Research Article

The Role of Data Analytics in the Enhancement of Co-production at Different Management Levels

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ABSTRACT

With the increasing need to gain actionable insight from the data, businesses seek the tools to help make the right decisions at the right time. Many have explored the capabilities of data-driven technologies and attempted to leverage the vast amount of data available on the Internet. Data analytics has become an inevitable choice in many business sectors. Nonetheless, the business needs to understand the purposes of different data analytics methods and how it can benefit from each method. This paper introduces various methods in data analytics and their relationship to customer co-production outcomes. The paper also examines whether these relationships will change when used by people at different levels of management.

Keywords: Data Analytics, Co-production, Management Level

บทความวิจัย

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บทคัดย่อ

ด้วยความต้องการที่เพิ่มขึ้นในการรับรู้ข้อมูลเชิงลึกที่สามารถนำไปปฏิบัติได้จริง ธุรกิจต่าง ๆ จึงแสวงหาเครื่องมือที่จะช่วยให้ตัดสินใจได้อย่างถูกต้องในเวลาที่เหมาะสม หลาย ๆ บทความวิจัยได้สำรวจความสามารถของเทคโนโลยีที่ขับเคลื่อนด้วยข้อมูลและพยายามใช้ประโยชน์จากข้อมูลจำนวนมหาศาลที่มีอยู่บนอินเทอร์เน็ต การวิเคราะห์ข้อมูลได้กลายเป็นตัวเลือกที่หลีกเลี่ยงไม่ได้ในหลายภาคธุรกิจ อย่างไรก็ตาม ธุรกิจจำเป็นต้องเข้าใจวัตถุประสงค์ของวิธีการวิเคราะห์ข้อมูลที่แตกต่างกัน และประโยชน์ที่ธุรกิจจะได้รับจากแต่ละวิธี บทความนี้นำเสนอวิธีการต่าง ๆ ในการวิเคราะห์ข้อมูลและความสัมพันธ์กับผลลัพธ์จากการร่วมผลิตของลูกค้า นอกจากนี้ บทความนี้ยังศึกษาว่า ความสัมพันธ์เหล่านี้จะเปลี่ยนแปลงไปหรือไม่ เมื่อการวิเคราะห์ข้อมูลถูกใช้โดยผู้บริหารในระดับที่แตกต่างกัน

คำสำคัญ : การวิเคราะห์ข้อมูล การผลิตร่วม ระดับผู้บริหาร

1. INTRODUCTION

Data analytics has become a basis of modern decision-making across industries, transforming how organizations derive insights and drive strategic initiatives. By harnessing vast volumes of data, businesses can uncover hidden patterns, trends, and correlations that provide invaluable insights into customer behavior, operational efficiency, and market dynamics. This capability enhances operational effectiveness and empowers companies to make informed decisions. In today’s data-driven world, the ability to effectively analyze and interpret data is not just a competitive advantage but a crucial component for achieving sustainable growth and innovation (Chou et al., 2022). Organizations face challenges managing different forms of data, such as customer transactions and user-generated content, which complicates the usage of this data to address business problems and opportunities. This leads to a growing need for actionable insights from stored data to aid timely decision-making. However, effectively applying data analytics to change organizational practices and achieve business goals, like customer satisfaction through tailored products and services, remains challenging (Koohang & Nord, 2021). There are plenty of studies that attempt to enhance the capabilities of data analytics, emphasizing the benefits of data analytics on various business applications. However, to the author's knowledge, very few studies, if any, investigate how effectively people in the organizations can apply different analytics methods to solve their business problems at hand. To fill this gap, this study preliminarily explores the application of data analytics, considering the perceptions of different management levels on different analytics methods.

Data analytics supports various functions, like forecasting, budgeting, resource planning, and performance improvement. In production and supply chain management, data analytics plays a pivotal role in enhancing capabilities and performance (Hallikas et al., 2021). During crises like the COVID-19 pandemic, data analytics helps organizations adapt by analyzing demand, capacity, and performance metrics to optimize resource allocation and production adjustments (Nudurupati et al., 2022). Moreover, data analytics influences marketing performance in data-rich environments by enabling competitive marketing decisions and enhancing customer satisfaction (Munir et al., 2022). Overall, investing in data analytics empowers organizations to leverage data effectively, gaining a competitive edge and enhancing performance across various operational facets. Furthermore, data analytics enhances operational efficiency by pinpointing inefficient areas, allowing organizations to implement changes that lead to smoother operations and reduced costs (Ochuba et al., 2024). For example, in the supply chain sector, data analytics can optimize inventory levels, reduce waste, and ensure the timely delivery of products (Bag et al., 2020). By analyzing customer data, businesses can gain deep insights into consumer preferences, behaviors, and needs. This information enables the personalization of products and services, leading to higher customer satisfaction (Liu et al., 2020). Marketing strategies can be refined using data analytics, ensuring campaigns are targeted more effectively and marketing budgets are spent more wisely.

In healthcare, it enables personalized medicine by analyzing patient data to predict outcomes and tailor treatments (Khanra et al., 2020). By harnessing massive amounts of data from electronic health records, medical imaging, and wearable devices, healthcare providers can uncover patterns and insights that were previously inaccessible. Additionally, data analytics streamlines hospital operations, optimizing resource allocation, reducing costs, and enhancing patient experiences. In finance, it enhances risk management, and fraud detection, leading to better investment strategies (Reddy et al., 2024). Financial institutions leverage data analytics to gain insights into market trends, investment opportunities, and risk management. By utilizing advanced techniques like machine learning and predictive modeling, organizations can forecast market movements, optimize portfolios, detect fraudulent activities, and enhance customer experiences. This data-driven approach not only improves accuracy and efficiency in financial operations but also offers a competitive edge by identifying patterns and trends that were previously unnoticed. Thus, data analytics has become an important part of strategic planning and operational management in the financial sector. The marketing sector also benefits from data analytics through personalized marketing, and enhanced customer experiences (Holmlund et al., 2020). With data analytics, organizations can extract valuable insights from vast amounts of consumer data, enabling them to tailor their marketing strategies precisely. Data analytics allows marketers to identify trends, predict consumer behaviors, and measure the effectiveness of their campaigns in real-time. In addition, advanced techniques, such as predictive analytics, empower businesses to anticipate customer needs, personalize interactions, and optimize resource allocation. Thus, data analytics not only enhances the efficiency and effectiveness of marketing efforts but also fosters stronger customer relationships and drives business growth. In manufacturing, it improves production processes, and quality control, leading to cost savings and increased productivity (Wang et al., 2022). Data analytics in manufacturing involves the application of data-driven techniques to enhance production efficiency, quality control, and overall performance. Manufacturers can gain deep insights into their processes that help in identifying patterns, predicting equipment failures, and optimizing supply chains. Data analytics helps in resource management, minimizing waste, and ensuring compliance with industry standards. Furthermore, in the transportation and logistics industry, data analytics optimizes route planning and delivery schedules, ensuring timely and cost-effective operations (He et al., 2022). Overall, data analytics provides actionable insights that drive informed decision-making in various business and public sectors. For example, the Thai government may consider the forecast of solar rooftop demand when initiating the incentive plans and policies (Chungcharoen et al., 2023). It also fosters innovation, drives cost savings, and supports the transition toward smart manufacturing and Industry 4.0.

