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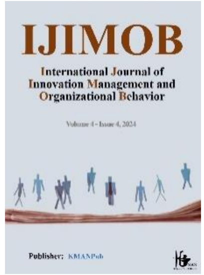

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The Impact of Digital Transformation on New Product Development with the Mediating Role of Organizational Intelligence

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ABSTRACT

Objective: This article aims to investigate the impact of digital transformation on new product development (NPD) with the mediating role of organizational intelligence.

Methods and Materials: The research employs a descriptive-correlational design, utilizing questionnaires and field studies to collect data from 100 experts in the rubber manufacturing industry, specifically from Barez and Artavil Tire companies. Confirmatory factor analysis (CFA) was used to assess the validity of the questionnaire, with structural equation modeling (SEM) conducted using Smart PLS software to test the hypotheses. The reliability and validity of the constructs were evaluated through composite reliability (CR), average variance extracted (AVE), and discriminant validity measures.

Findings: The study found that digital transformation significantly affects NPD performance (path coefficient = 0.586, t-value = 9.849), and organizational intelligence strongly mediates this relationship (path coefficient = 0.817, t-value = 12.838). Additionally, digital transformation directly enhances organizational intelligence (path coefficient = 0.296, t-value = 2.865). The R^2 value for NPD was 0.717, and for organizational intelligence, it was 0.688, indicating strong explanatory power.

Conclusion: Digital transformation significantly impacts NPD success, particularly when supported by high levels of organizational intelligence. Companies that invest in digital infrastructure and knowledge management systems are better equipped to handle the complexities of NPD, leading to more innovative and competitive products. Organizational intelligence serves as a key enabler in leveraging digital tools for successful product development.

Keywords: *Digital transformation, New product development, Organizational intelligence*

1 Introduction

In today's era, organizations have realized that survival is not possible without utilizing transformative technologies and modern business approaches. Digital transformation, a concept introduced at the beginning of this decade, has quickly gained a significant and strategic position in organizational literature (Hosseini-Nasab et al., 2021). The growth and advancement of digital technologies, both hardware and software, have led to numerous changes and innovations in human life and work (Dornberger, 2020). The intensity of advancements and changes has been particularly prominent in the industrial and production sectors (Gadre & Deoskar, 2020). To achieve digital transformation, a systematic perspective is needed that considers not only hard dimensions, such as technologies, but also soft dimensions like culture, skills, and regulations. It should also consider various stakeholders and leverage the benefits and drivers of technologies to address challenges. Furthermore, a clear vision, along with specific goals and plans, must be developed in this regard (Farzaneh Kondari & Rouhani, 2021). At the organizational level, digital transformation seeks innovative solutions that organizations use to integrate emerging technologies into their strategic goals to improve performance (Vial, 2019). These emerging technologies, referred to as transformative technologies, are creating fundamental and essential changes in organizations and businesses (Amini et al., 2022; Nouri et al., 2019). According to the United Nations report in 2020, digital transformation is now a vital part of the sustainable national development of many countries (UN, 2020).

Digital transformation encompasses all organizational dimensions, from processes to employees and products, and aims to bring about fundamental changes with new approaches in these areas. Despite several years since the introduction of digital transformation, there is still no uniform understanding of this concept among managers (Echterfeld & Gausmeier, 2018). One of the important business processes where companies can leverage information technology for growth is the new product development (NPD) process, as improving NPD practices leads to superior market performance (Durmusoglu & Kawakami, 2021). Recent changes in the global economy and market requirements compel organizations to adopt technological advancements fueled by digital transformation (Kamble et al., 2020). This has led to the development of more complex and smarter products with new capabilities. However, organizations are required to make profound changes in their NPD process to produce smart products (Nunes et al., 2017).

In the face of the new, highly competitive environment and the opportunities presented by Industry 4.0 technologies, organizations must not only develop and release new products but also create value for their stakeholders through lower costs and better quality (Haus-Reve et al., 2019). In the context of NPD, digital transformation creates an environment for collaboration and information sharing regarding materials, products, manufacturing processes, market data, information, knowledge, and resources among network participants, such as material scientists, system designers, software developers, and customer service, to facilitate a cost-effective co-creation that supports open innovation (Nellippallil et al., 2019). The use of advanced technologies in managing NPD offers a great opportunity to tackle their inherent complexity and develop smart and connected products within a smart and connected industrial system. Studies have observed a strong and inevitable link between product design, process design, and production system design in an Industry 4.0 environment based on big data (Kamble & Gunasekaran, 2020; Nellippallil et al., 2019; Nunes et al., 2017).

