Article history:
Received 21 September 2024
Revised 01 November 2024
Accepted 07 November 2024
Published online 26 November 2024

Journal of Resource Management and Decision Engineering

Volume 3, Issue 1, pp 84-94

Importance-Performance Matrix Analysis (IPMA) of the Open and Collaborative Innovation Model on a Digital Platform

Fariba Goodarzi[1], Hossein Moinzadeh[1*], Hossein Adab[1]

[1] Department of Industrial Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran

*** Corresponding author email address**: moinzad@iauctb.ac.ir

A r t i c l e   I n f o

Article type:
Original Research

How to cite this article:
Goodarzi, F., Moinzadeh, H., & Adab, H. (2024). Importance-Performance Matrix Analysis (IPMA) of the Open and Collaborative Innovation Model on a Digital Platform. *Journal of Resource Management and Decision Engineering, 3*(4), 84-94.
https://doi.org/10.61838/kman.jrmde.3.4.10

A B S T R A C T

The aim of this study is to analyze the Importance-Performance Matrix Analysis (IPMA) of the open and collaborative innovation model based on a digital platform. This research is exploratory in nature with regard to its objective and is classified as descriptive-analytical in terms of methodology. It was conducted through a cross-sectional survey using a mixed exploratory method that integrates qualitative (grounded theory) and quantitative (importance-performance analysis) approaches. The statistical population for the qualitative phase included managers and experts from IT industry companies in Tehran in 2023, while the quantitative phase involved an unlimited population of banking industry customers. Using purposive sampling, 14 individuals were selected for the qualitative phase, and according to Cochran's formula, 384 individuals were selected for the quantitative phase. Semi-structured interviews were employed to identify relevant components based on the grounded theory technique. In the quantitative phase, partial least squares (PLS) analysis was used to determine relationships among variables and their respective importance coefficients, while component ranking was carried out using Importance-Performance Matrix Analysis. Based on Delphi results, a researcher-developed questionnaire was used in the quantitative part. ATLAS.ti software was utilized in the qualitative phase, and SMARTPLS software was employed for the quantitative analysis. The results indicated that causal conditions had the highest degree of importance (0.715), while contextual conditions demonstrated the highest performance score (71.363). The analysis reveals that the success of the open and collaborative innovation model on a digital platform requires simultaneous attention to strengthening causal conditions and maintaining high performance in contextual conditions. Such an approach can ensure the long-term success of this model within organizations.

Keywords: *Open innovation, Collaborative innovation, Digital platform, IT industry, Digital transformation*

1. Introduction

The open and collaborative innovation model based on digital platforms represents a modern approach to the development of products, services, and processes. It enables organizations to achieve greater innovation by collaborating with various stakeholders, including customers, suppliers, universities, and even competitors (Serrano-Ruiz et al., 2024). Rather than confining the innovation process within the boundaries of the organization, this model extensively utilizes external resources. The digital platform serves as a dynamic and interactive environment that facilitates the rapid transfer and implementation of ideas and innovations (Volpe et al., 2021). In this context, the digital platform acts as a key enabler that accelerates innovation processes and fosters interactions (Vial, 2021).

Historically, organizations primarily relied on their internal resources for research and development. This traditional model, referred to as closed innovation, emphasized internal teamwork and in-house research activities (Daiberl et al., 2019). However, as competition intensified and market dynamics evolved rapidly, organizations realized that internal resources alone were insufficient to ensure survival and growth in today's complex and ever-changing world (Georgescu et al., 2021). This recognition led to the emergence of the open innovation model (Klos et al., 2021). The model allows organizations to exploit external ideas, technologies, and experiences, transforming the innovation process into a collective effort (Nambisan et al., 2019).

The digital platform plays a pivotal role in this model. It can take the form of online platforms, dedicated software, or integrated digital systems that enable different users to interact directly with one another (Sassanelli et al., 2020). These platforms facilitate real-time exchange of data, information, and ideas, thereby enabling both open and collaborative innovation (Butter et al., 2020). For instance, through digital platforms, customers can articulate their needs, suppliers can propose technological solutions, and academic institutions can share their research directly with industry stakeholders (Bertello et al., 2024).

Another key feature of the open and collaborative innovation model via digital platforms is the ability to access knowledge and information from diverse sources (Saura et al., 2023). These platforms effectively enable organizations to gather valuable information independently or collaboratively and use it to improve innovation processes. This approach is particularly effective in industries that demand continuous innovation, such as technology, healthcare, and automotive sectors (Putri & Fontana, 2022; Sarwar et al., 2023).