However, the adoption of data analytics is not without its challenges. Organizations must invest in the right technology and talent to harness the full potential of their data. This includes ensuring data quality, addressing privacy concerns, and integrating disparate data sources (Eni et al., 2023). In e-commerce, data analytics involves systematic computational analysis of data to reveal patterns, correlations, and insights that can drive business decisions and strategies. By utilizing data analytics, e-commerce businesses can gain a deep understanding of customer behavior, preferences, and purchasing trends (Laudon & Traver, 2023). This information can be used for personalizing marketing efforts, optimizing product recommendations, and enhancing the overall customer experience. Additionally, data analytics help in fraud detection, and identifying market opportunities, leading to increased efficiency, customer satisfaction, and profitability (Jha et al., 2020). The integration of data analytics tools and techniques allows e-commerce businesses to make data-driven decisions, stay competitive, and adapt quickly to changing market dynamics (Alrumiah & Hadwan, 2021). Overall, data analytics is a necessary tool in the modern business landscape. Its ability to provide actionable insights, predict future trends, enhance operational efficiency, and improve customer satisfaction makes it a critical component of any successful organization. While there are challenges to its implementation, the benefits far outweigh the hurdles, making data analytics a worthwhile investment for businesses aiming to thrive in a competitive environment.

With the benefits and challenges mentioned above, it is important to explore deeper into how organizations can leverage data analytics effectively so that they can fully enjoy the benefits of data analytics. This paper takes a closer look at the relationship between data analytics and co-production. More specifically, this paper studies the interactions between data analytics classifications and aspects of co-production (product innovation, product improvement, customer satisfaction, and brand image). This paper also investigates whether the magnitude of the interactions varies across different management levels.

2. LITERATURE REVIEW

2.1 Data Analytics Methods

Data analytics has transformed how organizations operate, providing profound insights that drive decision-making and strategic planning. Data analytics relies on various statistical techniques and advanced algorithms to uncover patterns and trends that might previously be overlooked (Koot et al., 2021). Data analytics includes a wide array of techniques, which can be divided into 5 main categories or methods: descriptive analytics, diagnostic analytics, predictive analytics, prescriptive analytics, and cognitive analytics (Brintrup et al., 2020). First, descriptive analytics summarizes historical data to describe what happened in the past using tools like charts, graphs, numerical summaries, cross-tabulations, and clustering techniques. It helps describe situations for further analysis, enabling organizations to understand the current state of customer experience (Holmlund et al., 2020). Descriptive analytics involves various statistical methods to describe the main features of a dataset, such as calculating means, medians, and standard deviations to summarize central tendencies and variability. Creating histograms and bar charts helps visualize the frequency distribution of data points, identify outliers, and compare different categories or groups (Schwabish, 2021). Furthermore, pivot table is another powerful tool for summarizing, analyzing, exploring, and presenting data. Using pivot table, large datasets can be quickly aggregated and displayed in a comprehensible format, enabling multi-dimensional and meaningful analysis. For instance, sales data can be summarized by product, region, and time period simultaneously, offering deeper insights into sales performance drivers (Domino et al., 2021). This type of analytics transforms raw data into meaningful information, describing historical performance and current conditions, and enabling informed decision-making based on empirical evidence (Agatić et al., 2021). For example, a study employed descriptive analytics to investigate the variation in electric vehicle charging prices across different factors to examine the dynamics of electric vehicle charging infrastructure within the United States (Trinko et al., 2021). Descriptive analytics demonstrates how the prices of EV charging vary in different geographic locations with various providers.

Second, diagnostic analytics includes a variety of techniques such as root cause analysis, data mining, correlation, diagnostic regression, and comparative analysis to identify patterns and relationships within data (Sarker, 2022). These techniques enable organizations to group data and identify relationships between variables by exploring correlations between groups. Diagnostic analytics go beyond the description of what happened to uncover the root causes of events or phenomena (Ahmed et al., 2021). In other words, diagnostic analytics attempts to answer why something happened, allowing the businesses to respond more appropriately to the situation. Diagnostic analytics helps organizations identify key drivers for improving performance and mitigating future risks. It allows organizations to understand the interaction between different factors and their contributions to issues, eventually aiding in production enhancement. For example, when an organization experiences a decline in sales, it can use diagnostic analytics to help identify factors influencing the decline in sales, e.g., market trends, changes in customer behavior, and internal operations.

Third, predictive analytics involves using statistical techniques, and data mining to analyze current and historical data to predict future events (Duan & Xu, 2024). The techniques in predictive analytics include inferential analytics, which are advanced statistical methods to make inferences about future outcomes (Sheng et al., 2021). The inferential techniques in predictive analytics enhance the accuracy and reliability of the predictions (Zaki et al., 2024). Applications of predictive analytics span across various industries, including finance, healthcare, marketing, and supply chain management. Healthcare industry can use predictive analytics to forecast disease outbreaks, patient visits, and revenue streams. Predictive analytics can also predict patient readmission rates, allowing healthcare providers to prepare proactive interventions (Rehman et al., 2022). In marketing, predictive analytics helps target potential customers by predicting their purchasing behaviors. Overall, predictive analytics can utilize raw data, that once sat idle in the data warehouse, and provide a useful forecast for organizations to plan for strategies or to improve their efficiency (Chou et al., 2022). Predictive analytics allows businesses to forecast future trends based on historical data. This forward-looking approach helps organizations anticipate market shifts, identify potential risks, and seize new opportunities before their competitors do (Duan & Xu, 2024).

