Linking Data-Driven Innovation to Firm Performance:

A Theoretical Framework and Case Analysis

Abstract This paper examines the impact of data-driven innovation (DDI) on firm performance, based on an exploratory case study of a manufacturing firm in China's textile and apparel industry. It explores the influence of various contextual variables on the firm's DDI and suggests ways to enhance DDI and thereby firm performance. Extending the literature on DDI, the paper proposes and validates a theoretical framework that incorporates the influence of various contextual factors on firms' DDI. The findings show that (1) individual context is associated with DDI; (2) organizational context is associated with DDI; and (3) DDI is associated with firm performance. This paper extends our understanding of how firm performance can be improved through DDI and shows that DDI should match a firm's contextual environment.

Keywords Data-Driven Innovation; Organizational and Individual Context; Firm Performance; Literature Review; Case Study

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1. Introduction

The textile and apparel industry has traditionally been regarded as a low-value manufacturing industry, with the exception of its high-end luxury market (Choi et al., 2012). Globally, customers are becoming increasingly value conscious (Tam et al., 2005). The textile and apparel industry is characterized by a large number of stock-keeping units, wide variance in demand, high volatility, and short product life cycles (Jin, 2006). As in other industries, competition in the textile and apparel industry is not limited to individual firms but involves the entire supply chain. To thrive in this rapidly changing industry, players must make their products more competitive by considering factors such as variety, quality, and price. Data-driven innovation (DDI) is a key way for firms to enhance their performance by delivering innovative applications and facilitating data monetization (Akter et al., 2021).

DDI is one of the most important emerging drivers of transformational product development opportunities in the digital world (Davenport and Kudyba, 2016; Delen and Demirkan, 2013). Large amounts of data are now stored in global data storage centers due to the emergence of advanced technologies such as big data tools, the Internet of things (IoT), artificial intelligence (AI), blockchain technology, and cloud computing (Waller and Fawcett, 2013; Wang et al., 2018). Using such large-scale data, digital firms can develop DDI in various ways, such as upgrading existing product lines or introducing new products (Ransbotham and Kiron, 2017). However, although the analytics revolution has dramatically accelerated value, innovation, and productivity, research in this area to date has focused on the development of transitional information products. The objective of our research was to examine the adoption of DDI under the influence of various contextual variables, using case study analysis.

Innovation has become the holy grail for many firms (Alexander and Knippenberg, 2014). The ability to innovate has always made a significant contribution to organizational success (Fichman, 2001). Creativity and innovation in the workplace are vital determinants of a firm’s success, performance, and long-term sustainability (Anderson et al., 2014). Sabherwal and Sabherwal (2005) defined innovation as the generation of new products, processes, ideas, or services that are subsequently accepted and implemented. Firms can differentiate themselves through product innovation, which helps them to remain competitive within a dynamic market environment. The process involves a series of decisions about the implementation, adoption, and evaluation of new technologies in a firm (Lavie, 2006). The importance of context, which refers to the "environment within which decision making comes about" (Moustakis et al., 1995, p. 184), has been addressed in numerous studies (e.g., Rampersad et al., 2010; Wuyts et al., 2004). In Appendix A, we present examples of studies focusing on DDI selected from business and management journals between 2018 and 2022. We find that research into the nature of DDI and the related contextual variables is limited. We fill this research gap by investigating the influence of such variables on DDI through an exploratory case study.

According to Alvesson and Sandberg (2011), gap-spotting (i.e., identifying gaps in the literature that should be filled) is the most common method of generating research questions from the literature. The studies in Appendix A indicate that the influence of various antecedents (components related to the organizational and/or individual context) on DDI leads to better performance. For example, Babu et al. (2021) studied the effects of technology (conventional, big data analytics (BDA), and artificial intelligence (AI), organizational resources, and environmental factors on DDI and found that they accelerate innovation, value and productivity. Battisti et al. (2022) investigated the impact of technology entrepreneurs, rule-setting, user engagement, and innovation collaborations on AI-based innovation in terms of social and economic value creation. Fuller et al. (2022) studied the influence of the organizational context, the perceptions of AI-based innovators, and implementation preferences for AI-based innovation on new business. Ylijoki et al. (2018) investigated the effects of the big data context (volume, velocity, and variety) on DDI and human-driven innovations through a data-driven business model. Sultana et al. (2022a) assessed the impacts of DDI capability on strategic competitive performance as mediated by strategic market agility. Sultana et al. (2022b) further proposed that management, infrastructure, and talent capabilities enhance DDI capability and lead to improved performance of new data products. The reviewed works are classified by methodology, independent variable(s), dependent variable(s), sample description, author, year, organizational/individual context, and the main findings, and supporting statements for each study are referenced. Appendix B lists all of the articles included in our literature review. Our review indicates that few studies have focused on the organizational and individual contexts of DDI. In this paper, we investigate the influence of organizational context and individual context on DDI and how it leads to better performance in Chinese industries, and particularly in the textile and clothing industry.

This study clearly addresses a research gap in the DDI literature. We offer the following research questions after identifying the specific limitations of current DDI research:

Research question 1. How and why does DDI improve firm performance?

Research question 2. How does environmental context (organizational and individual) influence DDI?

Our study is framed by the theories of dynamic capabilities (Vogel and Guttel, 2013) and strategic fit (Kristianto et al., 2011), and we developed a conceptual framework and research model to identify the relationship between DDI and firm performance in various environmental contexts. We then validated the proposed model based on the results of a case study of a manufacturing company in China's textile and apparel industry. We applied an exploratory case study method to investigate new ideas in the field of operations management (i.e., investigations of the effects of DDI on firm performance) (Barratt et al., 2011). As described by Meredith (1998), the case study approach is an interpretive method that involves examining qualitative data to understand phenomena. This means- or process-oriented approach enables the researcher to establish why certain effects or characteristics do or do not occur. In addition, the case study method is exploratory and thus can be applied to a phenomenon that is not fully understood and for which the variables are still unknown. The approach also addresses why and how a phenomenon occurs, rather than simply what is being investigated, thus providing a deeper understanding of its complexity and nature (Meredith, 1998). The findings of our study can inform firm managers and other decision-makers about DDI from the organizational perspective.