However, implementing an open and collaborative innovation model based on digital platforms also presents several challenges. One of the major challenges is managing complex collaborations and coordinating a large number of partners (Audretsch & Belitski, 2023). Continuous coordination among various stakeholders is crucial to ensure the effectiveness of innovation flow. Additionally, ensuring data security and protecting intellectual property within such platforms pose significant challenges. Organizations must adopt advanced security methods to safeguard sensitive information appropriately (Jugend et al., 2020).

Ultimately, the open and collaborative innovation model based on digital platforms not only acts as a tool to accelerate the innovation process but also serves as a key driver in reshaping business models and fostering strategic collaborations between organizations (Hanley et al., 2022). Especially in today's digital world, where knowledge and information are evolving rapidly, this model helps organizations create competitive advantage and respond effectively to emerging threats and innovative opportunities (Bao & Wang, 2022).

A review of the existing literature reveals a multidimensional understanding of digital innovation and collaborative value creation across industries. Eshaghian et al. (2022) proposed a business model innovation framework derived from expert insights in digital technology, identifying seven key domains including platforms, connectivity, role-based products, sensor-driven data collection, insight analytics, analytical interaction, and augmented interaction (Eshaghian et al., 2022). Asgharnia et al. (2022) explored the challenges of implementing digital transformation strategies in the telecom sector, noting unique hurdles such as service commoditization, demand for personalization, emerging external competitors, and disruptive software innovations (Asgharnia et al., 2022). Karimi et al. (2022) introduced a digital technology model for marketing environments and capabilities through axial coding based on a paradigm model, emphasizing digital strategic capability and business growth (Karimi Mousa et al., 2022). Wang et al. (2023) found that managerial digital attention mediates the link between government digital initiatives and corporate innovation, with corporate political agendas and digital leadership moderating these relationships (Wang et al., 2023). Putri et al. (2022) emphasized the critical role of co-innovation between banks and fintechs in enabling digital transformation, highlighting the dual role of organizational culture as either an enabler or barrier (Putri & Fontana, 2022). Marion and Fixson (2021) confirmed the significant positive effect of digital tools on inter-organizational co-innovation in product development (Marion & Fixson, 2021). These studies underline the importance of technological, organizational, and cultural drivers in fostering effective digital and collaborative innovation ecosystems.

The results of the Importance-Performance Matrix Analysis (IPMA) of the open and collaborative innovation model on digital platforms indicate that the model can elevate interactions among organizations, customers, and other stakeholders to new levels of efficiency and innovation. The matrix evaluates the importance and performance of each factor influencing open innovation on digital platforms. Factors such as ease of access to information, collaborative capabilities in digital environments, and data security features are identified as key contributors to the success of this model. At the same time, the analysis shows that, based on current performance levels, many organizations need to enhance their digital infrastructure and create more open spaces for collaboration in order to harness the full potential of the model.

This analysis also highlights that a correct understanding of the importance and performance of various components of open and collaborative innovation can help organizations allocate their resources more effectively, ultimately accelerating innovation processes and improving business outcomes. Therefore, organizations should prioritize the improvement of factors that are of high importance but exhibit low performance. This approach can lead to the long-term optimization of digital innovation strategies and synergy among all stakeholders, particularly in industries where continuous innovation is vital for competitive survival. Accordingly, this study seeks to answer the following question: What is the Importance-Performance Matrix Analysis (IPMA) of the open and collaborative innovation model on digital platforms?

2. Methods and Materials

This study is exploratory in terms of its objective and is classified as descriptive-analytical in terms of methodology. It was conducted as a cross-sectional survey and is based on an exploratory mixed-methods approach, combining qualitative (grounded theory) and quantitative (Importance-Performance Analysis – IPMA) methods. Grounded theory is a qualitative research method used to develop theories and models through systematic analysis of data. Unlike hypothesis-driven research, this method operates bottom-up, meaning data is considered the starting point of the research process, and the final theory is derived directly from the data. In this method, the researcher collects primary data (such as interviews, observations, or documents) and identifies and organizes key concepts through the processes of open, axial, and selective coding. These concepts are then used to establish connections and structure a coherent theory. Grounded theory is particularly valuable in research aimed at deep understanding of phenomena, discovering new relationships, or developing theoretical models, and is commonly used in social sciences, management, and health studies.