Fourth, prescriptive analytics goes beyond prediction to also suggest some alternatives and scenarios. It focuses on providing actionable recommendations and strategies to achieve desired outcomes. While predictive analytics can be used to forecast future trends, prescriptive analytics goes a step further by suggesting specific actions based on the insights derived from data (Lepenioti et al., 2020). It leverages advanced techniques such as optimization algorithms, simulation, and machine learning to evaluate different scenarios and determine the best course of action. In addition to employing advanced mathematical models, optimization techniques, and simulations, the approach discussed utilizes these tools to recommend actions in specific scenarios. This methodology aims to carefully weigh various constraints and trade-offs inherent in decision-making processes, including considerations of costs, resource availability, and potential risks (Frazzetto et al., 2019). Prescriptive analytics helps organizations analyze customer feedback, preferences, and purchase patterns to determine popular products and demand levels. Leveraging prescriptive analytics, organizations can make decisions on stocking products, managing inventory levels, and discontinuing items. It also supports customer co-production by suggesting new product features and service enhancements based on customer feedback and other data sources (Ibeh et al., 2024). Furthermore, prescriptive analytics assists in identifying profitable customer segments through demographic analysis, behavior insights, and purchase history.

Fifth, cognitive analytics refers to the process of analyzing and interpreting data using various technologies and techniques that simulate human thought processes. It goes beyond traditional analytics by incorporating elements of artificial intelligence (AI), machine learning, natural language processing, and pattern recognition to derive deeper insights from data (Agatić et al., 2021). Cognitive analytics also aims to replicate key aspects of human cognition, including perception, learning, and decision-making, leveraging advanced technologies. By simulating these cognitive processes, cognitive analytics enhances the depth of data analysis, uncovering intricate patterns and trends that traditional methods might overlook (Gudivada et al., 2016). This approach finds application in diverse fields such as sentiment analysis, image and speech recognition, and automated decision-making systems. By employing computational power to emulate human cognitive abilities, cognitive analytics not only expands the scope of data insights but also facilitates more informed and efficient decision-making processes (Majhi et al., 2021).

2.2 Co-production

Co-production refers to a collaborative production process where organizations and consumers work together to design, produce, and improve products or services, as well as the firm’s profitability (Sehgal & Gupta, 2020). Co-production promotes innovation development, enhances product customization, and leads to more efficient and sustainable production practices. This collaborative effort not only improves the overall quality and relevance of the goods produced but also strengthens relationships between customers and organizations (Naeem & Di Maria, 2022). The concept of co-production was introduced by Ostrom describing a collaborative process where public services were produced jointly by service providers and citizens. This approach challenges traditional top-down models by involving citizens in planning, decision-making, and service delivery, leading to more effective and sustainable outcomes (Ostrom, 1996). From several studies, the idea of co-production can be used in various industries to achieve both tangible outcomes, such as new product development and improvement (Lember, 2018; Chen & Liu, 2020; Chatterjee et al., 2022), and intangible outcomes, such as customer satisfaction and brand image (Addis et al., 2021; Sahi et al., 2022).

2.2.1 Tangible Outcome

Co-production yields tangible outcomes that foster shared knowledge, leading to innovative solutions through product innovation and product improvement that are more aligned with the needs of the stakeholders. The term "product innovation" refers to the introduction of new products or significant changes to existing products, such as introducing new features or creating a brand-new product (Heij et al., 2020). The majority of the Chief Executive Officers (84%) indicated that innovation is essential to the future success of their companies (McKinsey, 2020). A study proposed several strategies to encourage customer involvement in identifying market opportunities, such as inviting customers into development teams, organizing regular conferences, and establishing social bonds and formal rewards (Chen & Liu, 2020). The study also emphasized the importance of companies actively engaging in opportunity recognition and exploitation to facilitate customer participation in product innovation. In addition, digital technology presents an opportunity for businesses to deepen their understanding of customers (Lember, 2018). By analyzing various ways in which customers interact with the producers, businesses can identify patterns and trends that inform the development of new and innovative products and services (Barile et al., 2020). Product innovation through co-production leverages the collective creativity and insights of multiple stakeholders and fosters a sense of ownership and engagement among participants, leading to products that are more closely aligned with user needs and preferences (Han & Xu, 2021). Eventually, Product innovation from co-production can drive the creation of more relevant and high-quality products.

For product improvement, co-production can assist in modifying product design to decrease costs or develop new products or services that meet customers' preferences and address customer concerns (Chatterjee et al., 2022). It suggests that customer input such as design and ideas can improve customers' satisfaction. On the other hand, businesses also need to understand customer's needs, preferences, and motivations so that the company can provide incentives to potential co-producers and encourage their participation (Wang & Fan, 2020). In turn, businesses can analyze customer feedback to improve product quality, reliability, and overall performance. This ensures that the products better meet the needs of their customers, resulting in higher customer satisfaction.

2.2.2 Intangible Outcome

Co-production may also yield intangible outcomes including customer satisfaction and brand image. By actively involving users in the creation process, organizations can better meet their customer's needs and preferences, leading to higher satisfaction and loyalty (Casidy et al., 2022). Customer satisfaction refers to the extent to which a customer feels that their needs and expectations have been met by a product purchased or service received (Pizam et al., 2016). Customer satisfaction is usually one of the main concerns for businesses and marketers (Juntongjin & Charinsarn, 2019). Some studies in the public service sector showed a positive impact of co-production on stakeholder satisfaction (Li et al., 2023; Jiang et al., 2023). A study also showed a similar outcome in e-learning when involving the customers (the learners in this case) in customizing the contents to fit the learners' interests. When learners feel their contributions are valued and see their ideas incorporated into the learning experience, they are more likely to be satisfied with the outcomes (Erragcha & Babay, 2023). Another study also supported that customers were likely to have higher satisfaction when their opinions and comments were acknowledged and incorporated into the new product or service (Addis et al., 2021). Overall, many studies underlined the dual role of consumers as both users and innovators in the collaborative process and customer satisfaction as an outcome of co-production in various settings and industries.