The reminder of this article is organized as follows. The next section, Section 2, presents a literature review. In Section 3, we describe the theoretical foundations for studying our research questions and propose a conceptual framework for investigating the relationships between the focal contextual variables, DDI, and firm performance. We present the research design and data collection methods in Section 4. Section 5 outlines the empirical results of our case analysis and develops our propositions. We present the contributions and limitations of our study and future research directions in Section 6. Finally, the last section concludes the paper.

2. Literature Review

Innovation can be conceptualized in diverse ways—as the generation of a material artifact, idea, or a practice perceived as new by the adopter, for example (Sabherwal and Sabherwal, 2005). Within an organization, innovation can be understood as the development and implementation of ideas (Alexander and Knippenberg, 2014) or as a process that combines existing and new means of production (Van Den Bosch et al., 1999).

A data-driven approach to innovation was first proposed in 2009 (Kusiak, 2009). Acquiring, analyzing, and acting on consumer data can help firms to enhance their innovation (Lin et al., 2016). DDI depends on "the context of knowledge-based capital associated with digital information, innovative capacity and economic aspects." (Babu et al., 2021, p.4)

DDI has the potential to transform firms in all industries. It helps firms to exploit their existing value and enhance their product innovation by gathering and analyzing data (Rindfleisch et al., 2017). Examples include digital applications in digital firms (Chatterjee et al., 2021) and the usage of DDI technologies such as digital assistants (Balakrishnan and Dwivedi, 2021) and 3D printing (Bresciani et al., 2021). DDI has been widely applied in supply chain management in the manufacturing sector (Babu et al., 2021). Chai et al. (2021) pointed out that downstream customers and upstream suppliers can cooperate to achieve DDI. DDI leads to structural change in the labor market due to the automation of manual and cognitive tasks (Fukuda, 2020).

DDI is a process of innovation that "adopts techniques and technologies for processing and analyzing big data using data-based decision processes." (Babu et al., 2021, p.4). This process has multiple phases, such as data collection, data analysis, and decision-making (OECD, 2015). DDI delivers enhanced forms of service innovation to improve customer experience, such as modifying service offerings in real time and optimizing the service delivery process (Troilo et al., 2017). Recently, DDI management solutions, or data-driven decision making, have helped decision-makers to overcome challenges associated with the COVID-19 pandemic using analytics and patent information (Guderian et al., 2021; Kozak et al., 2021).

3. Theoretical Foundations

Models and theories can help researchers to interpret a topic or phenomenon under investigation. They work as paradigms to strengthen the research design (Ngai et al., 2015). We adopt the dynamic capabilities view (Vogel and Guttel, 2013), and strategic fit theory (Melnyk et al., 2004) as our overarching theoretical perspectives.

According to Schilke et al. (2018), innovation is one of the dynamic capabilities of a firm. Dynamic capabilities are collectively defined as a firm's "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997, p. 516). The dynamic capabilities view focuses on a company's ability to reconfigure, build, and integrate its resources and knowledge to deal with environmental uncertainty (Teece et al., 2007). The significance of strategic fit theory is evident from its increasing use in strategic and business-to-business marketing research (e.g., Chen et al., 2016). According to this theory, a firm can attain better performance by increasing the degree of fit between its environment and resources (Kashan and Mohannak, 2019). Swink et al. (2007) further showed that effective strategies are characterized by collaboration in key areas of decision-making.

Based on these theories, we develop an innovative conceptual framework linking contextual variables (as antecedents), DDI (as the mediator), and firm performance (as the outcome), as shown in Figure 1 The definitions of the major constructs used in the study are given in Table 1.

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3.1. Contextual variables

Seiler and Pfister (2009) defined "context" as the environment in which the organization is embedded, both literally and historically. Besner and Hobbs (2008) described contextual variables as the characteristics of the organization, the respondents, and the project. Although numerous contextual variables are relevant to DDI, such as market demand volatility, the competitive environment, and macroeconomic conditions, we selected only two for further analysis: organizational context and individual context.

3.1.1. Organizational context

Organizational context can be defined as the broad environment of an organization in which employees work. It has been shown to influence a number of individual employee outcomes, such as problem-solving and effort in semi-autonomous teams, organizational commitment, job satisfaction, and well-being (Morgeson et al., 2010). Although decision-makers may wish to act rationally in an organizational context, they are limited in their ability to communicate, retrieve, store, and receive information without error (Grover and Malhotra, 2003). Gomez (2003) identified eight context-related items such as supervisory attention, human relations, company reputation, company structure, and working conditions. Other scholars have also pointed out that contextual effects strongly influence innovation in an organization. For example, Ho et al. (2014) found that firms' assimilation of technological innovation is influenced by the interaction between innovation and context. Organizational innovativeness, including the number, radicalness, and relative advantages of the innovations adopted, is significantly influenced by aspects of organizational context, such as organization size, age, and volume of slack resources (Nystrom et al., 2002).

3.1.2. Individual context

Based on theories from behavioral economics, science, and psychology (Morgan et al., 2017), Hung et al. (2014) defined individual context as the essential characteristics of individual users. It captures decision-makers' personal characteristics, cognitive styles, and skills. Glynn (1996) pointed out that individual context includes motivation, personality, expectations, task novelty, and challenges, while organizational context includes problem novelty, learning capabilities, technology, values, norms, culture, degree of formalization, structure, size, innovation orientation, and challenges. Both individual context and organizational context influence organizational innovation.

3.2. Firm performance

Firm performance can be defined as the “achievement of the stated business goals measured in terms of profitability, market share, and shareholder value” (Malodia et al., 2020, p.1021). A firm’s competitive advantage depends on the combined value, scarcity, and interactions of its resources (Lavie, 2006). Companies with stronger technological capabilities perform better, as they can more easily use technologies to obtain competitive advantages in the innovation process. Companies that are highly innovative can differentiate their products to stay ahead in a dynamic environment (Tzokas et al., 2015).

Intuitively, a firm’s business success is positively related to its performance (Kroes and Ghosh, 2010). Gnyawali et al. (2010) pointed out that companies can achieve better performance through a complex set of action repertoires. In addition, firm performance can be increased by forming co-developer engagements or strategic alliances with partners for value co-creation (Liu et al., 2013).