The IPMA method is a management tool used to evaluate and prioritize the factors affecting performance within a system or organization. By analyzing both "importance" (the relative importance of each factor in achieving objectives) and "performance" (the current level of achievement of that factor), IPMA helps decision-makers allocate resources in the most optimal way. IPMA results are typically presented in a four-quadrant matrix: (1) high importance/low performance factors, which require immediate attention; (2) high importance/high performance factors, which should be maintained; (3) low importance/high performance factors, which may have received excessive resources; and (4) low importance/low performance factors, which require minimal attention. This method is particularly useful for identifying strengths and weaknesses and for formulating improvement strategies in areas such as marketing, human resource management, and innovation.

The study population was divided into two parts: the qualitative phase included experts from companies active in the IT industry in Tehran in 2023, and the quantitative phase included professionals and employees from IT companies, with no defined population limit. Using purposive sampling, 14 participants were selected for the qualitative phase. For the quantitative phase, 384 participants were selected based on Cochran's formula. Using semi-structured interviews, the intended components were identified through grounded theory analysis. In the quantitative phase, partial least squares (PLS) analysis was used to determine the relationships between variables and the associated importance coefficients, while IPMA was used for ranking components. Based on Delphi results, a researcher-developed questionnaire was used in the quantitative section. The ATLAS.ti software was used for the qualitative analysis, and SMARTPLS software was employed for the IPMA technique in the quantitative phase.

3. Findings and Results

The statistical description of the participants in both the literature-based and field-based sections is presented in Table 1.

Table 1

Demographic Characteristics of Interviewees

Variable	Category	Frequency	Percentage
Gender	Female	6	43%
	Male	8	57%
Education	Master's Degree	10	71%
	Doctorate and above	4	29%
Work Experience	15–20 years	5	36%
	20–25 years	7	50%
	Over 25 years	2	14%
Age	30–40 years	6	43%
	40–50 years	6	43%
	Over 50 years	2	14%

For the purpose of open coding, all interviews were imported into ATLAS.ti software. Necessary examinations were conducted, and the relevant codes were extracted. The labeling of codes was based on interview content, and the researcher ensured adherence to the participants' perspectives as much as possible to avoid any unintended bias. Throughout the coding process, the researcher remained committed to the principle of theoretical sensitivity, which is central to grounded theory methodology, to enhance the richness of the study.

Table 2

Open Coding of Qualitative Data

Selected Category	Axial Category
Causal Conditions	Innovation Culture
	Participatory Orientation
	Advanced Technological Infrastructure
	Knowledge and Expertise
	Ideation
Intervening Conditions	Political Conditions
	Economic Conditions
	Industry Conditions
	Security and Trust
Contextual Conditions	Innovation Financing
	Technical Innovation Potential
	Business Ecosystem
Strategies	Co-Development of Product
	Commercialization
	Innovation Targeting on Digital Platform
	Environmental Dynamism
	Creative Performance of Human Resources
Outcomes	National Growth and Development
	Project Management Development
	Industrial Development

Descriptive statistics were used to examine the demographic characteristics of the survey respondents. Frequency distributions were analyzed based on gender, age, and education levels.

Table 3

Demographic Characteristics of the Quantitative Section

Demographic Feature	Category	Frequency	Percentage
Gender	Male	230	60%
	Female	154	40%
Age	Under 25	50	13%
	26–35	138	36%
	36–50	184	48%
	Over 51	12	3%
Education	Less than Bachelor	73	19%
	Bachelor	96	25%
	Master's	119	31%
	Doctorate	96	25%
Total		384	100%

Descriptive indicators such as mean, standard deviation, and others were used to describe the main research variables. These indicators are presented in the following table.

Table 4

Descriptive Statistics of Research Variables

Main Factor	Mean	Standard Deviation	Skewness	Kurtosis
Causal Conditions	3.435	0.456	0.456	1.123
Contextual Conditions	3.111	0.876	-0.534	0.762
Intervening Conditions	3.293	0.345	-0.760	0.332
Strategies	3.245	0.233	-0.356	0.425
Outcomes	3.150	0.756	-0.369	0.376

To examine the state of the research variables, descriptive statistics such as mean, standard deviation, variance, skewness, and kurtosis were applied. According to the obtained mean values, it is evident that the "high" response option was more frequently chosen. Additionally, based on the values for skewness and kurtosis, all variables fell within the acceptable range of –2 to +2, indicating that the data are symmetric and normally distributed.