The increasing volume of information and rapid environmental changes, along with the necessity of maintaining continuous interaction with a complex and dynamic environment, require organizations to develop intelligent strategies (Dowali et al., 2022). The importance of the intelligence of new product development teams has been emphasized in the technology and innovation management literature over the past decade, where most successful NPD projects have been achieved through the collective efforts of individuals in teams (Adams et al., 1998). Several approaches have been proposed for managers to form and manage NPD teams, such as cross-functional integration, team learning, knowledge management, and collaborative technologies. One factor recently discussed is team intelligence, which seems important because it helps promote effective knowledge creation, enhance the learning process, and create an effective product implementation approach (Akgün et al., 2008).

Thus, having an intelligent NPD team certainly requires high organizational intelligence. Since the business environment is increasingly dynamic, complex, and ambiguous, planning and executing activities related to NPD with traditional methods is challenging for new organizations. Decisions must be made in the shortest possible time. As a result, many companies offering digital

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services operate under complex and uncertain conditions. Information and communication technology provides numerous tools for organizations and individual consumers, enabling direct and real-time interaction between them. As the number of competitors increases, they place themselves between organizations and customers, occupying profitable segments of the value chain. The digital technologies that underpin these competitive incentives are not new, but they are being used for new changes. Although digital transformation challenges existing business models in many traditional industries, such as automotive or banking, it creates many opportunities for businesses (Schweitzer et al., 2019).

Given these transformations, Iranian organizations have also not lagged behind the trend of fundamental changes in their businesses and have made extensive efforts in recent years to embark on the path toward digitalization. On the other hand, the concept of organizational intelligence is a multidimensional structure that includes various capabilities and must be operationalized as a multi-faceted and higher-order structure, encompassing both information processing and response capabilities to capture the complex nature of the NPD process. Enhancing organizational intelligence is essential for increasing innovation capacity. Moreover, management activities and performance must focus on organizational intelligence to ensure the survival of the organization. Organizational intelligence refers to the management of intelligence measures across various sectors of the organization. Thus, the main question of the research is whether digital transformation can, with the help of organizational intelligence, impact new product development.

2 Methods and Materials

The present study is applied in terms of its goal and descriptive-correlational in terms of its nature and method. The information obtained in this research was gathered through questionnaires, library studies, and field data collection in the relevant industry. A questionnaire was used to collect data and information for analysis. For the digital transformation variable, a researcher-made questionnaire was employed, while for the variables of new product development and organizational intelligence, the Cooper (2010) and Albrecht (2003) questionnaires were adapted and localized based on the study population. Their validity and reliability were assessed using the CVI index and Cronbach’s alpha, respectively. This index was presented by Waltz and Bausell. To calculate the CVI, experts were asked to rate the relevance of each item on a four-point scale. The number of experts who selected options 3 and 4 was divided by the total number of experts (which was 9). The resulting value for each item was calculated to be above 0.79, and questions that did not meet this threshold were revised. The questionnaire in this study consists of 65 questions. A five-point Likert scale, one of the most common measurement comparisons, was used for question design.

The statistical population of this research includes 100 experts from Barez and Artavil Tire companies, who hold a bachelor’s degree and have at least five years of experience in the industry. In this study, the selected sampling method is stratified random sampling, which is a subset of probabilistic methods. Cochran's formula, one of the most widely used methods for calculating sample size, was employed. The sample size for this study was calculated to be 80 people.

In this research, SPSS 22 and SmartPLS 2 software were used for data analysis. In analytical statistics, structural equation modeling was employed to test the research hypotheses.

