*, 2014.

[38] A. Rip and R. Kemp, "Technological change," in *Human Choices and Climate Change*, S. Rayner and E. L. Malone, Eds., Battelle Press, 1998, pp. 327–399.

[39] F. Buonocore, M.C.Annosi, D. Gennaro and F. Riemma,”Digital transformation and social change: Leadership strategies for responsible innovation”, *Journal of Engineering and Technology Management*, vol. 74. 2024.

[40] E. Battistoni, S. Gitto, G. Murgia, and D. Campisi, "Adoption paths of digital transformation in manufacturing SME," *International Journal of Production Economics,* vol. 255, p. 108675, 2023.

[41] H. Zhai, M. Yang, and K. C. Chan, "Does digital transformation enhance a firm’s performance? Evidence from China," *Technology in Society*, vol. 68, p. 101841, 2022. https://doi.org/10.1016/j.techsoc.2021.101841

[42] S. Du, L. Ma, Z. Li, and C. Ma, "Non-family shareholder governance and the digital transformation of family firms: Evidence from China," *Corporate Governance: An International Review*, pp. 1–27, 2023. https://doi.org/10.1111/corg.12517

[43] D. Plekhanov, H. Franke, and T. H. Netland, "Digital transformation: A review and research agenda," *European Management Journal*, vol. 41, no. 6, pp. 821–844, 2023. https://doi.org/10.1016/j.emj.2022.09.007

[44] P. Malakar, S. A. Khan, A. Gunasekaran and M. S. Mubarik, "Digital Technologies for Social Supply Chain Sustainability: An Empirical Analysis Through the Lens of Dynamic Capabilities and Complexity Theory," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 664-675, 2025, doi: 10.1109/TEM.2024.3524896.

[45] K. Pant and P. Palanisamy, P. “Industry 4.0 in the Perspective of Supply Chain Management: Evolution and Future Research Agenda,” *Engineering Management Journal*, vol. 37, no. 1, pp. 52–70, 2024. https://doi.org/10.1080/10429247.2024.2350287

[46] D. C. Hambrick, “Upper echelons theory: An update,” *Academy of Management Review*, vol. 32, no. 2, pp. 334–343, 2007.

[47] R. E. Freeman, *Strategic Management: A Stakeholder Approach*. Pitman Publishing, Boston, MA, 1984.

[48] Y.-H. Wang, "Board composition and corporate governance performance: Investigating the effects of diversity," *Entrepreneurship & Regional Development*, vol. 35, no. 5-6, pp. 578–591, 2023. https://doi.org/10.1080/08985626.2023.2191341

[49] M. C. Withers and M. A. Fitza, "Do board chairs matter? The influence of board chairs on firm performance," *Strategic Management Journal*, vol. 38, no. 6, pp. 1343–1355, 2017. https://doi.org/10.1002/smj.2587

[50] B. Sun, Y. Zhang, K. Zhu, H. Mao, and T. Liang, "Is faster really better? The impact of digital transformation speed on firm financial distress: Based on the cost-benefit

perspective," *Journal of Business Research*, vol. 179, p. 114703, 2024. https://doi.org/10.1016/j.jbusres.2024.114703

[51] N. Pandey, C. Andres, and S. Kumar, "Mapping the corporate governance scholarship: Current state and future directions," *Corporate Governance: An International Review*, vol. 31, pp. 127–160, 2023.

[52] P. J. Bezemer, A. Pugliese, G. Nicholson, and A. Zattoni, "Toward a synthesis of the boardstrategy relationship: A literature review and future research agenda," *Corporate Governance: An International Review*, vol. 31, pp. 178–197, 2023.

[53] M. Yu, "CEO duality and firm performance: A systematic review and research agenda," *European Management Review*, vol. 20, pp. 346–358, 2023.

[54] E. F. Fama and M. C. Jensen, "Separation of ownership and control," *The Journal of Law and Economics*, vol. 26, pp. 301–325, 1983a. https://doi.org/10.1086/467037

[55] D. Lange, S. Boivie, and J. D. Westphal, "Predicting organizational identification at the CEO level," *Strategic Management Journal*, vol. 36, no. 8, pp. 1224–1244, 2015.

