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Research Article

An Assessment of the Impact of Artificial Intelligence (AI) on New Product Development (NPD) and Strategic Sourcing/Procurement

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ABSTRACT

Artificial intelligence (AI) has become one of the disruptive technologies in the Fast-Moving Consumer Goods (FMCG) industries, specifically new product development (NPD) and strategic sourcing/procurement. This paper examines how AI affects these two key business processes, based on data gathered on 300 employees in the industry working in 5 of the largest FMCG firms in the Delhi-NCR area. The research design consists of quantitative research that uses cross-sectional survey Product Designing in which purposive and quota sampling methods are taken to ensure that respondents of the two departments are well represented. The role of AI in improving product innovation and procurement efficiency was tested by applying statistical methods (regression analysis and structural equation modelling (SEM)) with the help of SPSS and AMOS software. The results indicate that AI plays a vital role in accelerating and enhancing the speed of the process of developing products, enhancing the selection of suppliers, optimising costs, and efficiency in general procurement. Furthermore, AI-based technologies are used to improve decision-making processes, automatize processes, and become innovative due to predictive analytics and generative Product Designing. The research also adds value to the existing literature by evidence of the transformational nature of AI in FMCG operations that can be a great contribution to industry players, policymakers, and developers of technologies alike. The future research can investigate how AI will affect the supply chain sustainability in the long term, what issues may occur during the integration, and what role it will play in the future.

Keywords: Artificial Intelligence, New Product Development, Strategic Sourcing, Procurement, FMCG

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Introduction

AI is revolutionising business environments, with many implications on new product development (NPD) and strategic sourcing (procurement processes). AI-driven applications are transforming the way companies innovate, Product Designing and launch products in the market and also changing procurement by helping companies to streamline sourcing plans, decisions and achieve operational efficiency. Due to these two effects, this research seeks to evaluate AI application in new product development and strategic sourcing to fill the gaps in current empirical and theoretical studies.

AI implementation into the creation of new products is transforming the world of innovation, making the process of prototyping faster and more efficient, as well as enhancing the decision-making process. AI is a prediction machine (Agrawal, Gans, and Goldfarb, 2018), and the individual firms can use it to interpret large numbers of data and create insights that can underpin more efficient Product Designing s. As an example, AI-based digital prototyping and generative AI have been discovered to significantly shorten the development time (Bilgram and Laarmaan, 2023; Brossard et al., 2020). General Electric and other companies use AI to reduce their product Product Designing time by 50 percent, and it proves that AI can be a game-changer in industries (Bogaisky, 2019). In the same manner, artificial intelligence-powered applications enhance the accuracy and the user experience of Product Designing and can extract actionable insights on consumer-generated data (Columbus, 2020).

Besides, AI is becoming instrumental in the automation of complex engineering activities, promoting novel solutions in industries. Generative Product Designing, a form of AI, is applied in manufacturing to optimise product structures that result in higher efficiency and sustainability (Marr, 2023). By incorporating AI into the project management and product development processes, companies can predict the market trends and develop products to match them (Nieto-Rodriguez and Vargas, 2023). The examples of the companies that show AI helps improve the speed of the iteration processes are Siemens and Procter and Gamble, which accelerate the time-to-market and secure Product Quality improvements (Siemens, 2023; Procter and Gamble, 2022). The use of AI in NPD is likely to increase as the technology advances, providing companies with a competitive edge based on the use of data-driven innovations (Brem, Giones, and Werle, 2023; Forsey and Mishra, 2023).

Procurement is a strategic approach to companies today since companies use over half of their income to procure goods and services (van Weele and van Raaij, 2014; Bienhaus and Haddud, 2018). In addition to cost reduction, procurement also leads to the product Quality of products, supplier relationships, and the sustainability of the supply chain (Schutz et al., 2020; Luzzini et al., 2015). The use of AI in the procurement procedures is transforming the sourcing strategies, improving decision-making, and automating the intricate analytical assignments (Handfield et al., 2019).

