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Research article

# Government support, employee structure and organisational digital innovation: Evidence from China

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ABSTRACT

Digital innovation activities are data-driven, and the process of organizational digital innovation is inevitably influenced by their key participants, employees, as well as changes in the social institutional environment. How government support and employee structure impact organisational digital innovation was examined in this study. Since digital innovation activities are data-driven, the mediating role of data flows within digital innovation ecosystems was explored. A quantitative research design was employed, and data were collected by a survey from 299 firms in China. Results of structural equation modelling using SPSS and AMOS reveal that government support for enterprises in terms of policies and services, as well as the employee structure within enterprises, have a direct impact on organisational digital innovation. Data flows within digital innovation ecosystems mediate the relationship between government support and organisational digital innovation activities. Our findings provided evidence for theories of digital innovation ecosystems and employee-driven digital innovation. The results and conclusions in this study can provide reference for enterprises to achieve digital innovation breakthroughs, and for policy-makers to formulate digital-related policies and regulations.

## 1. Introduction

In recent years, China's digital economy has developed rapidly. In terms of total volume, the scale of the digital economy in China increased from 22.6 trillion Chinese yuan in 2016 to 50.2 trillion Chinese yuan in 2022, more than doubling of the total for 2016, ranking first in growth and second on a worldwide scale [1,2]. The proportion of the digital economy in GDP is also increasing year by year, accounting for 41.5 % of GDP in 2022 [2], and therefore, becoming a key driving force in China's economic growth [3]. Driven by the digital economy, the fast development of emerging digital technologies promotes the emergence of an era of intelligent interconnection of all things, and produces a new paradigm of enterprise innovation, namely, digital innovation [4]. The term refers to the extensive application of emerging digital technologies, data elements and their combinations in both the innovation process and outcomes of enterprises, including digital innovation behaviours that create business process improvement, develop new forms of intelligent products, provide new digital services and alter business models [5]. Compared with traditional enterprise innovation, the main distinguishing feature of digital innovation is the deep integration and application of data elements and digital technology.[6]At

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present, China's deepening digital innovation policy and super-scale advantages [6] have provided a rich practical scenario for the enterprises involved to conduct digital innovation activities [7]. Increasing numbers of companies are implementing digital innovation vigorously, and emerging digital technologies are used widely in process innovation, product innovation and service innovation. For example, Midea, a traditional manufacturing company in China, has integrated the Internet of Things deeply with physical home products to create smart homes [8]; during the pandemic, more than 10,000 enterprises resumed work on Alibaba's Ding Talk platform, thereby ensuring orderly conduct of daily business activities [6].

Although China has made remarkable achievements in digital innovation over recent years, and several outstanding digital innovation practice enterprises such as Alibaba, JD, Tencent and Haier have emerged, the motivation and investment in digital innovation by enterprises is still insufficient [9,10]. There is a lack of momentum for enterprises conducting digital innovation, and the degree of breakthrough innovation is still low. Most applications of digital economy technologies are still at the stage of imitation and copying, secondary innovation and reverse research and development account for the majority of enterprises, the transformation of digital economy models or formats has become mainstream and innovation in key areas is very rare [11]. In the fields of operating systems, industrial software, high-end chips and basic materials, the level of technology research and development and process manufacturing lags behind the international advanced level [12,13], and basic digital products and services are still heavily dependent on imports [14,15]. In addition, most enterprises are engaged in short-term profit-seeking, so it is difficult to plan and carry out original innovations that require long R&D cycles and opportunity costs [9], therefore, the degree of breakthrough innovation is still low [10]. According to the Global Innovation Index 2022 released by the World Intellectual Property organisational [16], between the two major industries of the digital economy, namely, ICT hardware & electronic equipment, and software & ICT services, and among the 13 high-tech enterprises whose R&D investment exceeded the industry average in 2020 and 2021, 10 are American, and there are only two equivalent companies in China, Baidu and Hon Hai Precision.

Existing research has paid attention to digital innovation, but most studies focus on the antecedents of digital innovation [17,18], the construction of digital innovation ecosystems [19,20] and the impact of digital innovation on organisational performance [21,22]. The complex causal mechanisms of external and internal factors that impact digital innovation are rarely explored in the same framework. Furthermore, most of the theoretical perspectives of existing studies have focused on the theory of the resource-based view - and tend to study organisational internal resources. There is still a lack of research on the mechanism of digital innovation deriving from the theory of digital ecosystems to consider the mobility and security of data as an innovative element in the digital ecosystem.

The process of enterprises' application of digital technology for innovation is inevitably affected by the social institutional environment [23]. Meanwhile, digital innovation activities are data-driven [24] and employees are identified as being key actors when developing and implementing innovations [25], and digital innovation can be affected by government innovation policies [26], employee structure [27,28], and a data-rich environment [29]. How exactly the effects of these factors impact digital innovation [30] and by which mechanism digital innovation is affected are not yet clear [5]. In light of this, this study explores the impact of government support and employee structure on digital innovation, and examines the mediating role of data flows. This study can, therefore, provide a decision-making basis for enterprises to achieve digital innovation breakthroughs and provide a reference for the government to improve digital-related policies and services. More specifically, this study attempts to answer the following questions.