[56] J. H. Davis, F. D. Schoorman, and L. Donaldson, "Toward a stewardship theory of management," *Academy of Management Review*, vol. 22, no. 1, pp. 20–47, 1997. https://doi.org/10.4324/9781315261102-29

[57] S. Finkelstein and R. A. D'Aveni, "CEO duality as a double-edged sword: How boards of directors balance entrenchment avoidance and unity of command," *Academy of Management Journal*, vol. 37, no. 5, pp. 1079–1108, 1994. https://doi.org/10.2307/256667

[58] S. Claessens, S. Djankov, and L. H. P. Lang, "The separation of ownership and control in East Asian corporations," *Journal of Financial Economics*, vol. 58, no. 1–2, pp. 81–112, 2000. https://doi.org/10.1016/s0304-405x(00)00067-2

[59] E. F. Fama and M. C. Jensen, "Agency problems and residual claims," *The Journal of Law and Economics*, vol. 26, pp. 327–349, 1983b. https://doi.org/10.1086/467038

[60] P. Qiao, A. Fung, J. Miao, and H. G. Fung, "Powerful chief executive officers and firm performance: Integrating agency and stewardship theory," *China & World Economy*, vol. 25, no. 6, pp. 100–119, 2017.

[61] S. Heaton, D. Teece, and E. Agronin, "Dynamic capabilities and governance: An empirical investigation of financial performance of the higher education sector," *Strategic Management Journal,* vol. 44, no. 2, pp. 520–548, 2023.

[62] L. Broccardo, E. Truant, and L. P. Dana, "The interlink between digitalization, sustainability, and performance: An Italian context," *Journal of Business Research*, vol. 158, p. 113621, 2023.

[63] R. Kamasak, "Determinants of innovation performance: A resource-based study," *ProcediaSocial and Behavioral Sciences*, vol. 195, pp. 1330–1337, 2015.

[64] A. Vafaei-Zadeh, J. Madhuri, H. Hanifah and R. Thurasamy, R., “The interactive effects of capabilities and data-driven culture on sustained competitive advantage,” *IEEE Transactions on Engineering Management*, vol. 71, pp. 8444–8458.

[65] A. Lockett, S. Thompson and U. Morgenstern, “The development of the resource-based view of the firm: A critical appraisal,” *International Journal of Management Reviews*, vol. 11, no. 1, pp. 9–28, 2009.

[66] M. Gruber, F. Heinemann, M. Brettel, and S. Hungeling, "Configurations of resources and capabilities and their performance implications: An exploratory study on technology ventures," *Strategic Management Journal*, vol. 31, no. 12, pp. 1337–1356, 2010.

[67] S. L. Newbert, "Value, rareness, competitive advantage, and performance: A conceptuallevel empirical investigation of the resource-based view of the firm," *Strategic Management Journal*, vol. 29, no. 7, pp. 745–768, 2008.

[68] I. Dierickx and K. Cool, "Asset stock accumulation and sustainability of competitive advantage," *Management Science*, vol. 35, no. 12, pp. 1504–1511, 1989.

[69] K. R. Bhandari, P. Zámborský, M. Ranta, and J. Salo, "Digitalization, internationalization, and firm performance: A resource-orchestration perspective on new OLI advantages," *International Business Review*, vol. 32, no. 4, p. 102135, 2023.

[70] F. M. Scherer and D. Ross, D. *Industrial Market Structure and Economic Performance,* (3rd ed.), Houghton Mifflin, 1990.

[71] J. Pfeffer and G. R., Salancik, *The External Control of Organizations: A Resource Dependence Perspective*, Harper & Row, New York, 1978.

[72] T. Zou, F. Xiong, S. Li and W. Zhang, "Understanding the Determinants of Firms’ Usage of A/B Testing: A Technology–Organization– Environment Framework," in *IEEE Transactions on Engineering Management*, vol. 72, pp. 378-400, 2025, doi: 10.1109/TEM.2024.3415500.

[73] W. W. Powell and P. J. DiMaggio, "The iron cage redux: Looking back and forward," *Organization Theory,* vol. 4, no. 4, p. 26317877231221550, 2023.

[74] D. Czarnitzki and K. Hussinger, "Input and output additionality of R&D subsidies," *Applied Economics*, vol. 50, no. 12, pp. 1324–1341, 2017.