In general, the relationships between variables in the Partial Least Squares (PLS) technique are classified into two categories:

1. **Outer Model**: The outer model is equivalent to the measurement model (confirmatory factor analysis) in structural equation modeling (SEM) and represents the relationships between latent variables and their observed indicators.
2. **Inner Model**: The inner model corresponds to the structural model (path analysis) in SEM and examines the relationships among latent variables.

Figure 1

Factor Loadings of the Research Model (Outer Model)

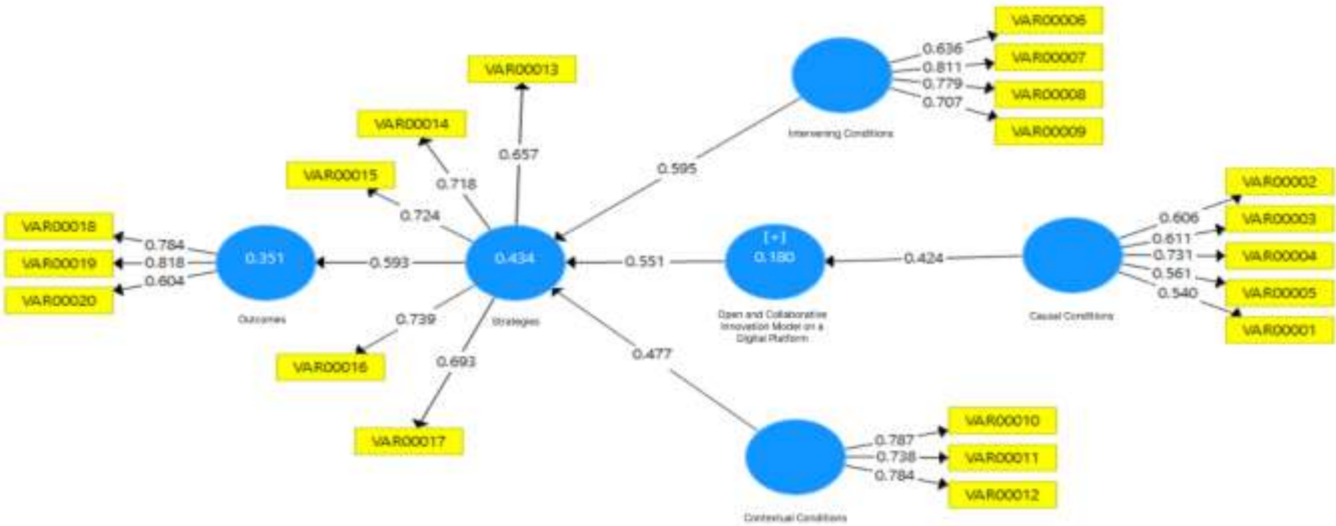
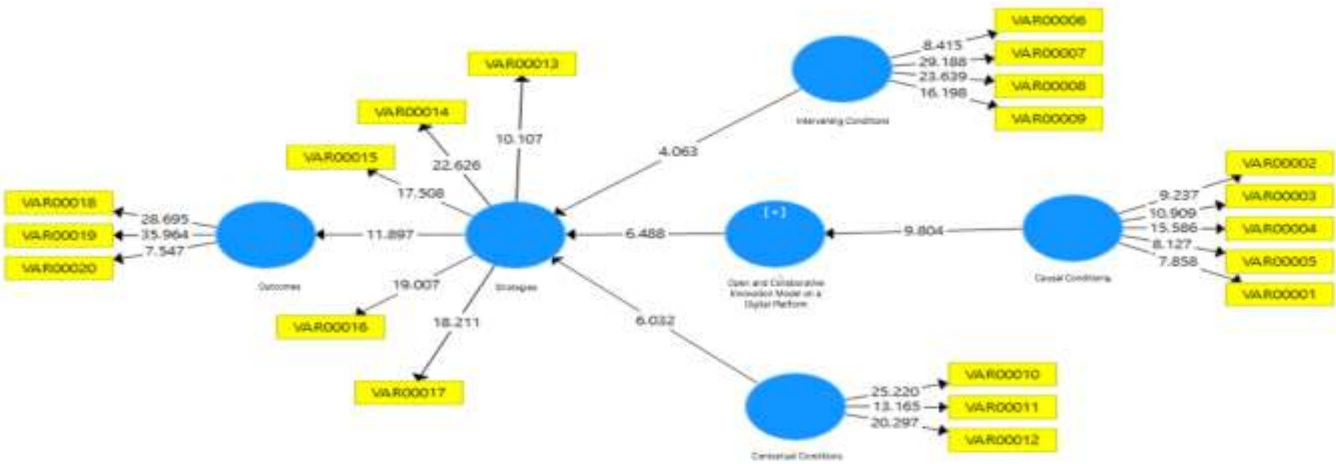


Figure 2

Bootstrapping t-Statistics of the Research Model (Outer Model)



To demonstrate that latent variables are accurately measured, the outer model is used. The results of the measurement model are presented in Table 5.