3 Findings and Results

To assess validity, confirmatory factor analysis (CFA) was employed. In conducting factor analysis, it is essential to ensure that the available data are suitable for analysis. In other words, are the data appropriate for factor analysis? For this purpose, the KMO and Bartlett tests were used. According to these two tests, the data are suitable for factor analysis when the KMO index is greater than 0.6, and the significance level (sig) of the Bartlett test is less than 0.05. The results of the KMO and Bartlett's tests for the questionnaire items indicate that the KMO value is 0.625, which suggests an acceptable level of sampling adequacy for factor analysis. Bartlett's test of sphericity shows a chi-square value (χ^2) of 1493.892 with 630 degrees of freedom and a significance level of 0.000, indicating that the correlations between the variables are sufficient for conducting factor analysis.

The confirmatory factor analysis (CFA) results for the research questionnaire are presented in the table below. To evaluate the model, this study used factor loadings, composite reliability (CR), average variance extracted (AVE), and the comparison of the square root of AVE with construct correlations. Composite reliability and average

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variance were tested to achieve convergent validity and correlation.

Table 1

Factor Loadings, Significance Statistics, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE)

Construct	Item	Factor Loading	Significance Statistic (t-value)	AVE	CR	Cronbach's Alpha
Digital Transformation	Q1	0.400	5.725	0.552	0.717	0.741
	Q2	0.419	9.941			
	Q3	0.339	2.099			
	Q4	0.527	5.568			
	Q5	0.627	12.866			
	Q6	0.686	2.612			
	Q7	0.585	6.816			
	Q8	0.467	11.092			
	Q9	0.506	2.022			
	Q10	0.478	3.237			
New Product Development	Q11	0.427	16.129	0.596	0.765	0.812
	Q12	0.618	4.087			
	Q13	0.854	9.284			
	Q14	0.742	8.829			
	Q15	0.420	2.023			
	Q16	0.551	3.086			
	Q17	0.585	3.659			
	Q18	0.481	7.680			
	Q19	0.535	9.784			
	Q20	0.641	2.232			
	Q21	0.751	7.841			
	Q22	0.856	14.591			
Organizational Intelligence	Q23	0.725	7.197	0.648	0.915	0.897
	Q24	0.574	5.337			
	Q25	0.359	2.200			
	Q26	0.465	3.658			
	Q27	0.634	5.157			
	Q28	0.668	6.832			
	Q29	0.583	6.534			
	Q30	0.747	12.531			
	Q31	0.707	10.227			
	Q32	0.779	12.887			
	Q33	0.590	19.995			
	Q34	0.785	15.599			
	Q35	0.764	11.149			
	Q36	0.567	5.851			

As shown in Table 1, the factor loading for no question is below 0.4, so no question will be excluded from the analysis (although two questions had a loading of 0.3, which can be accepted with some leniency). The closer the Cronbach's alpha and composite reliability values are to 1, the more reliable the questionnaire is. It should be noted that a value below 0.7 is usually considered weak, while a value above 0.7 is considered good. However, the closer the reliability coefficient is to 1, the better. Convergent validity exists when the composite reliability is greater than 0.7, and the AVE is greater than 0.5.

Table 2

Discriminant Validity

Variables	Digital Transformation	New Product Development	Organizational Intelligence
Digital Transformation	0.742		
New Product Development	0.328	0.772	
Organizational Intelligence	0.296	0.643	0.804

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To assess discriminant validity, the square root of the AVE of each construct is compared with the correlation coefficients between constructs. As seen in the table below, the values in the main diagonal of the matrix (the square roots of the AVE for each construct) are greater than the values below them (the correlation coefficients between constructs), indicating acceptable discriminant validity for the constructs (Table 2).

Table 3

Explained Variance and Predictive Power of the Model

Variables	R^2	SSO	SSE	$Q^2 = 1$ - SSE/SSO
New Product Development	0.717	1352.000	817.140	0.396
Organizational Intelligence	0.688	1120.000	726.257	0.352

The structural model fit was assessed through R^2 (explained variance) and Q^2 (predictive relevance) values. R^2 indicates the impact of an exogenous variable on an endogenous variable, with values of 0.19, 0.33, and 0.67 being considered weak, moderate, and strong, respectively. Based on Table 3, the R^2 values for the endogenous constructs in this study confirm the strong fit of the structural model. If Q^2 values for an endogenous construct reach 0.02, 0.15, and 0.35, they indicate weak, moderate, and strong predictive relevance, respectively. The table results show strong predictive relevance for the endogenous constructs, confirming the structural model fit.