[75] G. Iuliano, B. Cuadrado-Ballesteros, and M. Bisogno, "Citizens' e-participation in the digital world: Empirical insights from Europe," *Public Money & Management*, pp. 1–10, 2024.

[76] Z. Chen, Y. Xiao, and K. Jiang, "The impact of tax reform on firms' digitalization in China," *Technological Forecasting and Social Change*, vol. 187, p. 122196, 2023.

[77] C. L. Yu, G. G. Yang, and M. Y. Du, "Industrial policy and technological innovation of China's digital economy industries," *Statistical Research*, vol. 38, no. 01, pp. 51–64, 2021.

[78] G. Wang and H. Zhang, "Industrial policy choice to promote enterprise innovation: Perspective of policy tool combination," *Economic Dynamics*, vol. 10, 2020.

[79] B. Kucukaltan, R. Kamasak, B. Yalçınkaya, and Z. Irani, "Investigating the themes in supply chain finance: The emergence of blockchain as a disruptive technology," *International Journal of Production Research*, 2022. https://doi.org/10.1080/00207543.2022.2118886

[80] S. L. Pan and S. X. Zhang, "From fighting COVID-19 pandemic to tackling sustainable development goals: An opportunity for responsible information systems research," *International Journal of Information Management*, vol. 55, pp. 102–196, 2020.

[81] OECD, "Main Science and Technology Indicators," *OECD Data,* 2023. [Online]. Available: https://www.oecd.org/en/data/datasets/main-science-and-technology-indicators.html. [Accessed: Dec. 1, 2024].

[82] G. L. Tortorella, T. A. Saurin, F. S. Fogliatto, D. Tlapa Mendoza, J. Moyano-Fuentes, P. Gaiardelli, and E. Macias de Anda, "Digitalization of maintenance: Exploratory study on the adoption of Industry 4.0 technologies and total productive maintenance practices," *Production Planning & Control*, vol. 35, no. 4, pp. 352–372, 2024.

[83] S. Özsoy, O. Ş. Ergüzel, A. Y. Ersoy, and M. Saygılı, "The impact of digitalization on export of high technology products: A panel data approach," *The Journal of International Trade & Economic Development*, vol. 31, no. 2, pp. 277–298, 2022.

[84] W. Li, F. Wang, T. Liu, Q. Xue, and N. Liu, "Peer effects of digital innovation behavior: An external environment perspective," *Management Decision*, vol. 61, no. 7, pp. 2173–2200, 2023. [85] C. Yuan, T. S. Xiao, C. X. Geng, and Y. Sheng, "Digital transformation and division of labor between enterprises: Vertical specialization or vertical integration," *China Industrial Economics*, vol. 9, pp. 137–155, 2021.

[86] Y. Sun, X. Li, and Y. Hong, "Construction of Digital Economy Monitoring and Evaluation System Based on High-Quality Development—Case Study of Construction of Beijing as Global Digital Economy Benchmark City," *Bulletin of Chinese Academy of Sciences (Chinese Version),* vol. 37, no. 6, pp. 812–824, 2022.

[87] The State Council of the People's Republic of China, "12th Five-Year Plan and 13th FiveYear Plan achievements," *State Council of China,* 2021. [Online]. Available: https://english.www.gov.cn/. [Accessed: May 13, 2024].

[88] A. G. Hu, "The Five-Year Plan: A new tool for energy saving and emissions reduction in China," *Advances in Climate Change Research,* vol. 7, no. 4, pp. 222–228, 2016.

[89] G. Fang, L. Lu, L. Tian, Y. He, and Y. Bai, "Can China achieve the energy-saving and emission reducing objectives during the '13th Five-Year-Plan'?—A systematic evolutionary analysis," *Journal of Cleaner Production,* vol. 262, p. 121256, 2020.

[90] Y. Yang, W. W. Ingwersen, T. R. Hawkins, M. Srocka, and D. E. Meyer, "USEEIO: A new and transparent United States environmentally-extended input-output model," *Journal of Cleaner Production,* vol. 158, pp. 308–318, 2017.

[91] D. B. Audretsch and M. Belitski, "Digitalization, resource mobilization, and firm growth in emerging industries," *British Journal of Management*, vol. 35, no. 2, pp. 613–628, 2024.