The ability to analyse massive amounts of procurement data gives firms a better insight into how they spend, how their suppliers perform, and how they manage risks; AI enhances this ability (Giunipero et al., 2012; Marshall et al., 2015). The AI-based procurement technologies facilitate supplier assessment and contract negotiation to achieve better cost-efficiency and supplier compliance (Moretto et al., 2017; Zair et al., 2019). Predictive analytics can also be achieved with the growing popularity of AI-based smart platforms in procurement, which allow companies to foresee market changes, demand trends, and supply risks (Handfield et al., 2019; Loureiro et al., 2021).

Nonetheless, scholarly sources regarding AI in procurement are not developed as well as other business processes like marketing and sales (Linoff and Berry, 2011; Tirunillai and Tellis, 2014). Although the use of AI in risk management and supply chain operations is under investigation (Wu et al., 2017; Azan Basallo et al., 2018; Baryannis et al., 2019a, 2019b), an all-encompassing framework of AI-provided procurement is still lacking (Moretto et al., 2017; Handfield et al., 2019). This highlights a necessity to conduct the new investigation to standardise the use of AI in purchasing and assess its strategic productivity in the long term.

AI is a developing general-purpose technology, and it is constantly developing in its flexibility and use (Crafts, 2021; Åström et al., 2022). Since it is becoming more useful in aiding with human decision-making processes in various industries (Guo and Wong, 2013; Min, 2010), it is important to know its exact effect on procurement and NPD. Although the companies are still trying out AI-based procurement technologies and automation in NPD, the existing empirical data is, in fact, still in pieces, and it is hard to evaluate the full potential of AI (Lorentz et al., 2020).

In this way, the paper aims to make a contribution by estimating the measurable value of AI on the new product development and strategic sourcing based on the use of statistical analysis to evaluate how AI contributes to the improvement of innovations, high procurement efficiency, and changing business processes. The paper will fill these research gaps to offer a systematic basis on future AI-based procurement and NPD models.

Review of literature

1.1 Artificial Intelligence (AI)

The history of artificial intelligence (AI) as a field of study can be traced to the landmark Dartmouth Conference of 1956, where the earliest theorists of the field McCarthy, Minsky, Newell, and Simon, initially defined the discipline, which has been studied over several decades (Collins et al., 2021). According to these early researchers, AI is an intelligent system that is designed to execute some tasks without the need to programme it to do so, which is autonomous and adaptive (Lee et al., 2019, p. 1). AI has experienced a lot of evolution since it was first introduced. The 2000s saw the shift towards the era, when AI began to allow companies to make use of large datasets more efficiently, and its effects began to spread into academic theory as well as finding practical uses, especially in the area of New Product Development (NPD) (PwC, 2019).

The recent AI development is mainly based on the development of deep learning and machine learning, so machines are not only faster but also, in a few scenarios, more precise in carrying out complex tasks than people (Brynjolfsson & McAfee, 2017). A well-known case is Enlitic, a firm that uses deep learning to scan medical images to identify cancer, which presents AI with the transformative nature in more specific areas, including health care (Jha & Topol, 2016). Such an example represents a larger social change where AI can replicate the way humans think, and when it is actually differentiated is through the implementation of the technology across the digital landscape (Guszcza et al., 2017). AI is therefore generally accepted as the key factor that efficiency and technological progress in it is catalysed (Simon, 1995; Tang et al., 2020).

The topic of AI has gained rapid research interest since 2017, covering a wide range of areas and an increase in the application of AI (Collins, 2021). The current AI applications involve chatbots, intelligent personal assistant, robots, and advanced analytical AI, which are becoming more and more integrated into the organisational operations (Akter et al., 2023; Ponce et al., 2022; Prem, 2019). Notably, AI is recognised as a key facilitator of successful NPD, but its efficiency depends on the industry and company purpose as well as implementation plans (Huo et al., 2020; Kakatkar et al., 2020). This abundant and developing literature presents AI as a two-fold factor: as a technological innovation and a strategic resource in new product development and organisational efficiency.