**RQ1**. What is the relationship between government support and employee structure on organisational digital innovation?

**RQ2**. How do government support and employee structure affect organisational digital innovation?

## 2. Literature review and hypotheses development

### *2.1. Digital innovation and the digital innovation ecosystem*

Digital innovation has received attention from many scholars in recent years [31,32], and has become a study hotspot in the field of innovation management [33]. Yoo et al. [34] first proposed the definition of digital innovation as 'the process of combining digital and physical components to produce new products.' At present, research on digital innovation mainly focuses on three aspects: the innovation process, innovation outcomes and an overall perspective. From the perspective of the innovation process, digital technologies improve organisational innovation process and performance [35,36]. From the perspective of innovation outcomes, the recombination of digital technologies, digital resources, and physical components produces new products and new services [37,38]. From an overall perspective, digital innovation is a process as well as a result. Drawing on existing research, in this paper, digital innovation refers to the extensive application of emerging digital technologies and data elements and their combination in the innovation process and the innovation outcomes of enterprises, including digital innovation behaviours that bring about business process improvement, develop new forms of intelligent products, provide new digital services and alter business models [5].

In recent years, some scholars have studied organisational digital innovation deriving from the theory of digital innovation ecosystems. From a micro perspective, the digital innovation ecosystem emphasises the synergistic symbiosis between digital innovation subjects due to the introduction of digital elements, which leads to the reorganisation of factors and the logical change of system behaviour [39]. Producers, consumers, enablers, operators and researchers in the digital innovation ecosystem have established a close cooperative game relationship of risk sharing and benefit sharing and realised the continuous exchange of materials, energy, information and data with the ecological environment [21]. In the ecological context, enterprises use an open attitude and symbiotic logic to coordinate the relationship with other subjects and formulate interaction strategies, and the knowledge and resources that were originally limited to the organisation will now flow across the organisational boundaries and among multiple subjects [40]. The environment is the core factor that induces enterprise system change, and in different innovation scenarios, digital enterprises adopt adaptive mechanisms to achieve architectural and business innovation changes, reshape organisational and technical architectures and choose appropriate scenarios to drive innovation [41]. Meaning construction and its cross-level transmission are the prerequisites for promoting the construction of a digital innovation ecosystem and the cross-level meaning construction of core enterprises in the ecosystem, starting from the leadership level and the resource orchestration behaviour triggered by it, are the core mechanisms to promote the construction of a digital innovation ecosystem [42]. From a macro perspective, the ecosystem interaction rules formulated by the government and ecosystem leaders make the process of substantive cooperation between multiple actors using digital technology more standardised, avoid contradictions and thus help enterprises to be more open in their willingness and actions [43], so that enterprises can better realise the potential of digital technology [40].

### 2.2. Government support

Although there have been several studies on the impact of government support on innovation in recent years, there is no consensus on whether government support can foster innovation [44]. The innovation activities of enterprises have a certain degree of externalities, and enterprises usually cannot fully grasp the benefits brought by innovation activities, so the risks and costs of enterprise innovation activities are concomitantly high, but government support can reduce the risk and cost of enterprise innovation, thereby promoting enterprise innovation activities [45]. Government support mainly assists the development of enterprises and influences digital innovation through financial subsidies and tax optimisation [46]. The science and technology information platform actively built by the government can provide comprehensive information consulting services for innovative subjects. Based on this, innovative actors in the region can acquire new knowledge and technology at a lower cost, thereby injecting vitality into innovation activities [36]. However, some scholars believe that government support induces arbitrage and crowding out effects, thereby inhibiting innovation activities [47]. Xiao and Lin [48] analysed technological innovation in 36 industrial sectors and found that neither direct nor indirect government support can promote the efficiency of technological innovation. In the context of the digital economy, some researchers believe that the government's macroeconomic regulation and control can address the possible problem of market failure and foster rapid development in a less developed digital economy. However, as the digital economy develops nearer to maturity, too much government intervention may limit the improvement of digital innovation [49]. Furthermore, digital innovation activities are data-driven [24]. Data are everywhere, and the generation and flow of data exist in all organisations and all behaviours. As important subjects in the organisation, government and enterprises control the massive data resources and control the whole process of data flow [50]. While the free flow of data is fundamental to supporting the digitalisation of corporate activities, stricter data policies are expected to adversely affect industries that rely on data in production processes [51]. Given this, we propose $H_1$ and $H_2$ as follows.