[92] D. Zeng, J. Cai, and T. Ouyang, "A research on digital transformation: Integration framework and prospects," *Foreign Economics and Management*, vol. 43, no. 5, pp. 63–76, 2021.

[93] U. Sekaran and R. Bougie, *Research Methods for Business,* 7th ed. 2016.

[94] F. J. Gravetter and L.-A. B. Forzano, *Research Methods for the Behavioral Sciences*, 3rd ed. Belmont, CA, USA: Wadsworth, 2008.

[95] R. Kamasak, M. Yavuz, and S. Akin, "The reputational effects of corporate political activities: An empirical research," in *3rd World Conference on Technology, Innovation and Entrepreneurship*, 21–23 June, Istanbul, Turkey. Elsevier Procedia – Computer Sciences, vol. 158, pp. 552–556, 2019.

[96] D. Dikova, P. Sahib, and A. van Witteloostuijn, "Cross-border acquisition abandonment and completion: The effects of institutional differences and organizational learning in the international business service industry, 1981–2001," *Journal of International Business Studies*, vol. 41, pp. 223–245, 2010.

[97] D. A. Ackerberg, K. Caves, and G. Frazer, "Identification properties of recent production function estimators," *Econometrica*, vol. 83, no. 6, pp. 2411–2451, 2015.

[98] S. Bond and M. Söderbom, "Adjustment costs and the identification of Cobb Douglas production functions," *IFS Working Papers*, W05/04, Institute for Fiscal Studies, 2005.

[99] X. Guo, M. Deng, X. Wang, et al., "Population agglomeration in Chinese cities: Is it benefit or damage for the quality of economic development?" *Environmental Science and Pollution Research*, vol. 31, pp. 10106–10118, 2024. https://doi.org/10.1007/s11356-023-25220-4

[100] J. Li, B. Sun, and B. Yu, "Suitable Innovation in Industry 5.0: The Moderating Mechanism of Innovation Transmission Types in Innovation Ecosystem," *IEEE Transactions on*

Engineering Management, vol. 71, pp. 6031–6043, 2024. doi: 10.1109/TEM.2024.3369060.

[101] S. Grama-Vigouroux, S. Saidi, I. Uvarova, I. Cirule, and M. Sellami, "Drivers and barriers of national innovation ecosystems for implementing sustainable development goals: A Latvian case study," *IEEE Transactions on Engineering Management,* vol. 71, pp. 4188–4204, 2023.

[102] F. Cosenz, G. Noto, and A. Cavallo, "Understanding the Microfoundations of Entrepreneurial Ecosystems: Toward a Value-Based Method and Theory," *IEEE Transactions on Engineering Management,* vol. 71, pp. 7298–7310, 2024. doi: 10.1109/TEM.2023.3275097.

[103] F. Wei, N. Feng, B. Shi, and R. D. Evans, "Collaborative Innovation Performance Within Platform-Based Innovation Ecosystems: Identifying Relational Strategies With fsQCA," *IEEE Transactions on Engineering Management,* vol. 71, pp. 3496–3509, 2024. doi: 10.1109/TEM.2023.3348154.

[104] J. Dong, J. Tian, H. Lin, X. Suo, H. Wu, and R. Zeng, "Can Corporate Digital Innovation Speed Up Climate Change Mitigation? Evidence From China," *IEEE Transactions on Engineering Management,* vol. 71, pp. 7797–7814, 2024. doi: 10.1109/TEM.2024.3386181.

[105] R. Fan, J. Pan, M. Yu and H. Gao, H, “Corporate governance of controlling shareholders and labor employment decisions: Evidence from a parent board reform in China,” *Economic Modelling*, 108, 105753, 2022.

[106] T. Liu, J. Liu, Q. Li and S. He, "Digital technologies and Chinese digital firms’ green innovation", *Chinese Management Studies*, 2025. https://doi.org/10.1108/CMS-01-2024-0079

[107] J. Clampit, N. Gaffney, F. Fabian, and T. Stafford, "Institutional misalignment and escapebased FDI: A prospect theory lens," *International Business Review*, vol. 32, no. 3, p. 102099, 2023.

[108] X. Shi and Y. Shi, "Unpacking the process of resource allocation within an entrepreneurial ecosystem," *Research Policy,* vol. 51, no. 9, p. 104378, 2022.