Table 4

GOF Criterion

Variables	R^2	Communalities
Digital Transformation	-	0.552
New Product Development	0.717	0.596
Organizational Intelligence	0.688	0.648
Average	0.702	0.598
GOF		0.647

Using the GOF (Goodness-of-Fit) criterion, the overall model fit was also assessed. The values of 0.01, 0.25, and 0.36 are introduced as weak, moderate, and strong GOF values, respectively. Given that the obtained GOF value is 0.647, the overall model fit is confirmed as appropriate (strong).

Table 5

Hypothesis Testing Results

Hypothesis	Path Coefficient	t-value	Result
Digital Transformation -> New Product Development	0.586	9.849	Supported
Digital Transformation -> Organizational Intelligence	0.296	2.865	Supported
Organizational Intelligence -> New Product Development	0.817	12.838	Supported

In this section, the research hypotheses are tested using the partial least squares (PLS) method. The path coefficient indicates the strength of the relationship between two variables. For the path coefficient to be significant, the t-value must be greater than 1.96.

The results of the normality test are shown in Table 6:

Table 6

Bootstrap Results for Indirect Effect Significance Testing

Independent Variable	Mediating Variable	Dependent Variable	Indirect Effect	Upper Bound	Lower Bound	t-value	Estimation Error	Significance Level
Digital Transformation	Organizational Intelligence	New Product Development	0.287	0.328	0.242	2.793	0.087	0.005

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The bootstrap method was used to test this hypothesis. In this method, if the lower and upper bootstrap bounds are both positive or both negative, and zero does not lie between these two limits, then the indirect path is significant, and the hypothesis is accepted. Additionally, if the significance level is less than 0.05, the indirect effect is accepted. Based on this criterion, the significance or non-significance of the indirect path is provided in Table 6.

Figure 1

Model with T-Values

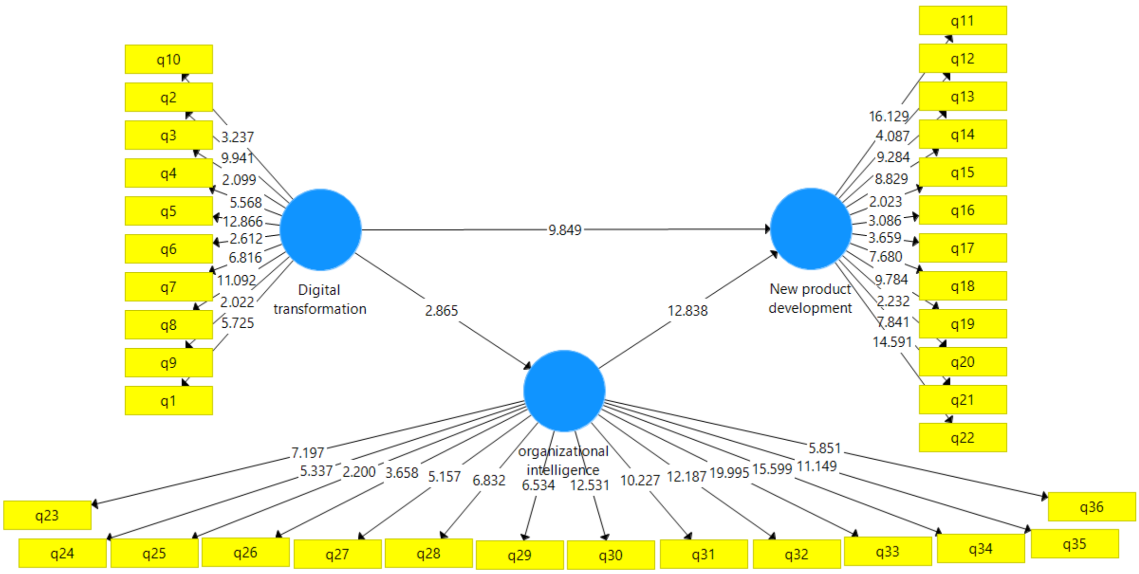
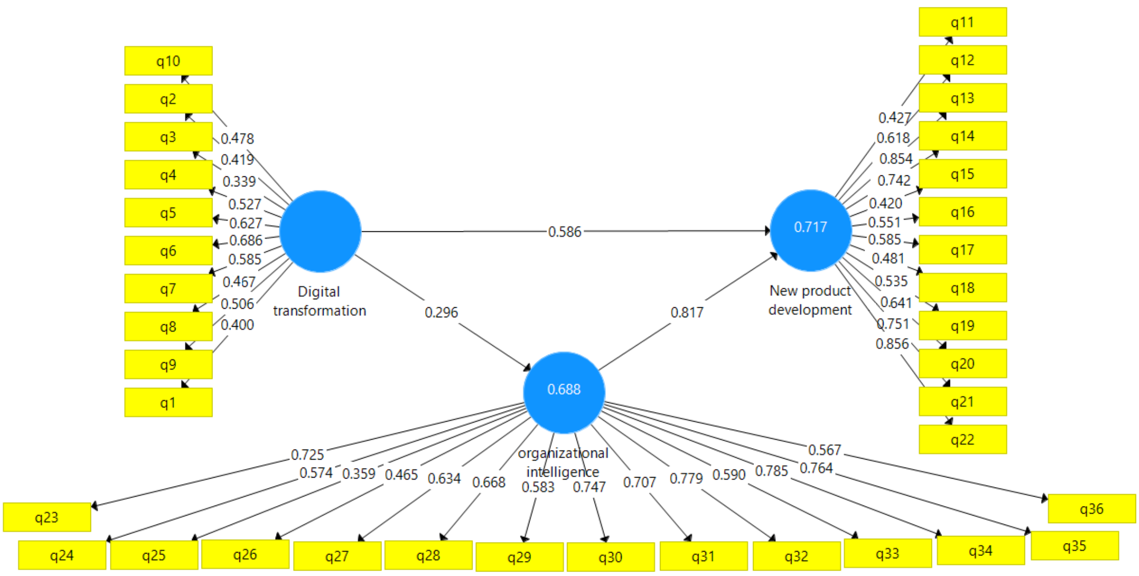