1.2 Artificial Intelligence (AI) and Its Impact on New Product Development

The 1960s and early 1970s literature on Engineering Management and Research and Development was instrumental in developing the studies on New Product Development (NPD) (Nambisan, 2003). In the 1970s, NPD as a process was formalised by companies and started to attract academic interest, with the pioneer researchers starting to research this field (Wind et al., 1997). As time passed by many models of NPD were formed with the most significant model being the seven step model created by Booz, Allen and Hamilton in 1982. The stages presented in this model include idea generation and screening, concept development and testing, business analysis, prototype and market testing, technical implementation, and commercialization planning (Pavlou and El Sawy, 2006, p.199). The importance of NPD to the firms was recognised at an early stage and the research had shown that managers should be trained to effectively implement NPD and where failures may occur, like in case of defects or poor execution of the processes involved in producing the products (Cooper, 1983). The study by Gryphon also highlighted the role of NPD in business and made an approximate estimation that almost 30 percent of the profits of a company can be attributed to the products that have been introduced within last 5 years (Gryphon, 1997).

Due to market competition and globalisation that was on the rise in the early 1990s, companies increased their NPD endeavours in order to become faster in their time to market and low cost aspects. NPD incorporation in the supply chain was developed to enhance the efficiency of operations and make the processes more efficient (Nambisan, 2003). This development has led NPD to be an interdisciplinary discipline especially in the Information Systems (IS) and later in management and Information Technology (IT). Nambisan (2003) has conceptualised NPD in four major dimensions; process management, project management, information and knowledge management, and collaboration and communication. Process management came up with such tools as Stage-Gate to enhance stability and order during stages of development (Cooper, 1990; Nambisan, 2003). The project management was concentrated on the allocation of the resources and real time coordination of the activities (McGrath and Lanszti, 1998; Nambisan, 2003). The dimension of information and knowledge management emphasised the augmented amount of shared data, enabling the choice-makers to mix shared knowledge in real-time (Nambisan, 2003). The involvement in NPD projects was no longer limited to teams but also extended to customers and suppliers (Dahan and Hauser, 2000) which increased the significance of collaboration and communication platforms that was modified to overcome the organisational, cultural, and regional differences (Nambisan, 2003).

Effective NPD is a matter of balance between creativity and efficiency (Naveh, 2005). Also important is the ability of firms to gain the capacity to foresee technological advancements at the same time as they innovate products or services (Chen et al., 2010). Even decades of research indicate that the issue of preventing NPD failures is still topical, and the efforts to enhance the implementation procedures are aimed at the reduction of a failure (Kahn et al., 2012). In line with the current tendencies, Zhang et al. (2021) revised NPD stages to reflect the modern realities of the practises, containing such stages as idea development, business analysis, product design, and testing, commercialization, post-commercialization, and operations management. Nevertheless, so many challenges are experienced by product developers in the modern world, as new procedures are appearing. NPD success factors should be continually researched to provide managers with the opportunity to employ the experience of previous failures and optimise the innovation process (Cooper, 2019; Tao et al., 2023).

Artificial Intelligence (AI) is transforming the new product development (NPD) process through Product Designing processes, faster time-to-market, and further efficiency by automating processes and utilising data to make decisions. The literature review highlights the importance of the role of AI in Generative Product Designing, predictive modelling, and digital prototyping in transforming conventional product development process of products. In different industries, AI is a driver towards innovation, optimization of processes, and organisations producing highly superior products using minimum resources.