**H1**. There is a direct relationship between government support and digital innovation.

**H2**. There is a direct relationship between government support and data flows.

### 2.3. Employee structure

According to Milgrom and Wilson's [52] theory of complementary mechanisms, ICT is an advanced production tool, and it needs matching labour force to promote productivity improvement. That is, ICT is closely related to organisational change, practice management and talent training. The complementary effect between information input and related factors through mutual empowerment can reduce the cost of innovation and improve output efficiency [53]. Workforce structure is a key element in the research of the ICT complementarity mechanism, and an appropriate workforce structure. As the core link of human capital to empower ICT, it can deepen organisational change and synergistically improve enterprise performance [54]. According to the two key elements of academic qualifications and skills in human capital theory, and fully considering the process of employee knowledge accumulation and participation in digital innovation, the employee structure can be divided into two dimensions: an academic structure and a skill structure [27]. Both dimensions are closely related to digital innovation. The essence of innovation activities is processes of creative destruction, which requires the implementation subject to complete the integration and transformation of new and old knowledge; consequently, there are high requirements for individual academic qualifications [28]. The learning capability and questioning spirit of a highly educated workforce can combine advanced ICT technologies effectively, new knowledge and new technologies appear with the emergence of learning by doing and the innovation vitality of such enterprises is functionally endless [55]. A highly skilled workforce can use advanced technology skilfully to make emergency decisions, deal with unknown situations, and complete more non-programmed tasks under the constraints of time conditions so that enterprises can thereby demonstrate higher productivity [56]. Furthermore, the flow of knowledge requires a digitally skilled labour force to condense and sublimate the factual records and regular records carried by the data [57]. By referring to the available literature, we find support for hypotheses $H_3$ and $H_4$.

**H3**. There is a direct relationship between employee structure and digital innovation.

**H4**. There is a direct relationship between employee structure and data flows.

### 2.4. Data flows

According to Buhe and Chen's [24] theory of the digital innovation ecosystem, data flow within the ecosystem of digital innovation in the form of innovation elements, thus activating, connecting, and aggregating the innovation activities of multiple subjects. The generation, transmission, aggregation, overlay, processing, and generation of new data constitute a complete flow cycle of data elements, but it is limited by corresponding organisational and institutional rules. At the organisational level, public data are mainly managed by government departments, and production and consumption data are generated and collected at the enterprise end. At the institutional level, because data have properties that are different from other production factors, institutional changes around data privacy, security and property rights are important factors affecting data flow [24]. In addition, data are also a manifestation of national sovereignty. Although data flow is not limited to technical, industrial and geographical boundaries at the technical level, as an integral part of national sovereignty and security, the regulatory regimes for cross-border data flow vary greatly from country to country [58]. Thus, we propose the following hypotheses :

**H5.** There is a direct relationship between data flows and digital innovation.

**H6.** Data flows mediate the relationship between government support and digital innovation.

**H7.** Data flows mediate the relationship between employee structure and digital innovation.

The conceptual framework in Fig. 1 illustrates the above hypotheses.

## 3. Data and method

### 3.1. Constructs measurement

According to the hypotheses proposed above, a survey instrument was devised to operationalise the 24 items under constructs (as shown in Appendix 1). Government Support (GS), Employee Structure (ES), Data Flows (DTFL) and Digital Innovation (DIIN) are the four constructs in this study. All the items measuring the above-mentioned constructs were adapted from previous literature. GS and ES are twos-order constructs with dimensions, both of which have respective items. After running the Exploratory Factor Analysisin SPSS 28, we extracted factors for GS and ES and converted them into second-order constructs. A 5-point Likert scale was applied to measure all the constructs, where '1' represents strongly 'disagree' and '5' represents 'strongly agree'.

GS is a second order construct and measures firms' external support by the government. It is measured through two first-order constructs, namely, Digital-related Regulations (GDR) and Government Service (GSV). Digital-related Regulations has three items, measuring the implementation of digital-related regulations by local government. Government Service has four items, measuring the quality and quantity of services local government provides to support firms' development.

ES is another second-order construct with two subdimensions: (1) Digital Skills (DRS), measuring employees' mastery of digital skills, has three items; and (2) Education and Training (DRE), measuring employees' education level and digital-related training experience, has four items. DTFL and DIIN are first-order constructs. Data Flows refers to the flow of data-based knowledge and its value in the digital space among multiple subjects participating in the whole life cycle of data elements [57], measuring the mobility of data elements within the digital innovation ecosystem. We used a five-item scale to assess the responses on the flows and security of sector and private data. Digital Innovation refers to both the process and outcomes of firms' digital innovation. A five-item scale was adapted to measure the extent of DIIN.

The initial pool of items developed in this study's survey were reviewed and got comments by two professors who were in depth of digital economy, two managers in the digital industry and one government officer responsible for government performance evaluation. The panel of experts mainly examined the initial pool of items from the aspects of question formulation, question ranking, whether the selected limb was comprehensive, and other detailed errors such as typos and language disorders. Referring to the expert's review,