4. Methodology

As noted in Section 1, limited research has been conducted into DDI, and exploratory research is particularly lacking. A qualitative case study relates the details of a research topic to the facts of a specific real-world situation. Our choice of methodology is largely determined by our research questions, which seek to explain various circumstances related to DDI. As our questions require an extensive and in-depth assessment of various phenomena related to DDI, the case study method is applicable. This method is useful in contemporary research (such as into DDI), but the accompanying behaviors cannot be revealed (Yin, 2009). Thus, given the exploratory nature of our work, a case study design is suitable (Yin, 2003). No similar study has previously been conducted on DDI adoption in the organizational context (Waller and Fawcett, 2013; Chai et al., 2021). We conducted an in-depth single case study of a manufacturing company in China's textile and apparel industry. Yin (1989) suggested that research constructs should be directly related to the topic of inquiry to accurately address the research questions. The main construct to be operationalized in our research framework is DDI, as the mediator between the contextual variables and firm performance (see Figure 1).

4.1. Case study

Our purpose was to generate a framework and a research model to explore the adoption of DDI under the influence of various contextual variables. We focused on the textile and apparel industry for several reasons. First, limiting our study to a single industry in a single country reduced noise from elements such as market demand volatility, complex manufacturing processes, differences in competitive environments, and changes in macroeconomic conditions. Second, DDI is widely adopted in the textile and apparel industry, based on the industry's unique characteristics. The textile and apparel industry is a consumer-driven industry in which the demands of consumers determine the development of products (Moon et al., 2012). Therefore, product innovation in this industry is generally market-oriented. For instance, the growth of DDI relies heavily on the dynamic and creative fulfillment of customers' changing needs at a time when the demand for novelty is high; fast fashion is an example (Akter et al., 2021). Third, Moon et al. (2012) confirmed that a small sample provides a sufficient basis for comparison in a single-industry design. Our case study was conducted in China, due to the country's vital role in global trade in textiles and apparel. China is the world's biggest manufacturer and exporter of textiles and clothing, as indicated by rapid growth in its domestic market (Fong and Dodes, 2006) and export records of US$106 billion for textiles and US$161 billion for clothing in 2016, according to the World Trade Organization (2017). Although many techniques, types of equipment, and processes are industry-specific, the textile and apparel industry faces many of the same opportunities and difficulties as other industries, such as impulse purchases, fluctuating demand patterns, short product lifecycles, and low predictability (Wong and Ngai, 2021). Therefore, the textile and apparel industry was an appropriate focus for this study.

4.2. Data collection

As our aim was to investigate DDI from a holistic perspective, we interviewed 12 managers, designer, directors, and vice president of a manufacturing company in China's textile and apparel industry. Background information provided by the firm (refer to Appendix C) and the respondents' descriptions of the firm (refer to Appendix D) were compared to determine whether their perspectives were consistent. The participants comprised the firm's merchandising, production, product development, sales, and shipping managers; its designer; its managing, merchandising, and sales directors; and its vice president. All of the participants were highly knowledgeable about the textile and apparel industry. The project took place over one year. We taped and transcribed our semi-structured interviews with the participants, resulting in approximately 150 pages of textual data.

4.3. In-depth semi-structured interviews

We followed Barratt et al. (2011) and identified the evaluation criteria before data collection to avoid interpretive bias. We carefully prepared a semi-structured interview protocol (see Appendix E) at the study design stage to ensure against any bias. Our aim was to avoid bias by skillfully framing the research questions and structuring the interview. Our case study protocol (as shown in Table 2), the research questions, and the data were reviewed by a senior (independent) researcher to obtain a second unbiased opinion. We also consulted four academics from a Hong Kong university to ensure the validity of the structure, appearance, format, and content of the interview protocol, along with a chief executive officer, two sales managers, one shipping manager, and three production managers from two manufacturing companies. The terminology, instructions, and format of the protocol were clarified according to their feedback.

<<Please insert Table 2 about here>>

Next, we used the validated semi-structured interview protocol to conduct interviews with the respondents at the case study company. The interviewees were asked a set of pre-arranged questions and invited to express their opinions on and insights into other issues of their choice. We audio-recorded or made hand-written notes during the interviews with the interviewees' permission. In cases in which satisfactory answers were not obtained, follow-up telephone interviews were undertaken for clarification and to ensure the rigor of data collection. In addition, we collected secondary data from published materials, company documents, and websites to provide a context and background for the primary research data obtained from the interviews. All of our participants were familiar with the textile and apparel business environment and some of them had extensive experience of DDI. Individual face-to-face interviews were conducted to elicit feedback on specific questions, resolve ambiguities, and investigate further after the initial responses (Yin, 2003). As DDI may have been new to some of our interviewees, we provided a cover letter that clearly explained what DDI is and why and how it can be applied by a manufacturing company. This ensured that every participant had at least a basic knowledge of DDI. The interviews focused on the participants' experiences and perceptions of how contextual variables affected their firm's DDI and performance, shedding light on the association between the contextual variables, innovation, and performance. Each of the interviews lasted for three hours and was conducted on a single day.

4.4. Data analysis

The unit of analysis was a single informant at the focal manufacturing company. The analysis sought common patterns through comparison with the multiple sets of interviews carried out in previous qualitative research (Van Maanen, 1983; Harris and Sutton, 1986; Choi and Hong, 2002; Oke & Gopalakrishnan, 2008). Any differences found were reconciled and noted (Poole and Van de Ven, 1999). Next, we performed a case analysis in which we compared the responses of the informants and developed a set of principles, ultimately leading to our propositions. Section 5 elaborates on these results.

5. Findings

The following subsections discuss the empirical findings of our case study analysis in the following two areas: 1) the effects of the contextual variables on DDI under different conditions; and 2) the influence of DDI on firm performance.

5.1. Relationships between contextual variables and DDI

In this sub-section, empirical observations are formulated concerning firms' reactions to DDI under different contextual variables. Case company was asked to report any contextual variables facing in their DDI operations. Based on their source and nature, two classes of contextual variables were identified as shown in Table 3. The core category of thematic codes represents the class of contextual variables, while the sub-category codes were developed by using NVivo. A deep dive into the constituents of core theme was performed in order to develop our propositions.

<<Please insert Table 3 about here>>

Case Study: Company A

Company A is a garment manufacturer whose products are sold mainly in the American and European markets, which are highly competitive. The company owns its own shipping company, which allows it to meet customers' needs flexibly despite a tight shipping schedule.