[109] O. Granstrand and M. Holgersson, "Innovation ecosystems: A conceptual review and a new definition," *Technovation,* vol. 90, p. 102098, 2020.

[110] Q. Feng, D. Li, and Z. Wu, "A Data Envelopment Analysis Approach for Resource Allocation and Reallocation," *IEEE Transactions on Engineering Management,* vol. 71, pp. 3295–3307, 2024. doi: 10.1109/TEM.2023.3340302.

[111] L. Liang and Y. Li, "How does government support promote digital economy development in China? The mediating role of regional innovation ecosystem resilience," *Technological Forecasting and Social Change*, vol. 188, 2023.

[112] K. Shao and X. Wang, "Do government subsidies promote enterprise innovation? Evidence from Chinese listed companies," *Journal of Innovation & Knowledge*, vol. 8, no. 4, p. 100436, 2023.

[113] M. Jütting, "Crafting Mission-Oriented Innovation Ecosystems: Strategic Levers for Directing Collaborative Innovation Toward the Grand Challenges," *IEEE Transactions on Engineering Management,* vol. 71, pp. 12053–12067, 2024. doi: 10.1109/TEM.2022.3171735.

[114] H. Chen, Z. Zhang, and C. Lin, "How to Enhance Regional Innovation Ecosystem Resilience in China? A Configuration Analysis Based on Panel Data," *IEEE Transactions on Engineering Management,* vol. 71, pp. 14401–14414, 2024. doi: 10.1109/TEM.2024.3453971.

[115] S. Dhliwayo and A. K. Chebo, "A framework for sustainable technological innovation capability: A research and policy direction," *European Journal of Innovation Management,* vol. 27, no. 3, pp. 851–871, 2024.

[116] J. K. Nwankpa, Y. Roumani, and P. Datta, "Process innovation in the digital age of business: The role of digital business intensity and knowledge management," *Journal of Knowledge Management*, vol. 26, no. 5, pp. 1319–1341, 2022.

[117] PwC, "2024 Digital trends in operations survey," PwC, 2024. [Online]. Available: https://www.pwc.com/us/en/services/consulting/business-transformation/digital-supply-chainsurvey.html

[118] The World Manufacturing Foundation, "2024 World Manufacturing Report," *World Manufacturing Foundation,* 2024. [Online]. Available: https://worldmanufacturing.org/wpcontent/uploads/14/6-WM-REPORT_2024_LD_E-Book_b_Final.pdf. [Accessed: Oct. 3, 2024].

Table 1. Variables of the study

Variables	Descriptions	N	Mean	SD	Q1	Mid	Q3

Innovation	Log of digital technology patent output and number of digital innovation patents.	11,379	0.777	1.580	0	0	0.693
Support	Logged government support	11,379	12.076	6.429	12.294	14.848	16.084
Asset scale	Logged asset size	11,379	21.418	1.349	20.488	21.252	22.158
Board size	Board size, total number of directors	11,379	8.574	1.679	7.000	9.000	9.000
Independence	Independence of the board of directors	11,379	0.373	0.055	0.333	0.333	0.429
CEO duality	Combined title of Board Chair and CEO (1/0)	11,379	0.280	0.449	0	0	1.000
Employee	Logged number of employees	11,379	7.773	1.146	6.971	7.689	8.479
Wage	Logged average wage of an employee	11,379	17.005	1.823	16.149	17.058	17.950
SOE	State ownership(1/0)	11,379	0.341	0.474	0	0	1.000
Market	The total value of an enterprise based on market share in the industry (log)	11,379	0.020	0.055	0.002	0.004	0.015
Leverage	Financial leverage, total liabilities / total assets	11,379	0.409	0.935	0.241	0.388	0.539
Tech intensity	Low- and medium-tech (1), medium- and high-tech (2), high-tech (3)	11,379	2.397	0.707	2	3	3