Figure 2

Model with Standard Coefficients



4 Discussion and Conclusion

The purpose of this article was to examine the impact of digital transformation on new product development (NPD) with the mediating role of organizational intelligence. Since the rubber manufacturing industries are seeking transformation, and some countries have implemented this transformation through digital transformation, their experiences can be leveraged. Global competition intensifies

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the drive for innovation, satisfying customers' demand for faster access to new, more personalized products of higher quality and lower cost (Abstein & Patrick, 2014; Dornberger, 2020). Additionally, the increasing complexity of products and processes due to digital transformation (Echterfeld & Gausmeier, 2018) has challenged companies worldwide to meet this customer demand (Heidenreich & Krämer, 2016). To foster innovation, managers use various tools and procedures, including harnessing high potential (Sommer et al., 2017), accelerating the development process (Stanko et al., 2012), and product and process innovation (Tatikonda & Rosenthal, 2000), to reduce the costs of new product development (Song & Song, 2010). Moreover, innovation managers strive to intensify knowledge exploitation and exploration through collaboration within and between companies (Lyytinen et al., 2016).

While the literature on digital transformation focuses on digitizing offerings (Schallmo et al., 2017; Schweitzer et al., 2019), the digital transformation of the NPD process has received less attention. This is unfortunate because the latter can be a crucial enabler for the former. Today, many companies face the challenge of producing personalized, digitally transformed, or improved products, leading to a significant increase in product and process complexity (Schweitzer et al., 2019; Dornberger, 2020). Given these issues, it is surprising that the current literature does not provide an answer regarding how digital transformation aids in NPD success to overcome specific challenges. For successful NPD projects, employees must have sufficient knowledge and intelligence about competition, regulations, and standards for developing and commercializing a new product. This helps the NPD team reduce errors and avoid redundant efforts. Furthermore, having a knowledge base allows the project team to recombine successful experiences that lead to superior solutions. The more functional areas in a team, the greater the team's ability to acquire, process, and use knowledge and adapt to changes in customer needs and demands, among others.