According to the interviewees, however, the company's performance is poor because it has not adopted mass customized operational processes in its plant; because the machinery in its plant is not highly automated; and because communication between its plant and its subsidiary shipping company is poor. Its managing director said, "Our strong culture discourages our employees from adopting innovation, as they do not readily accept new things. Our shareholders oppose change because they fear that their profits will suffer if the change is unsuccessful." The top management team (TMT) thought that the company could do better. The managing director added, "Data-driven culture helps us to raise performance by taking accurate decisions based on data-based insights, for example, application of AI and machine learning can help to reduce costing through better monitoring of electricity usage/ water consumption/ heat transfer (thermostat).”

To address the problems of insufficient plant automation and poor communication between supply chain partners, the TMT recently arranged for the Toyota Production System (TPS) to be introduced to the plant and subsidiary shipping company to improve the company’s performance. The information technology manager of Company A stated, “We expected that our company’s performance could be greatly enhanced by incorporating DDI through the TPS. As workers also earn more when the company’s performance better, we knew that this would be a win–win for all of us.” The TPS is a socio-technical system developed by Toyota that integrates a plant’s logistics and manufacturing functions and involves both suppliers and customers. Its main objectives are to avoid waste and reduce inconsistencies (i.e. by designing a process capable of smoothly delivering the required results) and to alleviate overburden (i.e. by ensuring that the process is flexible but not overburdened or under stress, because this generates waste). The merchandising director of Company A stated, “AI and big data analytics have been adopted in the TPS to provide practical and innovative solutions; for example, AI and machine vision can help companies to maintain and continuously improve their standards by reducing their defect outflow and automating their inspection methodology with the addition of networked sensors.” The same participant added, “With the help of sensors and automated systems, defective parts can be rejected sooner, which reduces the cost of a defect; big data can help to add predictive value to quality assurance by designing better testing processes.”

At the time of the interviews, Company A had invested in new machinery for automation and set up sophisticated digital information systems (such as ERP and Oracle) to develop internal links (between plant departments and between the plant and the shipping company) and external links (between the plant and the company’s customers). These systems allowed important information to be communicated and shared among supply chain partners, such as information on production and shipment schedules and prototype models, drawings, and designs. According to the company’s head of production, “It’s now possible to store and capture the desired level of data in operation to evaluate the performance of machinery through the greater connectivity and computerization of manufacturing equipment." The head of production added, "Earlier prediction and detection of breakdown is critical to minimize downtime."

To reduce waste and increase operational efficiency, workers in Company A's sewing lines are now required to remain within their designated work areas during shifts to reduce unnecessary movement (waste). In addition, output measuring devices have been installed in front of every sewing line and the line output is checked every hour to maximize efficiency. According to the company's sales director, "We are more comfortable with gradual changes than radical changes, especially given our large company size and the many departments involved." Company A thus foresaw difficulties during the initial stages of implementing TPS in the plant, such as reduced production efficiency and increased turnover, due to unfamiliarity with the system. Contextual factors, such as strong support from the TMT and a high level of motivation and shared vision throughout the organization, were important during these stages. According to the company's marketing manager, "We are more productive and innovative if we are motivated by our supervisor, or if our work is appreciated by customers." The interviewees expected the DDI to enhance firm performance. The vice president of Company A said, "Big data analytics leads to real-time assessment of the firm's operational and financial health, and it also helps us to implement build-to-order production by analyzing organizing inventory and customer buying patterns efficiently across multiple locations."

Therefore, on the basis of these findings, we formulate the following propositions and the research model depicted in Figure 2.

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First, organizational context strongly affected the DDI of the case study firm, leading to the following proposition.

Proposition 1. Organizational context is associated with DDI.

Second, individual context strongly affected the DDI of the case study firm, leading to the following proposition.

Proposition 2. Individual context is associated with DDI.

Various components of the organizational context have been found to influence DDI, including technology and organizational resources (Badu et al., 2021), technology entrepreneurs (Battisti et al., 2022), the big data context (Ylijoki et al., 2018), infrastructure capabilities (Sultana et al., 2022a) and management capabilities (Sultana et al., 2022b). In addition, various aspects of the individual context also have an effect, such as user engagement (Battisti et al., 2022), perceptions of AI-based innovators (Fuller et al., 2022), innovation ability (Sultana et al., 2022a), and talent capabilities (Sultana et al., 2022b). In this exploratory case study, we propose that the organizational and the individual context influence DDI and firm performance, and we conduct within-case analyses to explain how this proposition can advance the theoretical boundaries.

5.2. Effect of DDI on firm performance

The DDI technologies used in the TPS, such as artificial intelligence and big data tools, have proactively created new opportunities and increased operational efficiency for Company A. According to the company's merchandising manager, "Application of AI and machine learning can help to reduce costing through precise calculation of fabric/ accessories consumption." The production manager added. "Application of AI and machine learning can help to continuously improve standards by reducing defective outflow in cutting and sewing process." A firm's performance can be enhanced by increasing its profit margins and competitiveness. Therefore, we propose that:

Proposition 3. DDI is associated with firm performance.

Theoretically, DDI has been shown to enhance performance. For example, Sorescu (2017) noted that data-driven business model innovations can significantly improve a firm's value. Zilner et al. (2016) showed that DDI affects all sectors of the economy. The Organization for Economic Co-Operation and Development (OECD, 2015) highlighted that DDI has the potential to enhance social well-being, economic competitiveness, productivity, and efficiency.

The propositions presented in the previous sections are based on the common themes in the codes and represent the dominant view of the data. By using these propositions, a model (as shown in Figure 2) is suggested for examining the impact of DDI on firm performance. Our model posits that various contextual variables that we identified through our analysis enhance DDI and thereby firm performance. The framework drawn from theory and data extends our understanding of firm performance can be improved through DDI and shows that DDI should match a firm’s contextual environment.

6. Discussion

6.1. Summary

Scholars' interest in innovation in the organizational context arises partly from the widespread belief that firm performance can be improved through innovation (Wadho and Chaudhry, 2018), which leads to a competitive advantage (Ireland and Webb, 2007). Researchers have explored the various factors that influence firms' decision to engage in innovation (e.g., Cooper, 2019). We studied the implementation of DDI by a Chinese manufacturing company under the influence of two groups of contextual variables: organizational and individual. Our findings suggest that innovation gives firms new opportunities to improve their performance and indicate the importance to firms of applying DDI for future development under particular contextual conditions.