The concept of brand image has been around for more than 2 decades in the marketing discipline (Abbas et al., 2021). There are variations in the definition of brand image in many different studies. The concept of brand image is also confused with brand identity and brand equity (Malik et al., 2012; Lee et al., 2014; Sombultawee & Korfak, 2022), all have an impact on repeat purchases and brand loyalty (Jenareewong & Sombultawee, 2022). In this study, the definition of brand image is based on a well-established study from a widely accepted scholar. Brand image refers to consumers' perception of the brand (Aaker, 2012). A strong brand image can help a business differentiate itself in a competitive market and create a loyal customer base (Sahi et al., 2022). As a result, brand image fosters emotional attachment and trust, prompting customers to engage in co-production. This active involvement in the service delivery process, where travelers contribute to value creation, enhances their overall experience and strengthens brand loyalty (Mursid & Wu, 2022). A study suggested that when customers were actively involved in the process, it led to benefits for the consumer such as more customized and superior brand experiences (Carlson, 2019). This level of involvement empowers customers to have more influence over their interactions with the brand and helps to establish stronger connections with it. Co-production of service experiences was promoted through digital service innovation, which encouraged customers to actively participate in creating their experiences with brands (Casidy et al., 2022). To facilitate this, organizations have designed their digital service process using digital platforms, enabling real-time interactions for the co-created brand value. This collaborative effort improves the brand's image by creating a sense of partnership and increasing the perceived value of the product or service through the involvement of the stakeholders (Foroudi et al., 2019).

3. RESEARCH FRAMEWORK

From the study of the previous literature, data analytics is a powerful tool for enhancing co-production by leveraging the vast amounts of data generated in collaborative efforts. Data analytics enables organizations to understand the behaviors and preferences of their customers in more detail. By analyzing customer data such as purchasing patterns, feedback, and demographic information, businesses can customize their offerings more precisely. This customization ensures that products and services meet their target audience's needs, ultimately enhancing satisfaction and loyalty. Moreover, data analytics helps predict the fluctuations in demand and market trends (Holmlund et al., 2020). The organizations can use data analytics to examine historical data, and work with the customers, as co-producers, that can anticipate the outcomes from the collaboration in developing product innovation, as well as product improvement. By analyzing performance metrics and gathering feedback from all stakeholders involved, co-producers can identify areas for enhancement. This data-driven approach facilitates iterative improvements, allowing for the implementation of new ideas, and enhancing business performance (Chaudhuri et al., 2021). In addition, data analytics can be used to enhance customer satisfaction and brand image by providing deep insights into customer preferences, behaviors, and feedback. By analyzing this data, businesses can tailor their products and services to better meet customer needs, determine the trends, and address issues. Additionally, understanding customer sentiments and experiences helps in creating targeted marketing strategies and personalized interactions, which can improve overall brand perception. As an example, a study attempted to identify distinctive attributes for tourist destination branding from big data (Khumtaveeporn & Wattanasuwan, 2023). Figure 1 depicts the conceptual framework of our study.

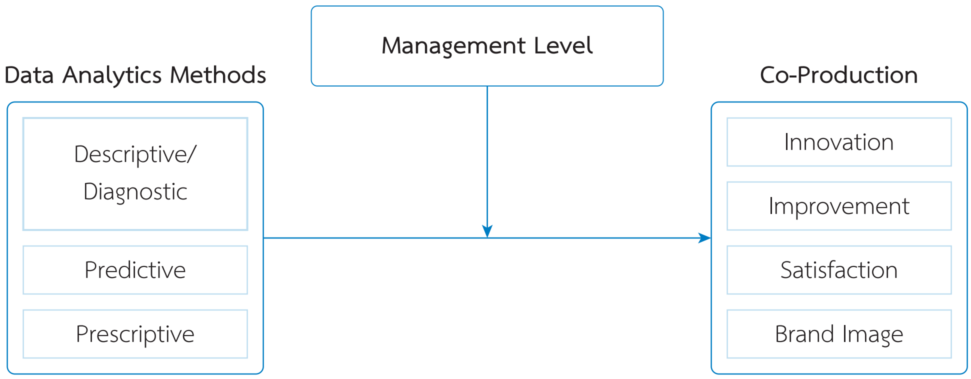

Figure 1: Conceptual Framework

The conceptual framework explores the relationship between data analytics methods and co-production outcomes, and how much different levels of management can influence this relationship. Building on this framework, the data analytics methods construct was operationalized as 3 variables in the research model: descriptive/diagnostic analytics (DDA), predictive analytics (PRED), and prescriptive analytics (PRES). Since both descriptive and diagnostic analytics use basic statistical techniques to summarize and explore the underlying causes, they are therefore grouped together in the model. Some previous studies related to data analytics also put them in the same category (Lepenioti et al., 2020). Our research model also excludes cognitive analytics as it has not been widely accepted nor has appeared in well-known textbooks. Recently, some literature has set it apart as a topic in machine learning studies (Bratu & Sabău, 2022; De Marco et al., 2021; Handfield et al., 2019). The co-production outcomes construct was operationalized as 4 variables in the research model: product innovation (INN), product improvement (IMP), customer satisfaction (SAT), and brand image (IMG). The first set of hypotheses (H1) posits that each data analytics method has a positive impact on co-production outcomes.

H1a – H1l: Data analytics methods positively influence co-production outcomes.

Our study also explores whether and how much different levels of management can influence the impact of data analytics methods on co-production outcomes. Management takes part in utilizing data analytics within an organization, ensuring that decision-making processes are based on accurate and relevant data. The management allocates resources to build robust data analytics teams, invests in advanced technologies, and prioritizes the development of data literacy across the organization. Additionally, management can oversee the strategic use of data analytics to enhance operational efficiency (Youssef et al., 2022). However, not everyone is proficient in data analytics. In general, people in the IT department are expected to possess decent data analytics skills, while people in some other departments are not expected much for such skills. Furthermore, their proficiency in different analytics methods may vary based on their job functions and positions, especially if they are at different management levels (Zhang et al., 2024). Therefore, it is important to understand how people at different management levels can apply different data analytics methods to enhance their work. This study includes the influence of different management levels as a moderating construct in the conceptual framework and operationalizes it as a latent variable in the research model. Hence, another group of hypotheses (H2) focuses on whether different management levels (ML) have different impacts on the relationship between each data analytics method and each co-production outcome. Table 1 shows the hypotheses in detail.

H2a – H2l: Different management levels positively influence the impacts of data analytics methods on co-production outcomes.