The use of AI as the Generative Product Designing and Prototyping can be seen as the revolutionary aspect of NPD that will help companies produce optimised product designs in a quicker and more

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efficient way. AI-driven Product Designing tools support the automation of iterative processes and help engineers to evaluate a variety of Product Designing options at the same time, which no longer requires relying on the manual process of trial-and-error (Bilgram & Laarmaan, 2023). Generative Product Designing with the help of AI optimises structural performance and material efficiency in the manufacturing industry and contributes to thermal costs decreasing and the improvement of the quality of products (Brossard et al., 2020). General Electric is one of the companies that have taken advantage of AI to cut product Designing times in half, proving the ability of AI to shorten the process of innovation (Bogaisky, 2019). The efficiency is not only enhanced by these advancements but also product customization is enhanced, the organisation is able to serve the consumer preferences more accurately.

Predictive Modelling and AI in Decision-Making: AI is important in modernising strategies of product development. AI can assist businesses in analysing consumer trends, market trends, and supply chain trends to make informed Product Designing and production decisions (Forsey & Mishra, 2023). Using AI, insights allow companies to predict the needs in the market, efficient resource usage, and mitigate the risk of failure in product development, product-market fit is ensured prior to making big production (Columbus, 2020). Simulation models created with AI help companies to detect defects in Product Designing, to test the durability of a product, and to predict performance results prior to physical prototyping and minimising the costs and enhancing the overall Product Quality of a product (Eastwood, 2023).

Another essential theme to Product Lifecycle Management (PLM) to consider in the role of AI in NPD is automation. AI allows the smooth connexion between Product Designing, engineering, and production, decreasing the number of bottlenecks and improving cross-functional coordination (Brem et al., 2023). When firms use AI-based digital twins, they will be able to recreate the real world and base Product Designing s on its predicted performance and real-time feedback (Siemens, 2023). The strategy enhances efficiency in production and better synchronisation of supply chains to ensure that the product development and the material availability, fluctuations in demand, and logistical limitations are aligned (Marr, 2023). AI also facilitates the automated Quality control and detection of defects of the products so that the products are not only of high industry standards but also reach the consumer (Procter & Gamble, 2022).

The use of AI in time to market acceleration can be seen in any industry where time to market is offered an opportunity with rapid product development. AI also slims down the prototype-to-production pipeline and minimises the need for human work over the process and shortens the decision-making process (Van Houtven & ChatGPT, 2023). ChatGPT and machine learning algorithms are AI-based tools that optimise the automation of workflow and deem unnecessary reliance on human-driven processes to ensure accuracy in Product Designing and implementation (Euchner, 2023). Moreover, AI-driven analytics systems help businesses to evaluate customer feedback, optimise product functionality, and introduce data-driven marketing initiatives that help companies ensure that emerging products are in line with market needs (Deeb, 2023).

AI has become one of the facilitators of new product development, which has created efficiency, innovation, and strategic decision-making. The AI-driven generative Product Designing speeds up prototyping, the predictive modelling enhances market responsiveness, and automation makes the process of product lifecycle management more cost-effective and time-efficient. The articles analysed show that AI has a revolutionary effect on the industry through creativity, optimization of production processes, and minimization of risks. With the ongoing development of AI technologies, companies should use smart automation and data-driven insights to stay competitive in terms of product innovation.

1.3 Artificial Intelligence (AI) and Strategic Sourcing/ Procurement Processes

Digitization of procurement has been noted to be a determining power numerically altering the mode in which upstream supply chain operations are handled. This change is compelling major stakeholders in the procurement and supply chain management to come up with new technological solutions (Lorentz et al., 2020). As Bag et al. (2020) note, the emergence of new technologies in the context of digitalization of procurement leads to the need to develop new frameworks that will reorganise various internal processes in companies. Although properly executed, this change may redefine the value proposition of procurement (Hallikas et al., 2021).

Nonetheless, online procurement is more than just a transition to the sophisticated technological platforms. Although it is designed to complement and improve manual work, the advent of smart systems brings automation to the next level of performing particular procurement functions without the involvement of a human (Glas et al., 2016).