Table 5

Partial Least Squares Outer Model (Measurement Model)

Dimension	Component	Indicator	Factor Loading	Significance Level
Causal Conditions	Innovation Culture	VAR00001	0.540	0.000
	Participatory Orientation	VAR00002	0.606	0.000
	Advanced Technological Infrastructure	VAR00003	0.611	0.000
	Knowledge and Expertise	VAR00004	0.731	0.000
	Ideation	VAR00005	0.561	0.000
Intervening Conditions	Political Conditions	VAR00006	0.636	0.000
	Economic Conditions	VAR00007	0.811	0.000
	Industry Conditions	VAR00008	0.779	0.000
	Security and Trust	VAR00009	0.707	0.000
Contextual Conditions	Innovation Financing	VAR00010	0.787	0.000
	Technical Innovation Potential	VAR00011	0.738	0.000
	Business Ecosystem	VAR00012	0.784	0.000
Strategies	Co-Development of Product	VAR00013	0.657	0.000
	Commercialization	VAR00014	0.718	0.000
	Innovation Targeting on Digital Platform	VAR00015	0.724	0.000
	Environmental Dynamism	VAR00016	0.739	0.000
	Creative Performance of Human Resources	VAR00017	0.693	0.000
Outcomes	National Growth and Development	VAR00018	0.784	0.000
	Project Management Development	VAR00019	0.818	0.000
	Industrial Development	VAR00020	0.604	0.000

Based on the results of the measurement model presented in Table 5, all observed factor loadings are greater than 0.3, indicating acceptable correlations between the observed variables and their corresponding latent constructs. To evaluate the validity and reliability of the constructs in measurement models using Partial Least Squares Structural Equation Modeling (PLS-SEM), the following indices are computed and reported: Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and Discriminant Validity using the Fornell-Larcker criterion.

Table 6

Convergent Validity and Reliability of Research Variables

Variable	Cronbach's Alpha	AVE	CR	Rho
Causal Conditions	0.755	0.522	0.810	0.800
Contextual Conditions	0.718	0.534	0.777	0.783
Intervening Conditions	0.832	0.529	0.793	0.830
Strategies	0.813	0.555	0.826	0.895
Outcomes	0.838	0.561	0.834	0.811

According to the results in the table above, Cronbach's alpha for all variables exceeds 0.7, confirming the reliability of all constructs. The Average Variance Extracted (AVE) for each construct is above the 0.5 threshold, thereby confirming convergent validity. The Composite Reliability (CR) values are also higher than both the AVE and the 0.7 standard threshold, indicating that each construct in the model possesses suitable reliability and validity. Furthermore, the Rho coefficient values also exceed 0.7, reinforcing internal consistency. The next step involves assessing discriminant validity using the Fornell-Larcker criterion.

Table 7

Fornell-Larcker Criterion

	Causal Conditions	Contextual Conditions	Intervening Conditions	Strategies	Outcomes
Causal Conditions	0.894				
Contextual Conditions	0.756	0.930			
Intervening Conditions	0.735	0.460	0.856		
Strategies	0.667	0.456	0.533	0.884	
Outcomes	0.420	0.646	0.640	0.756	0.850

As shown in Table 7, the values along the diagonal (main axis) of the matrix are greater than all other values in the corresponding columns, indicating that the model has acceptable discriminant validity.

Based on the results of the Partial Least Squares analysis, including factor loadings and bootstrapping statistics, the research hypotheses have been tested as follows:

Table 8

Hypothesis Testing and Path Analysis of the Model

No.	Independent Variable	Path Coefficient	t-Statistic	Significance Level	Status
1	Causal Conditions → Innovation Construct	0.424	9.804	0.000	Confirmed
2	Contextual Conditions → Strategies	0.477	6.032	0.000	Confirmed
3	Intervening Conditions → Strategies	0.595	4.063	0.000	Confirmed
4	Open and Collaborative Innovation on Digital Platform → Strategies	0.551	6.488	0.000	Confirmed
5	Strategies → Outcomes	0.593	11.897	0.000	Confirmed

According to the results from the structural equation model, the path coefficients for all hypotheses exceed 0.3. The significance levels for all hypotheses are below 0.05 ($p = 0.000$), meaning that all hypotheses are confirmed with 95% confidence.