Table 1: Detailed Hypotheses

Hypotheses		Description
H1	H1a	DDA positively influences INN.
	H1b	DDA positively influences IMP.
	H1c	DDA positively influences SAT.
	H1d	DDA positively influences IMG.
	H1e	PRED positively influences INN.
	H1f	PRED positively influences IMP.
	H1g	PRED positively influences SAT.
	H1h	PRED positively influences IMG.
	H1i	PRES positively influences INN.
	H1j	PRES positively influences IMP.
	H1k	PRES positively influences SAT.
	H1l	PRES positively influences IMG.
H2	H2a	ML positively influences the impact of DDA on INN.
	H2b	ML positively influences the impact of DDA on IMP.
	H2c	ML positively influences the impact of DDA on SAT.
	H2d	ML positively influences the impact of DDA on IMG.
	H2e	ML positively influences the impact of PRED on INN.
	H2f	ML positively influences the impact of PRED on IMP.
	H2g	ML positively influences the impact of PRED on SAT.
	H2h	ML positively influences the impact of PRED on IMG.
	H2i	ML positively influences the impact of PRES on INN.
	H2j	ML positively influences the impact of PRES on IMP.
	H2k	ML positively influences the impact of PRES on SAT.
	H2l	ML positively influences the impact of PRES on IMG.

4. RESEARCH METHODOLOGY

4.1 Research Design

This study uses a questionnaire survey conducted both online and offline using purposive sampling. More than 30 companies were contacted, but only 4 companies agreed to participate in this study. Therefore, a purposive sampling method is the only viable sampling method. With the permission of these companies, both the online and offline versions of the questionnaire were sent to the top management. The questionnaires were distributed internally, and the redacted responses were sent to the author. The data were gathered from 350 employees working in production-related companies, the manufacturers of well-known consumer products. The questionnaire consists of measurement items adopted from prior research (Adams et al., 1992; Bandura, 2006; Schwarzer & Luszczynska, 2008) and adapted to the context of this study. All items were on a 5-point Likert scale. Measurement items can be found in the appendix. In addition, the questionnaires also include demographic questions and questions about the respondent's position and years of experience. The top management of the participating companies also kindly assisted in categorizing each position into 3 categories: top, middle, and operational management. Each response was carefully checked for completeness and accuracy before data analysis. Then, Exploratory Factor Analysis (EFA) was conducted using IBM SPSS Version 29 to identify the relationships between observed variables and associated constructs. Confirmatory Factor Analysis (CFA) was then performed to confirm the loading of indicators on each construct. Finally, structural equation modeling was performed for data analysis using AMOS Version 29.

4.2 Data Analysis and Findings

For the descriptive statistics, the respondents consist of 53.4% males and 46.6% females. The age distribution shows 37.2% are 30 or younger, 36.5% are between 31 and 40, and 26.3% are over 40. Regarding work experience, 13.1% have less than 3 years, 60.6% have 3 to 10 years, and 26.3% have more than 10 years. For management levels, 11.7% are in top management, 29.4% in middle management, and 58.9% in operational management. Results of the EFA are as follows. First, DDA with items DDA1 to DDA3 shows a high-reliability score of 0.901 and factor loadings ranging from 0.846 to 0.868. Second, PRED with items PRED1 to PRED3, exhibits Cronbach's Alpha of 0.832 and factor loadings between 0.706 and 0.861. Third, PRES, measured by items PRES1 to PRES4, demonstrates a strong internal consistency with a Cronbach's Alpha of 0.928 and factor loadings from 0.826 to 0.885. Fourth, the INN variable (items INN1 to INN4) has a Cronbach's Alpha of 0.890, and factor loadings ranging from 0.801 to 0.855. Fifth, IMP (IMP1 to IMP3) exhibits a reliability score of 0.838 and factor loadings between 0.684 and 0.817. Sixth, SAT, measured by items SAT1 to SAT3, has a Cronbach's Alpha of 0.859 and factor loadings from 0.725 to 0.768. Finally, IMG with the items IMG1 to IMG4 has a Cronbach's Alpha of 0.891, and factor loadings ranging from 0.716 to 0.876. Hence, all variables associated with their constructs are reliable with Cronbach's alpha ranging from 0.832 to 0.928; all of which are above 0.7

(Hair et al., 2019). Additionally, a test for multicollinearity was performed to detect any multicollinearity issues. The Variance Inflation Factor (VIF) values of DDA, PRED, and PRES were 1.695 (Tolerance = 0.590), 1.87 (Tolerance = 0.527), and 1.463 (Tolerance = 0.684), respectively. All VIF values were close to 1 and well below 5, and the tolerance values were all above 0.2, indicating no multicollinearity issue (Chatterjee & Simonoff, 2013). Table 2 shows the factor loadings of the independent and dependent variables as well as their average variable extracted (AVE) and composite reliability (CR) values while Table 3 shows those values of the dependent variables. Finally, Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity was performed on the entire sample, and the results were 0.89 and 6,909.62 ($p < 0.001$), respectively.

Table 2: Factor Loadings, Average Variable Extracted, and Composite Reliability of Independent Variables

Independent Variables				Component		
IV	AVE	CR	Item	1	2	3
DDA	0.74	0.89	DDA1	0.22	**0.86**	0.21
			DDA2	0.21	**0.87**	0.21
				0.16	**0.85**	0.28
PRED	0.58	0.81	PRED1	0.15	0.14	**0.86**
			PRED2	0.29	0.40	**0.72**
				0.33	0.41	**0.71**
PRES	0.75	0.92	PRES1	**0.83**	0.24	0.27
			PRES2	**0.87**	0.11	0.19
			PRES3	**0.88**	0.23	0.16
				0.89	0.18	0.17

Table 3: Factor Loadings, Average Variable Extracted, and Composite Reliability of Dependent Variables

Dependent Variables				Component			
DV	AVE	CR	Item	1	2	3	4
INN	0.68	0.89	INN1	**0.81**	0.04	0.20	0.06
			INN2	**0.82**	0.09	0.23	0.13
			INN3	**0.86**	0.05	0.14	0.21
			INN4	**0.80**	0.04	0.28	0.11

Table 3: Factor Loadings, Average Variable Extracted, and Composite Reliability of Dependent Variables (Cont.)