6.2. Theoretical contributions

Our main theoretical contribution is to research on DDI. Our research framework shows how our DDI construct relates to firm performance (see Figure 1). Although studies have found that innovation affects firm performance (Baum et al., 2010; Tsai and Yang, 2013), the specific influence of DDI on performance has remained unclear to date. We identify contextual variables that enhance DDI and improve firm performance through DDI. Firms that seek to outperform their competitors and survive in a dynamic environment through DDI should allocate resources to both the organizational context and the individual context. We think that DDI offers a strong theoretical lens both for explaining the results of previous investigations and for establishing stringent research models in future studies.

Studies have shown that strategic fit theory provides an illuminating perspective on the environmental contingencies faced by firms and their effects on firm performance. However, there have been few studies of the association between DDI and performance in different environmental contexts. Drawing on strategic fit theory and the dynamic capabilities view, our study contributes to the IS literature by providing a theoretical framework for improving firm performance. We argue and demonstrate that a good fit between DDI and context can help firms to improve their firm performance. This also enriches strategic fit theory and the dynamic capabilities perspective, promoting future studies of DDI.

6.3. Practical implications

The findings have important implications for managers and other practitioners, as they offer insights into how contextual variables and DDI can enhance the performance of firms in the textile and apparel industry. We conducted an exploratory case study of a manufacturing company in China's textile and apparel industry and found that superior firm performance had been achieved by aligning the firm's DDI with its prevailing environmental context. The results of our case study suggest that DDI is a key way for an apparel and textile manufacturing company to gain a competitive advantage. Firms can apply DDI to combat strong competition from their rivals. Our proposed framework will help business managers to understand how better firm performance can be attained through DDI, and that the adoption of DDI for the exploitation of new opportunities should match an organization's contextual environment. From a practical perspective, a good fit between DDI and context may enhance firm performance.

6.4. Limitations and further research

This study has some limitations. First, the generalizability of our findings is limited, as they were obtained from a single case study and solely from the textile and apparel industry. Second, we studied only the influence of individual and organizational contexts on DDI, although other factors such as the organizational climate may also affect innovativeness (Nystrom et al., 2002).

Khazanchi et al. (2007) explained that innovation involves creating or improving methods of administrative operation, services, and production, and that effective innovation may enhance organizational creativity and responsiveness. The conceptual framework and research model suggested in this study, focusing on DDI, could be further applied and discussed in the supply chain context.

Several other domains deserve investigation. For example, fruitful findings could be obtained from exploring DDI in other settings, such as other industries. Quantitative or qualitative research on the topic could be carried out in various types of organizations. This would help to validate the framework and research model and enhance its generalizability.

Thus, more data should be collected from different companies and from various sources. We suggest that triangulation can be conducted in future studies. Multiple sources of information can enable researchers to comprehensively address the various DDI-related issues in their investigations. In addition, multiple sources of evidence (including an extended period of field observations, interviews of more key informants, and reviews of historical accounts and public records) can be triangulated in future DDI research (Yin, 2009).

7. Conclusion

We obtained evidence through an exploratory case study of a manufacturing firm in China's textile and apparel industry to determine why and how DDI improves performance and to determine how the environmental context (organizational and individual) influences DDI. A qualitative field study was conducted to assess the effects of DDI on firm performance. The findings of our study show that strong DDI improves firm performance, which confirms our proposition that DDI is directly associated with performance. We also found that the organizational context (i.e., data-driven innovation orientation; firm size, structure and formalization; culture, norms and values; technology; learning capabilities; and problem novelty and challenges) significantly affects DDI, thus confirming that such a context is directly associated with DDI. We also found that the individual context (i.e., motivation; personality; expectations; task, novelty, and challenges) significantly influences DDI, thus confirming our proposition that the individual context is also directly associated with DDI.

This research offers a valuable contribution to research associated with DDI. We believe that our study provides researchers and practitioners with important insight into understanding of how firm performance can be improved through DDI and shows that DDI should match a firm's contextual environment.

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Ethics declarations

Conflict of interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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Linking Data-Driven Innovation to Firm Performance:

A Theoretical Framework and Case Analysis

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Appendices

APPENDIX A - Selective Review of the Literature on Data-Driven Innovation on Performance

Author/ Year	Study	Sample description	Independent variables	Dependent variables	Contexts		Findings
					Organizational	Individual	
Babu et al. (2021)	Empirical analysis - Case study	23 interviews from UK manufacturing sector	1) Technology (conventional, big data analytics, AI); 2) Organizational resources; 3) Pre-conceptualization; 4) Environmental factors	**Mediators:** 1) Data driven innovation in manufacturing; 2) Dynamic capability (sensing, seizing & reconfiguring opportunities) **Outcomes:** Innovation outcomes	√		1) Technology and organizational resources are critical in data-driven innovations; 2) data-driven innovations are important in accelerating innovation, value and productivity
Battisti et al. (2022)	Empirical analysis - Survey	Longitudinal, in-depth, and unique case study of a meta-organization operating in Finland, Germany, and Italy	Meta-organization ecosystem (innovation collaborations, user engagement, setting rules, technology entrepreneurs)	AI-based social innovation (social value creation; economic value creation)	√	√	1) User engagement (such as users' motivations and behavior) and technology entrepreneurs are important in data-driven innovation; 2) data-driven innovation in meta-organizations can enable new business

							models by creating shared social value
Fuller et al. (2022)	Empirical analysis - Survey	150 AI-savvy innovation managers from various industries including energy, the public sector, healthcare, industrial, customer goods, financial services, professional services, media, and telecommunications.	1) Organizational context; 2) Perceptions of AI-based innovators; 3) Implementation preferences for AI-based innovation	AI-based innovation management	√	√	Developed a research model to determine the current usage of AI in data-driven innovation management, different implementation preferences, and differences among contextual and organizational configurations
Sultana et al. (2022a)	Empirical analysis - Survey	312 managers (e.g., IT, marketing, administrators) from various Australian industries (professional services, banking and finance, ICT, media and entertainment, and retail)	Data-driven innovation capability	**Mediators:** Strategic market agility; **Outcomes:** Strategic competitive performance	√	√	1) Data-driven innovation capability is a third-order construct with three second-order constructs: innovation talent capability, infrastructure capability, and market orientation capability; 2) Strategic market agility is a key mediator between data-driven innovation capabilities and

							strategic competitive performance
Sultana et al. (2022b)	Conceptual study	N/A	N/A	N/A	√	√	1) Talent capabilities, infrastructure capabilities, and management capabilities enhance data-driven innovation capability; 2) data-driven innovation capability enhances the performance of new data products
Ylijoki et al. (2018)	Empirical analysis - Case study	Three firms: a bus company, an HR solution provider, and a provider of system integrations	Big data context (volume, velocity, variety)	**Mediators**: Human and data-driven innovations; **Outcomes**: (Data-driven) business model	√		Proposed a multi-disciplinary framework to elucidate the role of data-driven and human innovations, and innovation capabilities in an organizational context