Table 2. Inter–item correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	VIF
(1) Innovation (log)	1.000												1.18
(2) Wage (log)	0.191***	1.000											1.77
(3) Employee (log)	0.184***	0.638***	1.000										4.17
(4) SOE	0.051***	0.174***	0.272***	1.000									1.19
(5) Market (log)	0.058***	0.277***	0.393***	0.107***	1.000								1.29
(6) Board size	0.082***	0.162***	0.263***	0.231***	0.094***	1.000							1.57
(7) Independence	0.052***	0.016*	–0.019**	–0.051***	0.015	–0.514***	1.000						1.41
(8) CEO duality	0.034***	–0.089***	–0.164***	–0.259***	–0.038***	–0.187***	0.116***	1.000					1.11
(9) Asset scale (log)	0.194***	0.623***	0.661***	0.305***	0.440***	0.272***	–0.021**	–0.185***	1.000				4.38
(10) Leverage	0.102***	0.300***	0.484***	0.264***	0.180***	0.146***	0.001	–0.133***	0.330***	1.000			1.36
(11) Support (log)	0.169***	0.196***	0.257***	0.111***	0.145***	0.087***	0.022**	–0.048***	0.277***	0.257***	1.000		1.10
(12) Tech intensity	0.267***	–0.044***	–0.098***	–0.031***	–0.208***	–0.055***	–0.008	0.025***	0.124***	0.036	0.056***	1.000	1.16

*** p< 0.01, ** p< 0.05, * p< 0.1

Table 3. Analysis results for digital innovation performance

	DV: Digital Innovation Performance (*DInnov*) + (*logDigInnov*)						
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Controls							
Constant	–3.564***	–3.840***	–9.910***	–3.227***	–4.129***	7.406***	5.352***
	(0.566)	(0.573)	(0.682)	(0.565)	(0.664)	(1.236)	(1.281)
Wage (log)	0.083***	0.082***	0.048***	0.079***	0.082***	0.055***	0.052***
	(0.010)	(0.011)	(0.0101)	(0.010)	(0.011)	(0.011)	(0.010)
Employee (log)	0.147***	0.155***	–0.152***	0.124***	0.155***	–0.150***	–0.146***
	(0.018)	(0.018)	(0.028)	(0.018)	(0.018)	(0.027)	(0.027)
SOE (1/0)	0.198***	0.228***	0.162***	0.186***	0.225***	0.115***	0.143***
	(0.035)	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)
Market (log)	2.117***	2.031***	0.282	1.815***	2.023***	2.026***	1.753***
	(0.379)	(0.379)	(0.393)	(0.379)	(0.379)	(0.400)	(0.401)
Leverage	–0.0967	–0.103	–0.352***	–0.0964	–0.0960	–0.438***	–0.114
	(0.091)	(0.091)	(0.093)	(0.091)	(0.091)	(0.092)	(0.091)
Independent Variables							
Independence		0.575**					
		(0.260)					
CEO duality		0.134***					
		(0.033)					
Asset scale (AS)			0.094***				
			(0.033)				
Support (GS) (log)				1.890***			
				(1.940)			
Technological intensity (TI)					0.209*		
					(0.183)		
Interactions							
AS X TI						0.138***	
						(0.009)	
GS X TI							3.591***
							(3.8110)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CityGroup FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,379	11,379	11,379	11,379	11,379	11,379	11,379
R^2	0.185	0.186	0.204	0.192	0.187	0.218	0.234

Standard errors in parentheses, *** p< 0.01, ** p< 0.05, * p< 0.1

Table 4. The summary of the results

Hypotheses	Results
H1: Compared to independent boards, CEO duality is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.	Rejected
H2: Asset scale is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.	Supported
H3: Government support is associated with better digital innovation performance for firms in the innovation ecosystem of the Chinese manufacturing industry.	Supported

H4a: The level of technological intensity within the ecosystem moderates the relationship between a firm's asset scale and its digital innovation performance.	Supported
H4b: The level of technological intensity within the ecosystem moderates the relationship between government support and firms' digital innovation performance.	Supported

Table 5. Difference analyses

Variables	Descriptions				Q1		Q3
N			Mean	SD			Mid
LP	TFP algorithm of LP method	11,379	15.283	0.976	14.535	15.100	15.738
OP	TFP algorithm of OP method	11,379	12.720	0.710	12.206	12.607	13.089

	Treatment	**Control**	**Difference**	***t*–value**
TFP–LP	15.283	15.264	0.018	0.644
TFP–OP	12.720	12.716	0.004	0.206