Dependent Variables				Component			
DV	**AVE**	**CR**	**Item**	**1**	**2**	**3**	**4**
IMP	0.59	0.81	IMP1	0.43	0.09	**0.68**	0.22
			IMP2	0.20	0.17	**0.82**	0.13
			IMP3	0.29	0.07	**0.80**	0.23
SAT	0.55	0.79	SAT1	0.26	0.38	0.21	**0.73**
			SAT2	0.14	0.40	0.07	**0.77**
			SAT3	0.09	0.35	0.32	**0.73**
IMG	0.65	0.88	IMG1	0.18	**0.72**	0.03	0.42
			IMG2	0.10	**0.83**	0.22	0.23
			IMG3	0.04	**0.88**	0.04	0.18
			IMG4	0.02	**0.80**	0.20	0.30

Moreover, CFA shows a chi-square (CMIN) of 957.374 ($p < 0.001$). In addition, the goodness-of-fit (GFI) is 0.832, and the comparative fit index (CFI) is 0.900. The root mean square error of approximation (RMSEA) is 0.080. All indices support the model fit.

The hypothesis testing results are shown in Table 4. A group of hypotheses (H1a–H1l) predicts the direct effects. First, DDA has a significant positive effect on INN ($\beta = 0.374$, $p < 0.001$), IMP ($\beta = 0.457$, $p < 0.001$), and SAT ($\beta = 0.122$, $p < 0.05$). Therefore, hypotheses H1a, H1b, and H1c are supported. Second, PRED has a positive and significant effect on only IMP ($\beta = 0.166$, $p < 0.01$). Hence, H1f is supported. Third, PRES has a significant positive effect on INN ($\beta = 0.293$, $p < 0.001$), IMP ($\beta = 0.117$, $p < 0.05$), SAT ($\beta = 0.255$, $p < 0.001$), and IMG ($\beta = 0.205$, $p < 0.001$). Thus, H1i to H1l are supported. Hypotheses H1d, H1e, H1g, and H1h are not supported.

Table 4: The Result of Hypothesis Testing

Hypotheses	Structural Path	Std Coefficient	Results
H1a	DDA ⟶ INN	0.374***	Supported
H1b	DDA ⟶ IMP	0.457***	Supported
H1c	DDA ⟶ SAT	0.122*	Supported
H1d	DDA ⟶ IMG	0.035	Not Supported

Table 4: The Result of Hypothesis Testing (Cont.)

Hypotheses	Structural Path	Std Coefficient	Results
H1e	PRED ⟶ INN	0.094	Not Supported
H1f	PRED ⟶ IMP	0.166**	Supported
H1g	PRED ⟶ SAT	0.046	Not Supported
H1h	PRED ⟶ IMG	0.073	Not Supported
H1i	PRES ⟶ INN	0.293***	Supported
H1j	PRES ⟶ IMP	0.117*	Supported
H1k	PRES ⟶ SAT	0.255***	Supported
H1l	PRES ⟶ IMG	0.205***	Supported
H2a	DDA × ML ⟶ INN	0.033	Not Supported
H2b	DDA × ML ⟶ IMP	0.151**	Supported
H2c	DDA × ML ⟶ SAT	0.096	Not Supported
H2d	DDA × ML ⟶ IMG	0.156**	Supported
H2e	PRED × ML ⟶ INN	0.087	Not Supported
H2f	PRED × ML ⟶ IMP	0.092	Not Supported
H2g	PRED × ML ⟶ SAT	0.011	Not Supported
H2h	PRED × ML ⟶ IMG	0.170**	Supported
H2i	PRES × ML ⟶ INN	0.102*	Supported
H2j	PRES × ML ⟶ IMP	0.122*	Supported
H2k	PRES × ML ⟶ SAT	0.028	Not Supported
H2l	PRES × ML ⟶ IMG	0.053	Not Supported

Another group of hypotheses examines the moderating effect of ML. The interaction terms (DDA × ML, PRED × ML, PRES × ML) were computed. The results of moderating effects show that DDA × ML has a significant positive effect on IMP ($\beta = 0.151$, $p < 0.01$), and IMG ($\beta = 0.156$, $p < 0.01$). Hence, H2b and H2d were supported. In addition, PRED × ML has a significant positive effect on IMG ($\beta = 0.170$, $p < 0.01$), so H2h was supported. Finally, PRES × ML has a significant positive effect on INN ($\beta = 0.102$, $p < 0.05$), and IMP ($\beta = 0.122$, $p < 0.05$). Thus, H2i and H2j were supported. The measurement model is illustrated in Figure 2.