The prioritization of the model's indicators in terms of importance and performance is derived from the Importance-Performance Matrix Analysis (IPMA), conducted through the IPMA output pattern in the Partial Least Squares method.

According to the results, the highest importance score is assigned to Causal Conditions (0.715), while the highest performance score is attributed to Contextual Conditions (71.363).

Table 9

Overall Importance and Performance of Model Indicators

Indicator	Importance	Rank	Performance	Rank
Causal Conditions	0.715	1	70.588	2
Contextual Conditions	0.709	2	71.363	1
Intervening Conditions	0.704	3	70.588	2
Open and Collaborative Innovation on Digital Platform	0.690	4	68.854	3

According to the IPMA model, the importance and performance levels of the components are relatively aligned, indicating that the model meets standardized measurement criteria.

4. Discussion and Conclusion

The findings of the present study offer empirical evidence on the structural relationships and importance-performance alignment of variables contributing to the open and collaborative innovation model on digital platforms. The analysis revealed that all research hypotheses were supported with high statistical significance ($p < 0.001$), and path coefficients in all cases exceeded 0.3, confirming the strength of relationships between causal conditions, contextual and intervening variables, strategic responses, and outcomes. Among the constructs, causal conditions—including innovation culture, participatory orientation, technological infrastructure, knowledge, and ideation—were shown to have the highest importance score (0.715), while contextual conditions—comprising innovation financing, technical potential, and business ecosystem—achieved the highest performance score (71.363). This dual finding emphasizes the model's robustness and alignment with contemporary management frameworks that integrate digital infrastructure with innovation dynamics.

These results align with the framework proposed by Eshaghian et al. (2022), who argued that innovation models based on digital technologies are formed through interrelated components such as platforms, connectivity, and data analytics (Eshaghian et al., 2022). Our identification of key causal factors mirrors their platform-centric approach, confirming that innovation culture and infrastructure readiness are foundational to digital transformation. The role of participatory mechanisms and ideation in our study further supports the notion that strategic collaboration across stakeholders enhances innovation capacity—an insight echoed in Putri et al. (2022), who emphasized co-innovation between banks and fintechs as essential for digital technology implementation (Putri & Fontana, 2022). Their recognition of organizational culture as both an accelerator and inhibitor of digital innovation parallels our finding that innovation culture is the strongest causal predictor in the model.

The critical impact of contextual factors such as innovation financing and ecosystem potential reflects findings by Karimi et al. (2022), who demonstrated that digital strategic environments and capabilities drive company growth (Karimi Mousa et al., 2022). The high performance of contextual conditions in our results suggests that companies investing in digital infrastructure and innovation ecosystems are more likely to implement successful strategies. Moreover, the path from contextual and intervening conditions to strategies is reinforced by the findings of Asgharnia et al. (2022), who highlighted the unique challenges and operational demands of digital transformation, particularly in industries facing software-driven disruption and commoditized services. Their assertion that digital transformation requires strategic alignment supports our conclusion that contextual preparedness directly influences the efficacy of strategy implementation (Asgharnia et al., 2022).

Additionally, the role of intervening conditions such as political, economic, industrial, and trust-related factors was shown to significantly impact strategic decisions. This mirrors Wang et al. (2023), who found that managerial digital attention and political context moderate the effect of governmental digital initiatives on corporate innovation (Wang et al., 2023). The significance of these intervening variables in our model suggests that digital innovation does not occur in isolation but is shaped by macro-level forces, including regulatory policies, market stability, and institutional trust. The bootstrapped path coefficient of 0.595 between intervening conditions and strategies substantiates this assertion and indicates that strategic agility in digital environments requires sensitivity to both internal and external pressures.

Furthermore, the findings affirm the mediating role of strategies—particularly co-development, commercialization, innovation targeting, environmental dynamism, and creative HR performance—in linking causal and contextual conditions to positive outcomes. The path coefficient of 0.593 from strategies to outcomes reinforces the idea that innovation success is not merely a function of resource availability but also of coherent and adaptive strategic deployment. Likewise, Marion and Fixson (2021) demonstrated that digital tools significantly enhance co-innovation in product development, underscoring our finding that the integration of human resource creativity and digital targeting strategies are pivotal in driving national growth, project management maturity, and industrial development (Marion & Fixson, 2021).