APPENDIX A - Literature on Data-Driven Innovation on Performance (continued)

Author/ Year	Supporting statement quoted from Literature
Babu et al. (2021)	*Statements related to influence of organizational context on DDI in manufacturing:* "The findings of the study also highlighted the role of multiple stakeholders for **DDI** in the **manufacturing** context. Throughout the DDI process, customers are regarded as the primary **sources** of data; however, in a manufacturing context, organizations have to consider other stakeholders such as suppliers, retailers, strategic partners as important as the consumers for generating data to conceptualize any innovation idea." (p.19) "Overall, in the manufacturing, big data-driven AI and machine learning have emerged as an exciting platform to accelerate innovation, value and **productivity**." (p.21)
Battisti et al. (2022)	*Statements related to influence of organizational context and individual context on DDI:* "2.2. **User engagement** in **data-driven innovations** … User engagement is required to promote active participation, problem-solving, transparency, and collaboration among all stakeholders."(p.3) "2.3. **Technology-driven** social innovation … New-age technologies such as the Internet of Things, AI, and machine learning enhance social innovations' efficiency and effectiveness (P. Gupta et al., 2020a), as well as strengthen networked relationships and enhance the impact on broader society." (p.4) *Statements related to impact of DD on performance:* "Overall, digital platforms created by meta-organizations could be viewed as a new business model perspective, in which **data-driven innovations** help **create an environment** in which retailers can provide their customers with key experiences of online and highly connected retail (see the conceptual framing in Fig. 3)." (p.10)

Fuller et al. (2022)	*Statements related to influence of organizational context and individual context on DDI:* "Our research framework (Fig. 1) consists of three key domains: (1) **perceptions** – to determine the perceived potential to improve innovation performance through AI-based methods and the importance of AI for various innovation tasks, as well as the current understanding of the impact of AI-based innovation management and perceived barriers and challenges in the innovation units; (2) implementation preferences – to learn more about what role AI plays in the innovation strategy and organizational setup, to measure the investments and **resource** allocations and identify preferred approaches on skill development; and (3) **organizational context** – to capture the experience with AI in general, the adoption of AI-based innovation management, the AI expertise in the innovation unit, and the related uncertainty, as well as more general information such as the organizations' digital maturity, size, and industry." (p. 6) "Our study provides first empirical evidence that AI affordances for innovation management may depend on factors such as **experience**, **expertise**, digital maturity, and **organization siz**e." (p. 18)
Sultana et al. (2022a)	*Statements shown organizational context and individual context in relation with DDI capability:* "Because of the hierarchical nature of the conceptual model, this study estimates the measurement properties of the higher-order construct, which is the t**hird-order DDIC construct** and **second-order market orientation capability**, **infrastructure capability** and **innovation talent capability** constructs in Table 5." (p.6) "Table 5 demonstrates that market orientation capability is reflected by competitor orientation (91%) and customer orientation (89%). In the same way, infrastructure capability is explained by data (84%) and technology (95%). Finally, innovation talent capability is explained by knowledge (90%) and training and development (97%)." (p.6) *Statements related to impact of DDI on performance:* "H1: Data-driven innovation capability has a significant positive impact on strategic **competitive performance**." (p.4) "The findings in this research suggest the **significant positive relationship** between DDIC and STCP would impact the decisions of the managers to prioritize and invest in developing data-driven products/services." (p.9)

Sultana et al. (2022b)	*Statements related to influence of organizational context and individual context on DDI capability:* "Proposition 1: **Management capability** enhances data-driven innovation capability." (p.11) "Proposition 2: **Infrastructure capability** enhances data-driven innovation capability." (p.12) "Proposition 3: **Talent capability** enhances data-driven innovation capability." (p.13) *Statements related to impact of DDI on performance:* "Proposition 5: Data-driven innovation capability enhances the **new data product performance**." (p.14)
Ylijoki et al. (2018)	*Statements related to influence of organizational context on DDI:* "**Data-driven innovation** suggests that the innovation processes could and should, be automated (Shaughnessy, 2015). This approach puts **technology** and **(big) data** at the core of the innovation processes. More and more data becomes available, technological and analytical capabilities are increasing and data processing costs are decreasing. Utilizing automation and vast volumes of different data will produce a more holistic view, leading to more data-driven decisions and more agile innovation processes." (p.172) "In this paper, we have presented a multi-disciplinary framework that contributes to research by pinpointing the role of human and **data-driven innovation capabilities** as a mediator between **big data** and the business model." (p.179)

Appendix B. Paper collected in literature review

Babu, M. M., Rahman, M., Alam, A., & Dey, B. L. (2021). Exploring big data-driven innovation in the manufacturing sector: evidence from UK firms. ***Annals of Operations Research***, 1-28, https://doi.org/10.1007/s10479-021-04077-1.

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Sultana, S., Akter, S., & Kyriazis, E. (2022a). How data-driven innovation capability is shaping the future of market agility and competitive performance?. ***Technological Forecasting and Social Change***, 174, 121260, 1-13, https://doi.org/10.1016/j.techfore.2021.121260.

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Ylijoki, O., Sirkiä, J., Porras, J., & Harmaakorpi, V. (2018). Innovation capabilities as a mediator between big data and business model. ***Journal of Enterprise Transformation***, 8(3-4), 165-182.