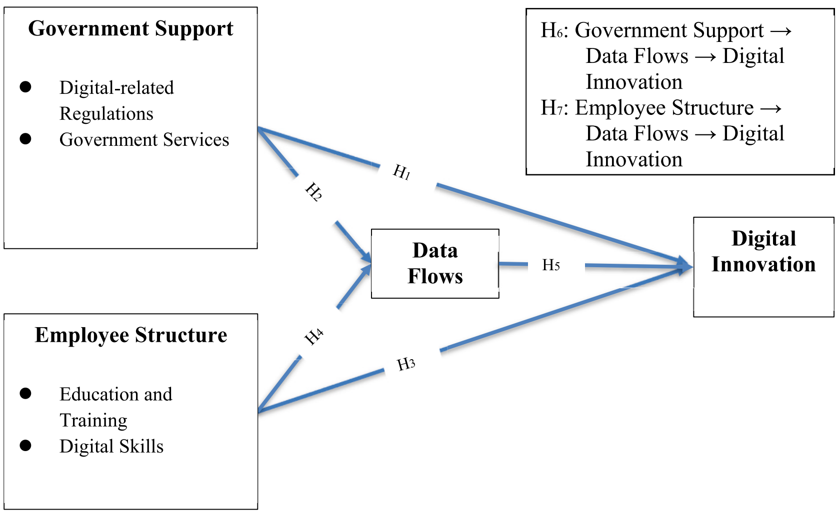


**Fig. 1.** Conceptual framework.

some phrasing modifications were made to the items. After accommodating changes to the questionnaire items based on preceding steps, instruments were ready for the pilot study. The instrument was pilot-tested by online questionnaires via the Questionnaire Star platform. Since the researcher's working city of Hangzhou has the reputation of being the 'e-commerce capital', many companies use digital technology. Therefore, in the pre-survey stage, this study selected companies in Hangzhou to collect data for the pilot study. From October to November 2023, the questionnaires were mainly collected through field research, WeChat and email, and a total of 46 questionnaires were distributed, with 33 valid questionnaires recovered. Among the valid responses, 17 out of 33 were working in traditional industries and 16 were from the core industries of the digital economy. The Cronbach alpha value for all 24 items was more than 0.7, indicating that this questionnaire could be a reliable tool to measure the conceptual model.

### 3.2. Sample and data collection

Practice has proved that under the dual influence of the digital economy and the COVID-19 pandemic, enterprises in the core industries of the digital economy and enterprises in traditional industries, such as biological, chemical, pharmaceutical and textile manufacturing have been actively carrying out digital innovation activities in recent years to create new consumer demand for enterprises. In addition, based on the theory of the digital innovation ecosystem, by integrating innovation in the core areas of the digital industry and the innovation of traditional manufacturing enterprises, the digital innovation ecosystem can be formed. Therefore, the study population is made up of enterprises in the core industries of the digital economy, such as Internet platforms, Internet wholesale and retail and Internet finance, as well as traditional industries, such as pharmaceutical, textile and garment manufacturing in China. According to data released by the National Bureau of Statistics of China, by the end of 2018, there were 18.57 million corporate entities in the country. From this, it can be inferred that the number of enterprises is within the scope of the target population at present is well over 1,000,000. Since the target population of this study are enterprises in the core industries of the digital economy as well as enterprises in traditional industries in China that already carried out or intend to carry out digital innovation, the specific size of the target population is not available at present. Considering the available data and the large scale of target enterprises in China, convenience sampling and snowball sampling are chosen to collect data. While five samples per manifest are satisfactory for the bootstrapping assessment [59], this study relied on 299 valid respondents from various enterprises.

This study selected top managers and ordinary employees as the survey objects. The sample of both top managers and employees was appropriate as study objects, as top managers know how new technological breakthroughs can be adopted to address organisational problems and needs [60], while 'ordinary employees', ranging from the R&D or ICT professionals to middle managers within the enterprise, as well as employees in other positions, such as employees in the departments of human resources, finance and accounting, are recognised as key contributors to the innovation process [61].

Data collection started in November 2023 and consisted of two stages. The first stage ran from 23 to November 27, 2023 during the second Global Digital Trade Expo. A seven-person team distributed 300 questionnaires in person to the participating managers and employees during the Expo. A total of 183 questionnaires were returned during the first stage, achieving a response rate of 61 %. After removing invalid questionnaires, 166 valid responses remained. The second stage of questionnaire distribution ran from 18 to 26 January. The questionnaire forms were designed using the Questionnaire Star platform and personally delivered through WeChat, Ding Talk, etc. to 200 owners/managers/employees of firms in China's core industries of the digital economy or enterprises in traditional industries carrying out digital innovation according to convenience sampling techniques and the snowball sampling method. The total number of questionnaire forms collected was 187 with 133 adjudged valid for data analysis. Table 1 shows the details of demographics. Respondents were anonymised in the survey for this study. Questionnaires were accompanied by a letter stating the anonymity and data were collected for study use only.

**Table 1**
Demographic information.

| Respondent Profile *(n=299)* | | | | | | | |
|---|---|---|---|---|---|---|---|
| Attributes | Distribution | Frequency | (%) | Attributes | Distribution | Frequency | (%) |
| Position | Senior manager | 41 | 13.7 | Education level | Vocational or Basic | 2 | 0.7 |
| | Middle manager | 100 | 33.4 | | Undergraduate | 187 | 62.5 |
| | R&D personnel | 23 | 7.7 | | Masters' | 74 | 24.7 |
| | ICT staff | 43 | 14.4 | | PhD | 6 | 2.0 |
| | Other | 92 | 30.8 | | Other | 30 | 10 |
| Firm Age (Year) | Less than 5 years | 45 | 15.1 | Annual turnover (CNY) | Less than 2 million | 21 | 7.0 |
| | 5–10 years | 80 | 26.8 | | 2-5 million | 20 | 6.7 |
| | 11–20 years | 76 | 25.4 | | 6-10 million | 28 | 9.4 |
| | More than 20 years | 98 | 32.8 | | More than 10 million | 230 | 76.9 |
| Number of employees | Below 100 | 80 | 26.8 | Industry | Digital efficiency improvement | 98 | 32.8 |
| | 101–200 | 38 | 12.7 | | Digital products manufacturing | 47 | 15.7 |
| | 201–500 | 38 | 12.7 | | Digital technology application | 29 | 9.7 |
| | 501–1000 | 36 | 12.0 | | Digital factors driving | 67 | 22.4 |
| | More than 1000 | 107 | 35.8 | | Digital products service | 58 | 19.4 |