Digital developments have had an effect on the procurement process over the years, including the simplification of procurement-related tasks, including Electronic data interchange (EDI), the rise of enterprise resource planning (ERP) as a supplier and purchase order management platform, and the automation of electronic invoicing (Kosmol et al., 2019). In the present days, the amount of generated data in both directions is increasing exponentially (Wang et al., 2016). In turn, the advanced analytics should become the engine of the procurement development, especially with respect to the provision of the strategic decisions. Greater transparency of spending trends and procurement operations is a key component of procurement strategy (Barrad et al., 2020), and the effect of analytics and artificial intelligence (AI) in this area is significant (Bienhaus and Haddud, 2018; Barrad et al., 2020).

Nevertheless, regardless of the possibilities of such technologies, studies by McKinsey Global Institute (2017) show that most of the new AI-based procurement initiatives are still in the initial stages and that many of them are initiated by AI solution vendors, not internal members. Even big companies that invest in such innovations believe that they are in the first stages. Consequently, it is difficult to evaluate tangible outcomes (Lorentz et al., 2020), and there is not much empirical evidence of successful AI application in procurement. Moreover, the scholarly source is short of quantitative studies and analyses which investigate procurement in terms of processes.

As an example, Chehbi-Gamoura et al. (2020) carried out a literature review of big data analytics in supply chain management through the Supply chain operations reference (SCOR) model, which views procurement as a minor part of a bigger picture. Likewise, Moretto et al. (2017) viewed procurement in the strategic and tactical light but did not consider the operational aspect, which is greatly affected by the automation of AI. Although the process of digital transformation of procurement is being studied in different studies (e.g., Chowdhary et al., 2011; Baryannis et al., 2019a; Baryannis et al., 2019b; Zair et al., 2019), the vast majority of them are conducted with specific regards but do not cover the whole process. According to the objectives and the thematic review of literature, the following hypotheses are put forward in this study to determine the impact of artificial intelligence (AI) on new product development and strategic sourcing:

H1: Artificial Intelligence (AI) AI has impact on New Product Development in FMCG Sector.

The AI technologies play a crucial role in the new product development process, cutting down the Product Designing time, enhancing prototyping using generative AI, decision-making and predictive analytics to forecast the market conditions.

H2: Artificial Intelligence (AI) AI has impact on Strategic Sourcing Efficiency in FMCG Sector.

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AI in strategic sourcing is the ability to improve the efficiency of procurement by means of automation of suppliers, better contract negotiations, cost structure optimization, and supply chain transparency, through predictive analytics and real-time data processing.

Research Methodology

This research adopted quantitative research design as the structural equation modelling (SEM) to analyse the impact of Artificial Intelligence (AI) on New Product Development (NPD) and Strategic Sourcing Efficiency (SSE). The research methodology is explanatory, and the study seeks to establish hypothesised relationships between latent constructs statistically using statistical modelling. SEM was chosen due to the fact that it enables the possibility of simultaneous measurement of several dependent relationships while considering measurement error.

The target audience was comprised of the professionals and decision-makers in different industries in the city of Jaipur, Rajasthan, India. The respondents were selected based on purposive sampling approach as it was necessary to find those who were aware of the AI adoption in their organisation, innovation processes, and sourcing strategies. There were 400 participants in the study, which is a representative sample of the sectors and the organisational functions. This is a sufficient sample size to carry out SEM analysis that is sufficient in terms of statistical power and model stability.

The structured questionnaire was used to collect primary data that was collected to the 400 respondents. The research constructs were validated multi-item scales on Artificial Intelligence (AI), New Product Development (NPD), and Strategic Sourcing Efficiency (SSE) included in the questionnaire. The 11 items used to measure the AI construct represented different aspects of AI implementation and use. NPD was measured through four dimensions that represented the stages of product innovation process which include: Idea Generation, Concept Development, Product Designing and Commercialization. Five indicators were used to measure the SSE and included Responsiveness, Flexibility, Cost Reduction, Product Quality and Lead Times. The answers of respondents were presented in a Likert scale to show the extent to which they agreed or the frequency.