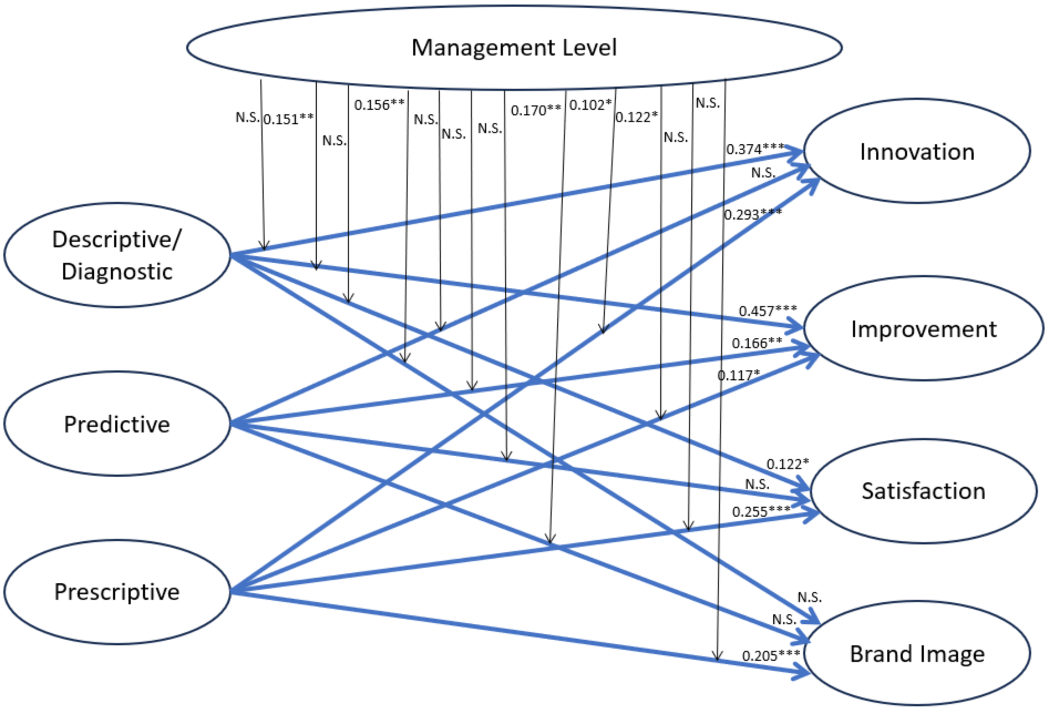

Figure 2: Measurement Model

Further analysis of the moderating effect of ML on the relationship between data analytics and co-production was conducted. Table 4 shows 5 significant moderating effects; 3 of them moderate direct relationships that were statistically significant, the others moderate direct effects that were not significant. Nevertheless, further analysis was performed on all 5 significant moderating effects. The data was divided into 3 sets based on the management level. Simple linear regressions were then performed and plotted as line charts to analyze in more details as shown in Figure 3. Figure 3 consists of 5 separate charts; each shows the regression lines of the direct effect between 2 variables with the data from 3 subsets. The first 3 charts, labeled Fig. 3a – Fig. 3c, represent the direct relationships that were significant in the main measurement model (DDA-IMP, PRES-INN, and PRES-INN), whereas the others represent those that were not significant (DDA-IMG and PRED-IMG). More details can be found in the appendix.

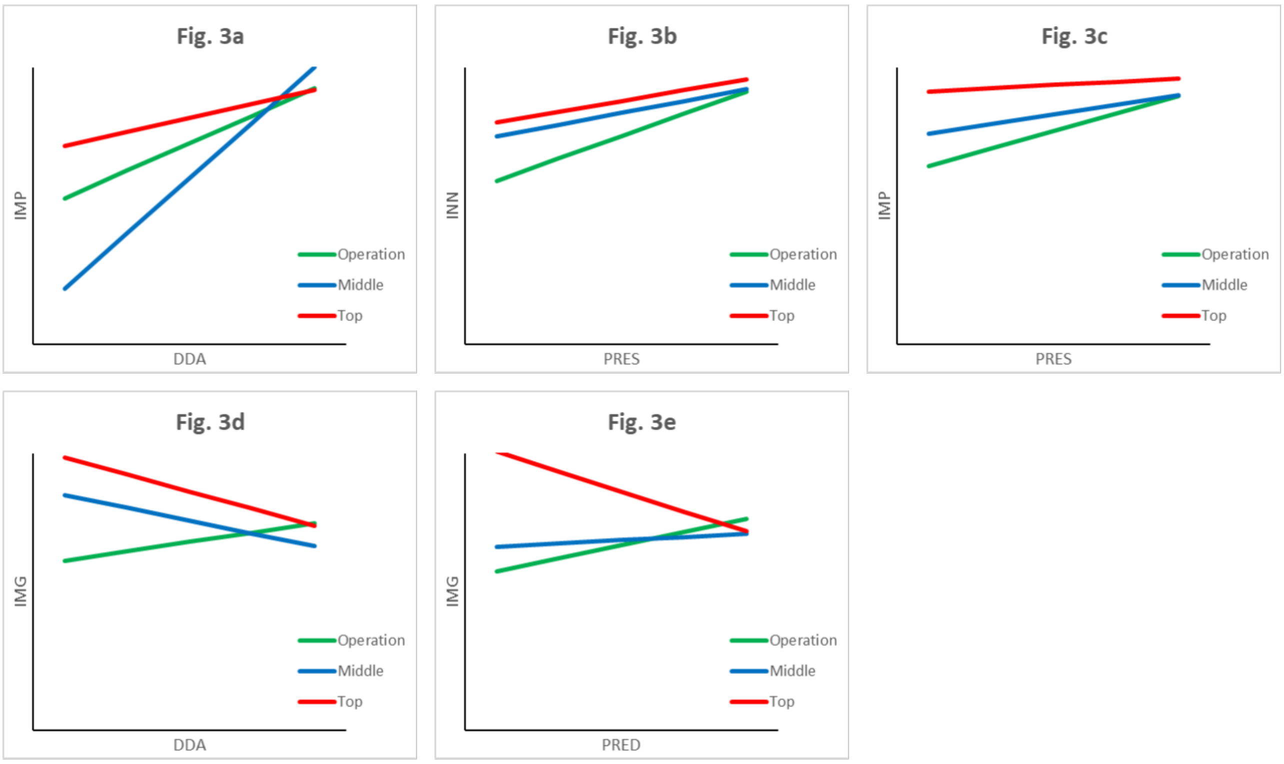

Figure 3: Further Analysis Results

Figure 3a shows different slopes for all management levels while Figure 3b and 3c show a noticeably different slope only for the operational management level. Hence, it can be inferred that different management levels perceive the usefulness of descriptive/diagnostic analytics towards product improvement differently, with the middle management level having the highest perception of the usefulness of descriptive/diagnostic analytics towards product improvement. In addition, only the operational management level has a higher perception of the usefulness of prescriptive analytics towards product innovation and product improvement.

The other 2 charts, Figure 3d and Figure 3e, depict the moderating effects that were significant in the main measurement model on the direct effects that were not significant. Therefore, the interpretation of these results must be taken with care. It can be inferred from Figure 3d that the operational management level perceives the usefulness of descriptive/diagnostic analytics towards brand image in a positive way while the other levels perceive negatively. It can also be inferred from Figure 3e that the top management perceives negatively about the usefulness of descriptive/diagnostic analytics towards product improvement while the other levels perceive positively.

5. CONCLUSION AND DISCUSSION

The power of data analytics is beneficial to the business in several ways. The potential of data analytics is far-reaching, and if used properly, the business might gain useful insight from the data. The results provide insights by adding a new perspective to the current knowledge and provide some useful implications for the business sectors. In terms of the theoretical contribution, this study provides an exploratory step to fill the gap that few other studies have explored. This study initiated an investigation on the moderating effects of the management level to provide different perspectives of the producers and inform academia of the existing gaps in the current knowledge base.

In general, the evidence shows strong belief from the producers that the most basic levels of data analytics methods, descriptive and diagnostic, can enhance customer co-production outcomes in the aspects of product innovation, product improvement, and customer satisfaction, but not in the aspect of brand image. While predictive analytics is believed to enhance the product improvement aspect, prescriptive analytics is believed to enhance all four aspects. In addition, management intervention helps increase the effect of data analytics on (1) product improvement through descriptive analytics, (2) brand image with descriptive and predictive analytics, and (3) product innovation through prescriptive analytics.