## 4. Results

### 4.1. Common method variance

Since the data are collected from a single source (rater or participant) and self-presentation is the only way to respond, this method of data collection is more liable to common method variance (CMV) [62]. Common method biases (CMB) refer to an artificial covariation between predictors and standard variables due to the same data source, the same measurement environment and the characteristics of the project itself [63]. The connotations of CMV and CMB are essentially the same, but the difference is that researchers use the CMV concept to describe the size of this variation objectively, while the CMB concept tries to establish a numerical boundary to determine how large the variation of the common method will have to seriously affect the validity of the research results [64]. To test the CMB, we employed Harman's single-factor test. Results show that the unrotated first factor explained only 35.46 % of the total variation, which is less than the 50 % threshold, which indicated that there was no significant CMB in the study data [65].

### 4.2. Measurement model

We modelled and analysed the measurement model before modelling the inter-relationship of latent constructs in the structural equation model. We used SPSS 28 and Amos 28 to assess and analyse the measurement model. We adopted both Cronbach's alpha and Composite reliability (CR) to assess the reliability of this study (as shown in Table 2). The Cronbach's alpha and CR of all the first-order and second-order constructs in this study were more than 0.7, indicating that the reliability and internal consistency of each latent construct had been achieved [66].

Three types of validity were assessed in the measurement model. Average variance extracted (AVE) and factor loading were employed to assess the convergent validity. The values of AVE for every construct were more than 0.5, while the factor loadings of all the first-order and second-order constructs were more than 0.6, (as shown in Table 2), indicating that convergent validity is achieved [67]. By running the confirmatory factor analysis (CFA) using AMOS 28, the fitness indexes for each construct and the pooled- CFA achieved the required level (ChiSq/df $= 1.646 < 3$, CFI $= 0.960 > 0.9$, and RESEA $= 0.047 < 0.08$), which indicated a good fit of the items and the whole measurement model, so construct validity was achieved. The Fornell-Larcker criterion was employed to measure the discriminant validity of the measurement model. As shown in Tables 3 and 4, all the inter-construct correlations were smaller than the AVE's square root (in bold) in the same column, indicating that discriminant validity was achieved [68].

### 4.3. Structural equation modelling results

Structural Equation Modelling (SEM) is a second-generation statistical technique developed for analysing the inter-relationships among multiple variables in a model [69]. Structural Equation Modelling (SEM) researcher begins with a theory where the researcher intends to test the relationship among constructs of interest in the study [69]. The structural equation model in this study

**Table 2**
Reliability and validity.

| Constructs | | Items | Loading >0.6 | | Alpha >0.7 | | CR >0.7 | | AVE >0.5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **ES** | DRS | DRS1 | 0.73 | **0.93** | 0.852 | **0.870** | 0.860 | **0.837** | 0.674 | **0.721** |
| | | DRS2 | 0.93 | | | | | | | |
| | | DRS3 | 0.79 | | | | | | | |
| | DRE | DRE1 | 0.64 | **0.76** | 0.808 | | 0.826 | | 0.547 | |
| | | DRE2 | 0.62 | | | | | | | |
| | | DRE3 | 0.83 | | | | | | | |
| | | DRE4 | 0.84 | | | | | | | |
| **GS** | GDR | GDR1 | 0.71 | **0.80** | 0.796 | **0.863** | 0.798 | **0.733** | 0.569 | **0.579** |
| | | GDR2 | 0.77 | | | | | | | |
| | | GDR3 | 0.78 | | | | | | | |
| | GSV | GSV1 | 0.80 | **0.72** | 0.892 | | 0.892 | | 0.673 | |
| | | GSV2 | 0.84 | | | | | | | |
| | | GSV3 | 0.82 | | | | | | | |
| | | GSV4 | 0.82 | | | | | | | |
| DTFL | | DTFL1 | 0.73 | | 0.878 | | 0.872 | | 0.576 | |
| | | DTFL2 | 0.81 | | | | | | | |
| | | DTFL3 | 0.80 | | | | | | | |
| | | DTFL4 | 0.75 | | | | | | | |
| | | DTFL5 | 0.70 | | | | | | | |
| DIIN | | DIIN1 | 0.82 | | 0.864 | | 0.872 | | 0.578 | |
| | | DIIN2 | 0.77 | | | | | | | |
| | | DIIN3 | 0.81 | | | | | | | |
| | | DIIN4 | 0.74 | | | | | | | |
| | | DIIN5 | 0.65 | | | | | | | |

Note: Results of second order constructs are shown in bold.