The data obtained was processed in Structural Equation Modelling (SEM) with Maximum Likelihood (ML) estimation and the NLMINB optimization algorithm. The specialised software that was used to perform SEM was able to manage latent constructs and measurement models. Confirmatory factor analysis (CFA) was used as the first step to measure reliability and validity of the constructs in the measurement model. The structural model then tested the hypothesis of the relationships between AI and the outcome variables NPD and SSE. Standardised path coefficients, standard errors, z-values, p-values, and 95% confidence intervals were used, as the evaluation criteria, to define the strength and significance of the relationships. Model fit measure was also gauged so as to have an acceptable fit between the model and the data.

The study complied with the ethical issues such as informed consent, confidentiality, and voluntary involvement. The respondents were guaranteed that the information they provided would be anonymized and it would only be used academically.

Result

Table 1 - Models Info

Estimation Method	ML
Optimization Method	NLMINB

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Number of observations	400	
Model	Artificial Intelligence (AI) =~AIU1+AIU2+AIU3+AIU4+AIU5+AIU6+AIU7+AIU8+AIU9+AIU10+AIU11	
	NPD=~Idea Generation +Concept Development +Product Designing +Commercialization	
	Strategic Sourcing Efficiency =~Responsiveness+Flexibility+Cost Reduction+Product Product Quality +Lead Times	
	New Product Development ~Artificial Intelligence (AI)	
	Strategic Sourcing Efficiency ~Artificial Intelligence (AI)	

The given model in table 1 has been estimated by the Maximum Likelihood (ML) estimation technique equipped with an NLMINB optimization algorithm, and the evaluation is done on a sample of 400 observations. The framework combines measurement and structural elements, which is consistent with the organisation of a structural equation model (SEM). This modelling method allows the simultaneous evaluation of numerous interrelationships between the observed and the latent variables to comprehend the contribution of artificial intelligence (AI) to organisational operations.

Three latent constructs, Artificial Intelligence (AI), New Product Development (NPD), and Strategic Sourcing Efficiency (SSE), are operationalized as measurement models. The AI construct is assessed by eleven indicators (AIU1-AIU11) which could reflect various aspects of AI use or perception in the organisation. New Product Development can be described as a process which has four indicators, namely; Idea Generation, Concept Development, Product Designing and commercialising, which are an indication of the stages of innovation of a product. Strategic Sourcing Efficiency refers to five main areas of Responsiveness, Flexibility, Cost Reduction, Product Quality, and Lead Times, that, altogether, reflect the operational capabilities that ensure the sourcing became more effective.

The structural component of the model hypothesises two straight causal associations. To start with, it assumes that the Artificial Intelligence has a positive impact on New Product Development (NPD ~ AI). It means that the more AI technologies are used in an organisation, the easier it will become to generate ideas, design, and commercialise some of them, which will positively affect the overall innovation performance. Secondly, it indicates that there is a direct correlation between Strategic Sourcing Efficiency (SSE ~ AI) and Artificial Intelligence. This is an indicator of the belief that AI-based analytics and automation increase sourcing responsiveness, lower costs, and flexibility as well as lead times.

All in all, the model emphasises AI as a disruptive capability that can improve the quality of innovation-driven and operational results. The hypothetical trajectories imply that AI may be viewed as a two-fold enabler which will promote efficiency in the sourcing activities and at the same time enhance innovation by way of enhancing product development mechanisms. Provided the empirical support, the findings would indicate the value of AI adoption as a strategic tool of gaining a competitive advantage due to excellent operational and product development.