After extensive reviews of the past literature and considering that the present research is of an applied nature and the relationships between the variables are collinear, structural equation modeling using Smart PLS software was utilized. The results showed that, first, the level of digital transformation in the key stages of the product life cycle (from idea generation to production) positively affects NPD performance. This is the first empirical evidence of the positive impact of digital transformation level on NPD performance, aligning with current literature assumptions. For instance, it states that digital transformation increases information availability and positively impacts economies of scale (Butschan et al., 2019; Loebbecke & Picot, 2015). As a result, it enhances productivity and significantly reduces costs (Barua et al., 2001; Bosch-Mauchand et al., 2013). Ultimately, our findings suggest that managers should also be aware that product customization may play an important role in the effectiveness of digital transformation, whereas revenue and customer industry seem to have no effect.

Second, our analysis shows that the positive impact of digital transformation enhances organizational intelligence in companies. This contradicts current observations that startups gain more benefits from digital transformation (Horlacher & Hess, 2016; Vial, 2019). Our results encourage managers of larger companies to embark on the digital journey. Third, we concluded that organizational intelligence can be effective in the relationship between digital transformation and new product development. Therefore, knowledge management overlaps with team intelligence. Specifically, NPD team intelligence represents a team's ability to utilize information processes through project-related activities that achieve a desirable goal or perform a specific value activity during the project. Additionally, knowledge base, information technology utilization, and cross-functional diversity have been identified as determinants of NPD team intelligence. Although these antecedents have been explored in the organizational intelligence literature, there is no empirical evidence demonstrating how they impact new product development in light of digital transformation. Hence, it can be concluded that for the NPD team to remain competitive in a digitally transformed market, organizational intelligence and the enhancement of organizational knowledge in this area are necessary.

Based on the model and the research hypotheses' results, which confirmed all four hypotheses, the following recommendations are provided: Examining the current status of the digital technical infrastructure, such as available bandwidth, and assessing the current use of new technologies, such as the Internet of Things (IoT), social networks, artificial intelligence, blockchain, and cloud computing, along with the challenges and obstacles to their proper utilization, and outlining the desired status in the organization can be highly influential across all organizational sectors. Furthermore, examining the current status of digital culture and digital skills among employees, as well as the country's digital regulations, and outlining the desired status, is recommended. To enhance digital culture,

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a serious and in-depth review of the effective role of a learning organization's culture by management is necessary, as organizations that understand the importance of knowledge have sought creative solutions. In this regard, it is recommended to invest in workshops and training programs to increase knowledge capacities in research and development while striving to create a culture with the characteristics of a learning organization. In such an environment, experts and professionals can better combine their knowledge with existing knowledge through constructive interactions, promoting knowledge creation within the organization.

Today, organizations need empowered and effective employees to achieve comprehensive growth and development. Knowledge and information exchange in an environment with a supportive culture of knowledge creation, retention, and optimal application is one of the most influential factors affecting employee and organizational performance. Recent literature suggests that one possible way to accomplish these tasks and improve NPD performance is through the digital transformation of product lifecycle management (PLM) using IT-enabled PLM systems, which offer several solutions focused on a specific element of the NPD process. For instance, CAD software is used for product design, while MS Project assists in project management. Thus, it is not surprising that PLM systems equipped with IT have gained popularity as tools to enhance NPD performance in complex manufacturing industries like aerospace, automotive, and machinery production. These PLM systems enable companies to control the product lifecycle of successive product versions and parallel product lines from the early stages of concept and idea development to the later stages of design, engineering, and ultimately manufacturing and order processing.

Managers and company executives are encouraged to create conditions that allow employees at all levels to take calculated risks in cultivating new ideas, where risk-taking is viewed positively. The company should consider failure and mistakes as inevitable in the innovation process, accepting such failures to achieve greater successes. Managers should foster team intelligence to facilitate NPD project success in the manufacturing industry by implementing a defined IT system for effective team communication and information exchange, as well as installing email systems, team message boards, electronic newsletters, web pages, and oral electronic communication tools to strengthen the team's knowledge base. Management should form and organize the project team based on members' previous experiences and skills, creating diversity in the team with individuals from different functional areas. Management should establish councils, panels, and customer groups to facilitate interactions between project team members and customers, creating knowledge bases from previous projects and studies to help revisit past learning.

Finally, future researchers are encouraged to empirically examine the antecedents and consequences of NPD team intelligence from a managerial perspective, including factors that affect NPD team intelligence and how this impacts project outcomes. Investigating the determinants of team intelligence can help project managers understand how to enhance team capabilities and how to utilize these capabilities for successful NPD project outcomes.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

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.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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