**Table 3**
Fornell-Larcker Criterion of first-order constructs.

| | DRS | DRE | GDR | GSV | DTFL | DIIN |
|---|---|---|---|---|---|---|
| DRS | **0.821** | | | | | |
| DRE | 0.705 | **0.740** | | | | |
| GDR | 0.394 | 0.303 | **0.754** | | | |
| GSV | 0.396 | 0.416 | 0.577 | **0.820** | | |
| DTFL | 0.328 | 0.233 | 0.486 | 0.383 | **0.759** | |
| DIIN | 0.621 | 0.492 | 0.546 | 0.495 | 0.509 | **0.760** |

**Table 4**
Fornell-Larcker Criterion of second-order constructs.

| | ES | GS | DTFL | DIIN |
|---|---|---|---|---|
| ES | **0.849** | | | |
| GS | 0.569 | **0.761** | | |
| DTFL | 0.342 | 0.573 | **0.759** | |
| DIIN | 0.662 | 0.684 | 0.509 | **0.760** |

explains the hypothesised relationships between constructs. Tables 5 and 6 show the results of hypotheses testing. When testing the direct impact without a mediator, ES and GS are positively and significantly related to DIIN as the standardised beta estimate for the direct effects of these two exogenous variables on DIIN is 0.403 and 0.454, respectively. The critical ratio (C.R.) value is 4.652 and 4.699 (>1.96) respectively while the p-value is less than 0.001, confirming the significance of the relationship. After adding DTFL into the structural model, ES and GS also positively and significantly affect DIIN, but the direct effects are weakened, as the standardised beta values are 0.399 and 0.363 respectively. According to the standardised beta estimate ($\beta = 0.560$) and the less-than-0.001 p-value, GS is significantly and positively related to DTFL. The results in Table 5 also show that DTFL was positively and significantly associated with DIIN ($\beta = 0.165$ , C.R. $= 2.357 > 1.96$ , $p = 0.018 < 0.05$). Therefore, the mediation effect of DTFL between GR and DIIN is supported [56]. However, the effect of ES on DTFL is not significant as indicated by the C.R. value (C.R. $= 0.255 < 1.96$) and the p value ($p = 0.799 > 0.05$), indicating no mediating effect of DTFL between ESand DIIN.

Confirmed by running the bootstrapping method (performed with 1000 bootstrapping samples, resulting in bias-corrected percentile method at the 95 % confidence level), the indirect effect of GS on DIIN is 0.092 with the p-value = 0.043, which is significant, indicating that mediation exists between GS and DIIN (as shown in Table 6). In the meantime, the direct effect of GS on DIIN is also significant but somewhat weakened ($0.363 < 0.454$) after adding the mediator DTFL, indicating a partial mediation of DTFL between GS and DIIN [70]. However, the indirect effect of ES on DIIN is 0.004 with the p-value = 0.609, which is not significant, indicating mediating effect of DTFL not existing between ES and DIIN. Therefore, the empirical results show only the direct effect of ES on DIIN without mediation. The structural equation model with standardised beta measures and their significance are shown in Fig. 2.

## 5. Discussion

### *5.1. Findings*

This study explores the impact of GS and ES on organisational digital innovation through data flows. Combining the testing results of $H_1$, $H_2$, $H_5$ and $H_6$, GS affects organisational digital innovation positively and directly. Moreover, GS in terms of the regulatory environment affects data flows positively, while data flows affect organisational digital innovation positively, indicating that the mediating effect of data flows between GS and digital innovation exists. After entering the mediator variable DTFL, the direct effect of GS on organisational digital innovation was still significant, but somewhat weakened. The path coefficient reduced from 0.454 to 0.363. GS in the regulatory environment can reduce the risk and cost of enterprises investing in digital innovation. For instance, the special funds or guidance funds set up by the government, as well as various loan discounts, project subsidies, post-incentives and other capital subsidy mechanisms, can improve the digital innovation of the corresponding enterprises effectively. Related promotion policies and regulations can enhance their willingness and motivation to invest in digital innovation activities. As an important

**Table 5**
Hypothesis 1-5 results.

| Hypothesis | Path | S.T.D. (β) | C.R. | p-Value | Results |
|---|---|---|---|---|---|
| H1 | Government Support→Digital Innovation | 0.454 | 4.699 | *** | Supported |
| H2 | Government Support→Data Flows | 0.560 | 4.759 | *** | Supported |
| H3 | Employee Structure→Digital Innovation | 0.403 | 4.652 | *** | Supported |
| H4 | Employee Structure→Data Flows | 0.023 | 0.255 | 0.799 | Not Supported |
| H5 | Data Flows→Digital Innovation | 0.165 | 2.357 | 0.018* | Supported |

Note: ***$P < 0.001$ **$p < 0.01$ *$p < 0.05$.