The importance-performance matrix analysis (IPMA) results also provided key insights into the prioritization of constructs. The fact that causal conditions held the highest importance while contextual conditions had the highest performance suggests a possible strategic gap. Organizations recognize the value of innovation culture and ideation, but their actual efforts are more concentrated on infrastructure and ecosystem development. This mismatch may point to a need for better integration of internal innovation practices with external readiness.

Another important takeaway from our findings is that all diagonal values in the Fornell-Larcker matrix exceeded the off-diagonal values in their respective columns, confirming strong discriminant validity. This ensures that constructs in the model are conceptually distinct, reinforcing the theoretical foundation proposed by prior scholars. In particular, the high reliability values for constructs (Cronbach's alpha > 0.7, CR > 0.8) and AVE > 0.5 indicate that the model's measurements are robust and capable of capturing the multifaceted nature of digital innovation systems. In agreement with (Eshaghian et al., 2022; Marion & Fixson, 2021), our model suggests that meaningful innovation emerges from the synergy of technological tools, institutional readiness, and stakeholder collaboration.

Despite its contributions, this study is not without limitations. First, the sample was limited to the IT industry in Tehran, which may restrict the generalizability of the results to other industries or geographic contexts. Second, while the mixed-methods approach enhanced theoretical richness, the qualitative phase involved only 14 experts, which may not fully capture the diversity of perspectives in broader ecosystems. Third, this study employed a cross-sectional design, which limits the ability to make causal inferences over time. Finally, while the IPMA technique offers valuable prioritization insights, it does not account for dynamic interactions among components, which may evolve as organizational or environmental contexts shift.

Future research should consider replicating this study in other sectors such as healthcare, education, or manufacturing to assess the adaptability of the open and collaborative innovation model in different ecosystems. A longitudinal design could also provide deeper insights into how digital transformation strategies evolve over time and under varying institutional pressures. Additionally, future studies may explore the role of emerging technologies such as artificial intelligence, blockchain, and the Internet of Things in enhancing or complicating co-innovation processes. Another fruitful area of investigation could involve comparative analyses between firms operating in highly regulated versus less regulated markets to determine how governance structures influence innovation behavior.

For practitioners, the findings suggest a need to balance internal innovation capabilities with external infrastructure investments. Organizations should focus on strengthening innovation culture and participatory mechanisms, not just building digital platforms. Strategic priorities must also include fostering trust, navigating political-economic contexts, and cultivating flexible HR systems capable of supporting dynamic co-innovation. Managers should use IPMA to identify areas of underperformance in high-priority domains and reallocate resources accordingly. Moreover, aligning strategic goals with both organizational culture and technological readiness will be critical in ensuring sustainable digital innovation across sectors.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

References

Asgharnia, M., Ahmadi Zadeh, A., & Farhadi, R. (2022). Challenges and Requirements for Implementing Digital Transformation Strategies in the Telecom Industry. *Business Reviews*, *6*(2), 98-117. https://ensani.ir/fa/article/523117/

Audretsch, B. D., & Belitski, M. (2023). The limits to open innovation and its impact on innovation performance. *Technovation*, *119*, 102519. https://doi.org/10.1016/j.technovation.2022.102519

Bao, Z., & Wang, C. (2022). A multi-agent knowledge integration process for enterprise management innovation from the perspective of neural network. *Information Processing & Management*, *59*(2), 102873. https://doi.org/10.1016/j.ipm.2022.102873

Bertello, A., De Bernardi, P., & Ricciardi, F. (2024). Open innovation: status quo and quo vadis - an analysis of a research field. *Rev Manag Sci*, *18*, 633-683. https://doi.org/10.1007/s11846-023-00655-8

Butter, M., Gijsbers, G., Goetheer, A., & Karanikolova, K. (2020). Digital innovation hubs and their position in the European, national and regional innovation ecosystems. In D. Feldner (Ed.), *Redesigning organizations*. Springer. https://doi.org/10.1007/978-3-030-27957-8_3

Daiberl, C. F., Oks, S. J., & Roth, A. (2019). Design principles for establishing a multi-sided open innovation platform: lessons learned from an action research study in the medical technology industry. *Electron Markets*, *29*, 711-728. https://doi.org/10.1007/s12525-018-0325-2

Eshaghian, Z., Jafari, S. M. B., & Yazdani, H. R. (2022). The Innovation Framework of Business Models Based on the Application of Digital Technologies. *Innovation Management in Defense Organizations*, *5*(2), 1-26. https://www.qjimdo.ir/article_152706.html