Appendix C - Background information on the firm in the exploratory study

Firm pseudonym	Product sector	Turnover (2020 approx.) (USD, Millions)	Approximate number of employees	Main markets are:	Number of interviews	Position of interviewees (number of interviewees)
Company A (Manufacturer)	Men's rough wear	45-50	> 500	U.S./ Europe/ Asia Pacific region	12	Designer (1), Head of production (1), Information technology manager (1), Managing director (1), Merchandising director (1), Merchandising manager (1), Product development manager (1), Production manager (1), Sales director (1), Marketing manager (1), Shipping manager (1), Vice president (1)

Appendix D. - Sample descriptions

Demographic		N	%	
Total number of Interviewees		12		
Gender (Male)		7	58%	
Average age				40
Area of expertise (%)	Design & product development	2	17%	
	Information technology	1	8%	
	Merchandising & manufacturing	4	33%	
	Sales & marketing	2	17%	
	Shipping & logistics	1	8%	
	Management teams	2	17%	
Years in their expertise area	5 or below	0	0%	
	5 - 9	5	42%	
	10 or above	7	58%	
Education	Graduate degree	6	50%	
	High school diploma	3	25%	
	Postgraduate degree	3	25%	

Appendix E. The interview protocol

The research objectives, an explanation of the relevant concepts, and the information that we aimed to collect were presented to each informant before the interview.

Sample interview questions

1) Please describe your firm's application of data-driven innovation.

2) Please describe the role of data-driven innovation in your firm's data management decisions, communications, and marketing.

3) Please describe your thinking or practices in terms of the presentation, storage, and distribution of data that facilitate data-driven innovation in the manufacturing sector, in terms of the influence of the overall data-driven innovation process on manufacturing.

4) Please describe the feedback from the market that is collected and applied during data-driven innovation.

5) Please describe the context of your firm and the aspects of this context that concern you most.

6) Please describe the influence of key contextual factors on the design of operating systems in your firm.

7) Please describe the influence of key contextual variables on the application of data-driven innovation in your firm.

Figure

Figure 1 – Research framework

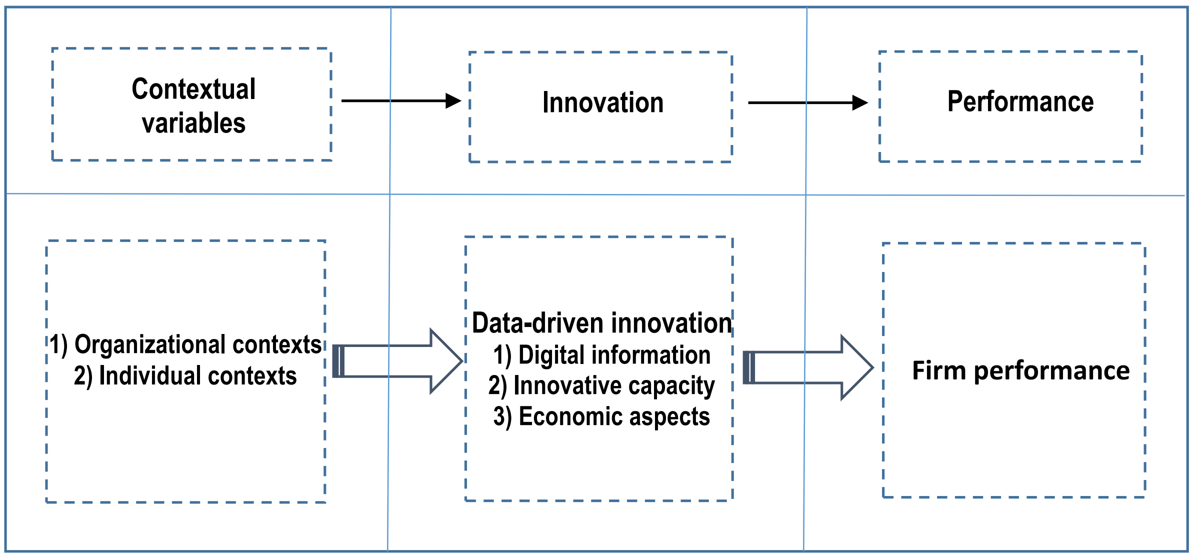
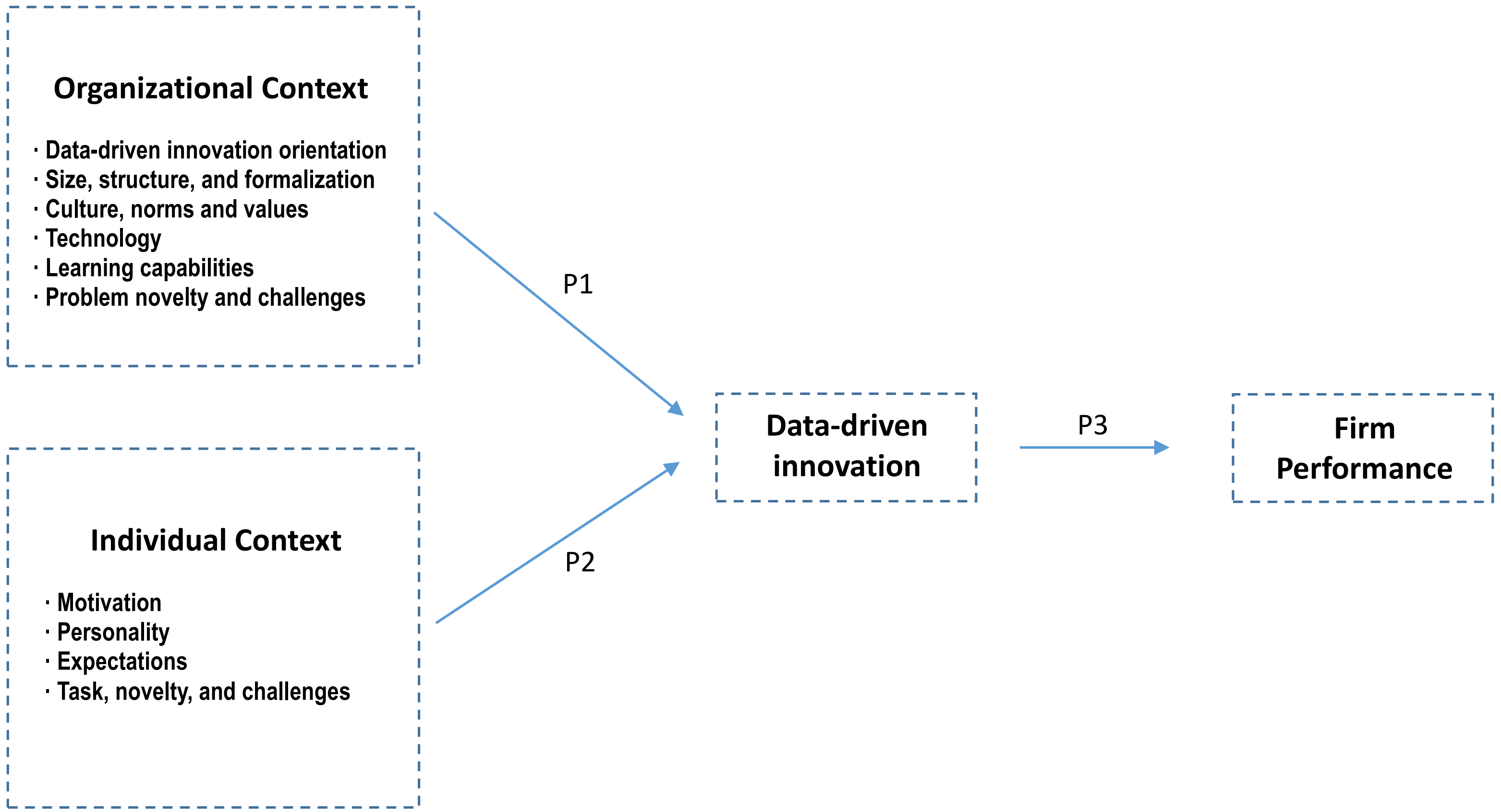