**Table 6**
Hypothesis 6-7 results.

| Hypothesis | Path | Direct effect | Indirect effect | Result |
|---|---|---|---|---|
| H6 | Government Support→Data Flows→Digital Innovation | 0.363** (p = 0.006) | 0.092* (p = 0.043) | Supported (Partial mediation) |
| H7 | Employee Structure→Data Flows→Digital Innovation | 0.399** (p = 0.002) | 0.004 (p = 0.609) | Not Supported (No mediation) |

Note: ***P < 0.001 **p < 0.01 *p < 0.05.

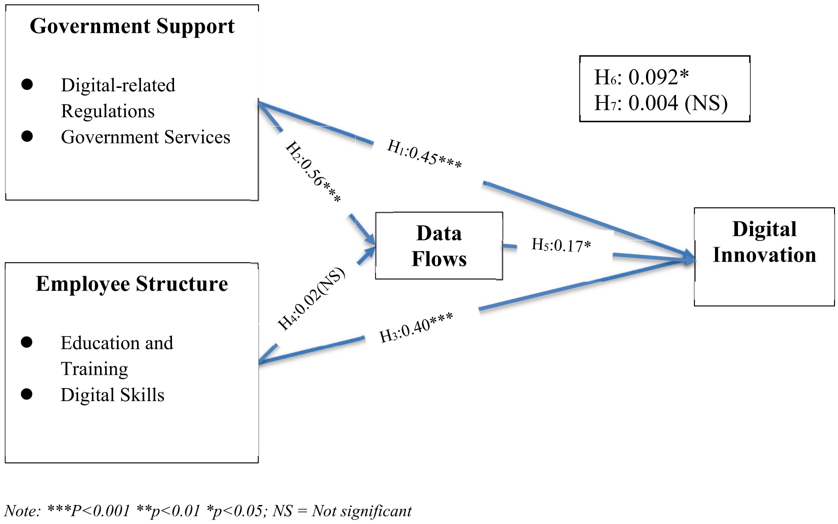


**Fig. 2.** Structural equation model results with beta measure and significance.

component of the digital innovation ecosystem, the government formulates and implements digital-related regulations which have a profound impact on the whole process of data flows, while the mobility of data is fundamental to support the organisational digital innovative activities, thus ultimately facilitating organisational digital innovation. Therefore, this finding can help to solve the research problem of insufficient motivation for digital innovation.

Combining the testing results of $H_3$, $H_4$, $H_5$ and $H_7$, ES affects digital innovation positively and directly. This can be rendered more proactive through education and ICT-related training and employees mastering digital skills. As the most dynamic subject of digital innovation, the initial motivation for carrying out digital innovation activities is the need for survival, and it is also based on the accumulation and reserve of human capital to explore the world. Innovation determines the survival and competitive advantage of enterprises, and the resource-based view holds that innovation is the essentially process of transforming a series of resources such as knowledge, skills and capital into market demand. People are the owners and users of knowledge and skills, and education is the way to disseminate knowledge and skills, and it is also the most effective way to acquire human capital. Employees who have received higher education often have the professional knowledge and skills required for digital innovation, and the combination of highly educated human capital and physical capital can bring benefits to enterprises through digital innovation. Therefore, for enterprises, highly educated human capital with the professional knowledge and skills required for digital innovation implies stronger digital innovation capabilities and higher labour productivity. However, since there is no significant relationship between ES and DTFL, the indirect relationship between ES and DTFL does not exist. Employees' readiness for digital innovation can influence the flow of production and consumption data between multiple platforms and multiple agents in the digital innovation ecosystem but may have no significant impact on the flow of public data, which is a main component of data in China. This finding can help address the research problem of insufficient investment in digital innovation by enterprises.

### *5.2. Contributions and implications*

Based on the theory of digital innovation ecosystems, this research studied the impact of internal and external factors on organisational digital innovation, expanding and deepening the research on digital innovation behaviour. Furthermore, this study revealed the mediating effect of data flows on the relationship between GS and organisational digital innovation, which is the complex mechanism of the digital innovation process of enterprises, and thereby enriches the research on the theory of digital innovation ecosystem Meanwhile, this study provided evidence for theories of digital innovation ecosystems and employee-driven digital innovation.

In addition, the results of this study provide a decision-making basis for enterprises in the core industries of the digital economy as well as in traditional industries in China to effectively integrate external resources, such as government support and internal resources to facilitate digital innovation. Enterprises should take effective legal and compliance construction actions, explore and seize the favourable factors in the institutional environment immediately, and tilt more internal resources towards digital skills training for ordinary employees. The findings will also provide a reference point for policymakers to formulate and implement digital-related policies and regulations, especially facilitating the mobility and security of data elements.

### *5.3. Limitations and suggestions for future research*

Although this study addresses the factors that affect the digital innovation of enterprises from both external and internal aspects, in reality, there are many such influencing factors, and in the future, more influencing factors should be included to explore the digital innovation of enterprises. At the same time, this study finds that the mediating effect of data flows on the relationship between government support and organisational digital innovation is only a partial mediation, and the bootstrap analysis shows that there may be other intermediaries. Future research can start from this clue to find more mediating variables. In addition, the amount of data collected in the form of questionnaires in this study is still relatively limited and only from firms in China, so more sample data from other countries and regions are needed to verify and support the results in the future.