However, the results of this study do not provide any support for the influence of predictive analytics on the following aspects of co-production: product innovation, customer satisfaction, and brand image. Predictive analytics provide predictions based on past data. Hence, it may not be so useful for production innovation and brand image. Descriptive and diagnostic analytics may better serve the purpose of product innovation since innovation requires the collection of ideas and feedback from customers as the initial input. Our study also provides support for this claim. For customer satisfaction, it comes as a surprise that the data does not support the influence of predictive analytics on customer satisfaction. It was conceived that customers may be more satisfied if the company can predict customers' needs and provide exactly what they need. However, this effect may be partially diverted to the path from predictive analytics to product improvement. Further study is required for a better understanding.

For the moderating effects of the management level, the results provide support for 5 out of 12 hypotheses, as mentioned earlier. In addition, further analysis was performed on these moderating effects to provide more explanation. However, this study serves as exploratory research attempting to expand the current knowledge body. There are remaining gaps for future research to investigate further on these moderating effects, or possibly the effects of other factors.

For business implications, the power of data analytics is perceived to be most helpful for operational management in enhancing the outcomes of customer co-production, especially in the aspects of product innovation and product improvement. Operational management level may enhance product innovation and product improvement using prescriptive analytics. However, different management levels still have notably different perspectives on how they can enhance product improvement using descriptive/diagnostic analytics, although they all agree on the usefulness of descriptive/diagnostic analytics on product improvement. Table 5 presents a matrix summarizing all findings in a format that may be useful to businesspersons.

However, the scope of this study is limited to the producers' perspective. For comprehensive understanding, the customers' perspective should also be considered. Further research may focus on the impacts in different industries, cultures, and technological contexts. Some other plausible aspects are the scale of the business and the technical strength of the IT or Data Analytics Department.

Table 5: Summary of the Findings for Business

Co-production Aspect	Analytics Method			Management Level								
				Operational			Middle			Top		
	DDA	PRED	PRES	DDA	PRED	PRES	DDA	PRED	PRES	DDA	PRED	PRES
Production Innovation	✓		✓			High			Med			Med
Product Improvement	✓	✓	✓	Med		High	High		Med	Low		Med
Customer Satisfaction	✓		✓									
Brand Image			✓	Pos	Pos		Neg	Pos		Neg	Neg	

Remark: DDA = Descriptive/Diagnostic Analytics, PRED = Predictive Analytics, PRES = Prescriptive Analytics

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Appendix

Table A1: Measurement Instruments

Construct	Measurement Item
Descriptive Analytics	I am confident that I could efficiently summarize historical data to understand what has happened in the past.
	I can always use basic statistical methods such as mean and frequency to analyze data accurately if I try hard enough.
	It is easy for me to use pivot tables or cross-tabulations to compare and analyze data across multiple dimensions.
Predictive Analytics	It is easy for me to use historical data to predict future outcomes under the assumption that similar events will occur again.
	I can always use statistical methods to predict probabilities, trends, and future possibilities.
	I am confident that I could use inferential statistics (e.g. regression) or sample-based data analysis to make generalizations about the entire dataset if I try hard enough.
Prescriptive Analytics	I can always use advanced mathematics and simulations to support decision-making and planning.
	It is easy for me to use advanced mathematics to analyze customer feedback for product customization.
	I am confident that I could use optimization techniques to recommend new product features or service improvements based on customer data if I try hard enough.
	I can use optimization techniques and advanced mathematics to help businesses identify the most profitable customer segments using demographics, behavior, and purchase history if I invest necessary effort.
Product Innovation	Using data analytics would enhance my effectiveness in product design and innovation.
	Using data analytics would improve my performance in the development of new product functions
	Using data analytics would enable me to develop new production technology more quickly.
	I would find data analytics useful in enhancing the development of cutting-edge manufacturing technology

Table A1: Measurement Instruments (Cont.)

Construct	Measurement Item
Product Improvement	Using data analytics would improve the production processes.
	Using data analytics would improve the product quality.
	Using data analytics would enable me to reduce production-related problems.
	I would find data analytics useful in shortening the production time.
Customer Satisfaction	Using data analytics would increase customer satisfaction with the product.
	Using data analytics would improve satisfaction with product functionalities.
	Using data analytics would enable me to gain useful insight to enhance satisfaction with pre-sale product information.
	I would find data analytics useful in the improvement of satisfaction with after-sales service.
Brand Image	I would find data analytics useful in strengthening brand image.
	Insight from data analytics would make it easier to improve brand image.
	Using data analytics would increase brand awareness.
	Using data analytics would enhance brand identity and make the brand stand out.

Table A2: Regression Results for Outcome Variable Brand Image (IMG) by Management Level (ML)

Predictor:		DDA			PRED		
Management Level	**N**	**R2**	**Coeff. (β)**	**Intercept**	**R2**	**Coeff. (β)**	**Intercept**
Top	41	0.0571	–0.31	5.24	0.0894*	–0.36*	5.40
Middle	103	0.0411**	–0.23**	4.48	0.0029	0.06	3.25
Operational	206	0.0345***	–0.17***	2.90	0.0694***	0.24***	2.63

Remark: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, DDA = Descriptive/Diagnostic Analytics, PRED = Predictive Analytics

Table A3: Regression Results for Outcome Variable Product Improvement (IMP) by Management Level (ML)

Predictor:		DDA			PRES		
Management Level	**N**	**R2**	**Coeff. (β)**	**Intercept**	**R2**	**Coeff. (β)**	**Intercept**
Top	41	0.0219	0.25	3.33	0.0174	0.06	4.50
Middle	103	1.0000***	1.00***	0.00	0.0444**	0.17**	3.63
Operational	206	0.2388***	0.50***	2.14	0.1146***	0.32***	2.90

Remark: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, DDA = Descriptive/Diagnostic Analytics, PRES = Prescriptive Analytics

Table A4: Regression Results for Outcome Variable Product Innovation (INN) by Management Level (ML)

Predictor:		PRES		
Management Level	**N**	**R2**	**Coeff. (β)**	**Intercept**
Top	41	0.0174	0.06	4.50
Middle	103	0.0444**	0.17**	3.63
Operational	206	0.1146***	0.32***	2.90

Remark: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, PRES = Prescriptive Analytics