Georgescu, A., Avasilcai, S., & Peter, M. K. (2021). Digital innovation hubs-The present future of collaborative research, business and marketing development opportunities. In J. L. R. M. K. P. R. C. S. L. Á. Rocha, s. Z. Bogdanović Ser - Smart innovation, & V. O. L. technologies (Eds.), *Marketing and smart technologies*. Springer. https://doi.org/10.1007/978-981-33-4183-8_29

Hanley, D., Li, J., & Wu, M. (2022). High-speed railways and collaborative innovation. *Regional Science and Urban Economics*, *93*, 103717. https://doi.org/10.1016/j.regsciurbeco.2021.103717

Jugend, D., Fiorini, P. D. C., Armellini, F., & Ferrari, A. G. (2020). Public support for innovation: A systematic review of the literature and implications for open innovation. *Technological Forecasting and Social Change*, *156*, 119985. https://doi.org/10.1016/j.techfore.2020.119985

Karimi Mousa, S., Sannavi Fard, R., & Hamidi Zadeh, A. (2022). Designing a Digital Technology Model on the Environment and Strategic Marketing Capabilities of Hamadan Oil Products Distribution Company. *Strategic Studies in Oil and Energy*, *14*(53), 39-54. https://ensani.ir/fa/article/508942/

Klos, C., Spieth, P., Clauss, T., & Klusmann, C. (2021). Digital transformation of incumbent firms: a business model innovation perspective. *Ieee Transactions on Engineering Management*. https://portal.findresearcher.sdu.dk/en/publications/digital-transformation-of-incumbent-firms-a-business-model-innova

Marion, T. J., & Fixson, S. K. (2021). The transformation of the innovation process: How digital tools are changing work, collaboration, and organizations in new product development. *Journal of Product Innovation Management*, *38*(1), 192-215. https://doi.org/10.1111/jpim.12547

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy*, *48*(8), 103773. https://doi.org/10.1016/j.respol.2019.03.018

Putri, S. R. R., & Fontana, A. (2022). Surviving digital transformation era through strategic entrepreneurship with collaborative innovation between bank and fintech. Proceeding of the International Conference on Family Business and Entrepreneurship,

Sarwar, Z., Gao, J., & Khan, A. (2023). Nexus of digital platforms, innovation capability, and strategic alignment to enhance innovation performance in the Asia Pacific region: a dynamic capability perspective. *Asia Pac J Manag*. https://doi.org/10.1007/s10490-023-09879-4

Sassanelli, C., Panetto, H., Guedria, W., Terzi, S., & Doumeingts, G. (2020). Towards a reference model for configuring services portfolio of digital innovation hubs: The ETBSD modelBT - Boosting collaborative networks 4.0. PRO-VE 2020. In H. A. L. M. Camarinha-Matos, A. O. S. E. R. I. a. i. information, & V. O. L. communication technology (Eds.). Springer. https://doi.org/10.1007/978-3-030-62412-5_49

Saura, J. R., Palacios-Marqués, D., & Ribeiro-Soriano, D. (2023). Exploring the boundaries of open innovation: Evidence from social media mining. *Technovation*, *119*, 102447. https://doi.org/10.1016/j.technovation.2021.102447

Serrano-Ruiz, J. C., Ferreira, J., & Jardim-Goncalves, R. (2024). Relational network of innovation ecosystems generated by digital innovation hubs: a conceptual framework for the interaction processes of DIHs from the perspective of collaboration within and between their relationship levels. *J Intell Manuf*. https://doi.org/10.1007/s10845-024-02322-5

Vial, G. (2021). *Understanding digital transformation: A review and a research agenda*. Managing Digital Transformation. https://doi.org/10.4324/9781003008637-4

Volpe, M., Veledar, O., Chartier, I., Dor, I., Ríos Silva, F., Trilar, J., & Kiraly, C. (2021). Experimentation of cross-border digital innovation hubs (DIHs) cooperation and impact on SME services. In X. B. L. M. Camarinha-Matos, H. A. S. E. R. I. a. i. information, & V. O. L. communication technology (Eds.), *Smart and sustainable collaborative networks 4.0. PRO-VE 2021*. Springer. https://doi.org/10.1007/978-3-030-85969-5_39

Wang, X., Li, Y., Tian, L., & Hou, Y. (2023). Government digital initiatives and firm digital innovation: Evidence from China. *Technovation*, *119*, 102545. https://doi.org/10.1016/j.technovation.2022.102545