## 6. Conclusion

This study constructs a research framework on the relationship between government support, employee structure, and organizational digital innovation, and reveals the mechanism of the above variables. Hypotheses were developed based on theoretical and empirical support from previous literature. The findings of this study can be summarized to achieve the research objectives and answer the research questions. At the institutional level, the findings of the analysis for hypothesis H1 and H2 revealed a statically significant and positive relationship between government support and organizational digital innovation, supporting the previous view that government supportive policies and regulations can help firms access resources such as capital and legitimacy, which can further enhance the willingness and motivation of start-ups to engage in knowledge strategy activities. Government rules around data privacy and security have a profound impact on the flow of data and ultimately organisational digital innovation. At the organisational level, the findings of the analysis for hypothesis H3 and H4 revealed that there is a significant positive and direct association between employee structure and digital innovation in China. The educational background, talent training, and digital skills within the organisation are closely related to ICT technology and empower each other to produce complementary effects, thereby reducing the digital innovation cost and improving innovation output efficiency. The findings of the analysis for hypothesis H5, H6 and H7 provide evidence that the flow of data within the digital innovation ecosystem activates, connects, and aggregates the digital innovation activities of multiple actors. The flow of data elements is limited by the corresponding organisational and institutional rules. The results and conclusions in this study can provide solutions to the problems of insufficient power of the digital economy and the imperfect digital innovation system, to provide a new reference point for digital enterprises and traditional enterprises, like enterprises in the manufacturing or agricultural industry, to achieve digital innovation breakthroughs, and for the government to formulate new policies related to the digital economy, such as data flow restrictions, and improve the service level of local governments.

## Consent for publication

All the authors read and agreed to publish this article.

## Data availability statement

The data that support this study are available from the corresponding author upon reasonable request.

## CRediT authorship contribution statement

**Yue Xia:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Md Gapar Md Johar:** Validation, Supervision.

## Declaration of competing interest

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

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## Appendix 1. Measurement items

| Constructs | | Items | Item contents | Sources |
|---|---|---|---|---|
| ES | DRS | DRS1 | The company has sufficient employees with scientific research and technical services. | Trigler [71] |
| | | DRS2 | The company has sufficient employees with digital-related skills. | Trigler [71] |
| | | DRS3 | The company's existing digital-related technical staff can meet the personal skill level of the job requirements. | Trigler [71] |
| | DRE | DRE1 | There are many colleges and universities in the local area that cover digital economy-related majors such as e-commerce and digital trade. | Zhang and Ma [72] |
| | | DRE2 | There are many service agencies in the local digital human resources market. | Zhang and Ma [72] |
| | | DRE3 | A large proportion of employees in your company receive digital-related technical training. | Trigler [71] |
| | | DRE4 | The company's employee training expenses in digital-related technologies account for a large proportion of the annual operating income. | Trigler [71] |
| GS | GDR | GDR1 | The local government has corresponding regulatory measures against unfair competition in the digital market (such as platform monopolies). | Zhang and Ma [72] |
| | | GDR2 | The local government has corresponding regulatory measures for the quality of online platform services and online goods. | Zhang and Ma [72] |
| | | GDR3 | The local government has corresponding regulatory measures for the protection of online intellectual property rights and the securityD of personal information and data. | Zhang and Ma [72] |
| | GSV | GSV1 | The service mode of the local digital government platform is highly complete. | Zhang and Ma [72] |
| | | GSV2 | The local digital government platform has a wide range of services. | Zhang and Ma [72] |
| | | GSV3 | The service guide of the local digital government platform is highly accurate. | Zhang and Ma [72] |
| | | GSV4 | The online services of the local digital government platform are highly efficient. | Zhang and Ma [72] |
| DTFL | | DTFL1 | Data controllers/processors are required to comply with the relevant provisions on data retention periods. | ECIPE [73] |
| | | DTFL2 | Data controllers/processors must comply with the relevant restrictions imposed on online content (e.g. approval and filtering of web content, bandwidth requirements, etc.). | ECIPE [73] |
| | | DTFL3 | Data intermediaries (e.g. social media platforms) must comply with relevant intermediary liability provisions (e.g., notice-takedown regimes, etc.). | ECIPE [73] |
| | | DTFL4 | Data controllers/processors must comply with administrative procedures established by regulators to lawfully process personal data. | World Bank Group [74] |
| | | DTFL5 | Data controllers/processors must comply with the relevant security requirements for the automatic collection of personal data. | World Bank Group [74] |
| DIIN | | DIIN1 | Digital technologies are automating your firm's processes. | Xu [75] |
| | | DIIN2 | The introduction of digital technology in your firm enhances management communication inside and outside the organization. | Xu [75] |
| | | DIIN3 | Your firm updates the data or related information carried by infrastructure (such as data centers), production equipment, R&D tools, etc. in a timely manner. | Xu [75] |
| | | DIIN4 | Your firm can continuously and in real time obtain various internal and external information through digital technology. | Xu [75] |
| | | DIIN5 | Your firm is improving its products or services based on digital technologies. | Xu [75] |

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