Figure 2 – Research model



Table

Table 1. – Definitions of major constructs in the research

Construct	Definition	References
Contextual variables	A wide range of variables, including the characteristics of the organization, the respondents, and the project.	Besner and Hobbs (2008)
Data-driven innovation (DDI)	DDI is a process of innovation that adopts techniques and technologies for processing and analyzing big data using data-based decision processes. It depends on "the context of knowledge-based capital associated with digital information, innovative capacity and economic aspects.	Babu et al. (2021)
Firm performance	The achievement of the stated business goals measured in terms of profitability, market share, and shareholder value.	Malodia et al. (2020)
Individual context	Essential characteristics of individual users, including skills and cognitive styles.	Hung et al. (2014)
Organizational context	Broad environment of an organization, which influences employees' problem-solving and effort in semi-autonomous teams, organizational commitment, job satisfaction, and well-being.	Morgeson et al. (2010)

Table 2. – Case study protocol

<table>
<tr><td rowspan="2">Research questions:</td><td colspan="2">1. How and why does DDI increase firm performance?</td></tr>
<tr><td colspan="2">2. How does environmental context (organizational and individual) influence DDI?</td></tr>
<tr><td>Unit of analysis:</td><td colspan="2">Firm level</td></tr>
<tr><td>Organization:</td><td colspan="2">Company A (manufacturing company)</td></tr>
<tr><td rowspan="8">Analysis:</td><td>Issue in the research constructs</td><td>Data collection protocol</td></tr>
<tr><td rowspan="4">DDI Increase firm performance</td><td>Description of company's use of DDI.</td></tr>
<tr><td>Description of the roles of DDI in firm's data management decisions, communication, and marketing</td></tr>
<tr><td>Description of respondents' thinking/practice in terms of the presentation, storage, and distribution of data that facilitate DDI in the manufacturing sector, in terms of the influence of the overall DDI process on manufacturing.</td></tr>
<tr><td>Description of the feedback from the market that is collected and applied during DDI.</td></tr>
<tr><td rowspan="3">Environmental context (Organizational and individual) influence DDI</td><td>Description of the context of company and which aspects of this context concern respondent most.</td></tr>
<tr><td>Description of the influence of key contextual factors on the design of operating systems.</td></tr>
<tr><td>Description of the influence of key contextual factors on the application of DDI.</td></tr>
</table>

Table 3. – Contextual variables with sample quote

Core category (Nature of contextual factors)	**Sub-category in NVIvo** (Contextual factors)	**Sample quote**
Organizational context	Data-driven innovation orientation	"AI and big data analytics have been adopted in the TPS to provide practical and innovative solutions; for example, AI and machine vision can help companies to maintain and continuously improve their standards by reducing their defect outflow and automating their inspection methodology with the addition of networked sensors" – **Merchandising director**
	Size, structure, and formalization	"We are more comfortable with gradual changes than radical changes, especially given our large company size and the many departments involved." – **Sales director**
	Culture, norms, and values	"Our company is highly market-oriented and our policy is to support product and service innovation." – **Marketing manager**
		"Data-driven culture helps us to raise performance by taking accurate decisions based on data-based insights, for example, application of AI and machine learning can help to reduce costing through better monitoring of electricity usage/ water consumption/ heat transfer (thermostat)." – **Managing director**
	Technology	"It's now possible to store and capture the desired level of data in operation to evaluate the performance of machinery through the greater connectivity and computerization of manufacturing equipment." – **Head of production**
		"We apply AI and machine vision to automate the inspection process with the addition of networked sensors" – **Production manager**
		"We apply AI and big data analytics to provide a better weather forecast for the shipping schedule" – **Shipping manager**
	Learning capabilities	"We learn from our past experience as a guideline for any changes, and we're always ready to adapt to any changes." – **Vice president**
	Problem novelty and challenges	"Big data analytics leads to real-time assessment of the firm's operational and financial health, and it also helps us to implement build-to-order production by analyzing organizing inventory and customer buying patterns efficiently across multiple locations." – **Vice president**

		“We’re encouraged to solve problems creatively through brainstorming.” – **Managing director**
Individual context	Motivation	“We are more productive and innovative if we are motivated by our supervisor, or if our work is appreciated by customers.” – **Marketing manager**
	Personality	"“We have highly creative people, and they are scarce resources in our company.” – **Designer**
	Expectations	"“We expected that our company’s performance could be greatly enhanced by incorporating DDI through the TPS. As workers also earn more when the company’s performance better, we knew that this would be a win–win for all of us” – **Information technology manager**
		“Our clients have high expectations of our team and products, and our staffs have high expectations of DDI” – **Sales director**
	Task novelty and challenges	“We always create valuable, useful new products and services for our customers.” – **Product development manager**
		“We are proud of our job because we have made a major change in the industry. We have a strategic advantage because of our DDI” – **Merchandising director**