Table 2 - Model tests

Label	X^2	df	p

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User Model	4489	167	<.001
Baseline Model	10086	190	<.001

In the table 2 Model Tests, the chi-square (X 2) test values of both the User Model and the Baseline Model are to be found thus helping to determine the overall model fit. The User Model chi square value is 4489 with 167 degrees of freedom (df) and a p-value of less than 0.001, and this implies that the model does not fit perfectly as compared to a perfect fit model does. Equally, Baseline Model depicts a greater chi-square value of 10086 at 190 degrees of freedom and a less p-value of 0.001 also indicates that it also is not well fit. When considering the two models, the User Model will be the better fit of the two because it has a lower chi-square value. Nevertheless, both p-values are significant which means that, though the User Model is more accurate than the Baseline Model, there is still a deviation between the proposed model and the observed data, which implies that the model can be further refined to achieve better model accuracy.

Table 3 - Fit indices

		95% Confidence Intervals		
SRMR	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
0.160	0.254	0.248	0.260	<.001

The table 3 Fit Indices shows the major statistical indicators that are applied to assess the general goodness of the fit of the model. The Standardised root mean square residual (SMR) is 0.160 that is greater than the acceptable standard of 0.08 meaning that there is a significant difference between the actual and the expected correlation. The value of the Root Mean Square Error of Approximation (RMSEA) is 0.254, with 95 percent confidence interval of 0.248-0.260, and a p -value of less than 0.001. These findings indicate that the model is not very appropriate to data, since RMSEA values below 0.08 are normally considered to have a good fit and values above 0.10 depict a bad fit. Thus, the large value of SRMR and RMSEA, as well as the large p-value, all point to the fact that the current form of the model might not actually represent the observed data with the improvement that will allow attaining a satisfactory fit.

Table 4 - Parameters estimates

				95% Confidence Intervals				
Dep	**Pred**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
New Product Development	Artificial Intelligence (AI)	1.23	0.0585	1.12	1.35	1.10	21.0	<.001
Strategic Sourcing Efficiency	Artificial Intelligence (AI)	1.18	0.0549	1.07	1.28	1.12	21.4	<.001

In table 4 The 400 observations were used to test the structural model and the relationships were estimated by applying the Maximum Likelihood (ML) method with the NLMINB optimization algorithm. The findings also point to the existence of statistically significant and high degree of

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relation between Artificial Intelligence (AI) and the two dependent variables, New Product Development (NPD) and Strategic Sourcing Efficiency (SSE).

The estimate of the path between AI and NPD is 1.23 with a standard error of 0.0585. The 95 percent confidence interval is in the range of 1.12 to 1.35, which means an accurate and consistent estimation. A coefficient of 1.10 is a very strong positive correlation implying that AI has a significant effect on NPD. The values of z=21.0 and p=0.001 are less than equal to 21.0, which proves that this relationship is very important. It means that the deployment or incorporation of AI-based systems and tools will contribute to the improvement of a new product development process significantly, specifically, in the fields of the idea generation, conceptualization, and commercialization. The findings support the perception that artificial intelligence is an important driver of efficiency in innovation processes, creativity, and process improvement of product development functions.

Likewise, AI and Strategic Sourcing Efficiency relationship gave an unstandardized estimate of 1.18 with a standard error of 0.0549. High precision in the estimation is once again evidenced by the 95 percent confidence interval (1.07 -1.28). The standardised coefficient (1.12) is strong and positive, which implies that an increased dependence on the AI technologies is correlated with better sourcing performance. The fact that the z-value of 21.4 is less than the p-value of 0.001 is a confirmation that this relationship is statistically significant. This observation shows that AI is useful in enhancing sourcing efficiency through improved responsiveness, cost-saving, flexibility, and quality of products. These results show operational perfection due to increased automation, data integration, and predictive analytics in procurement and supply chain management.

In general, the findings are very favourable to the developed hypotheses that artificial intelligence has a strong and positive impact both on the ability to develop new products (innovation capability) and operational capability (strategic sourcing efficiency). Effect sizes and confidence intervals are always large, and this indicates a strong and well-fitting structural model. Theoretically, these conclusions indicate the strategic value of AI as a performance-enhancing aspect that makes the transition between technological adoption and real organisational performance in the context of modern companies, making it both an engine of innovation and efficiency.

Figure 1 - Path Model

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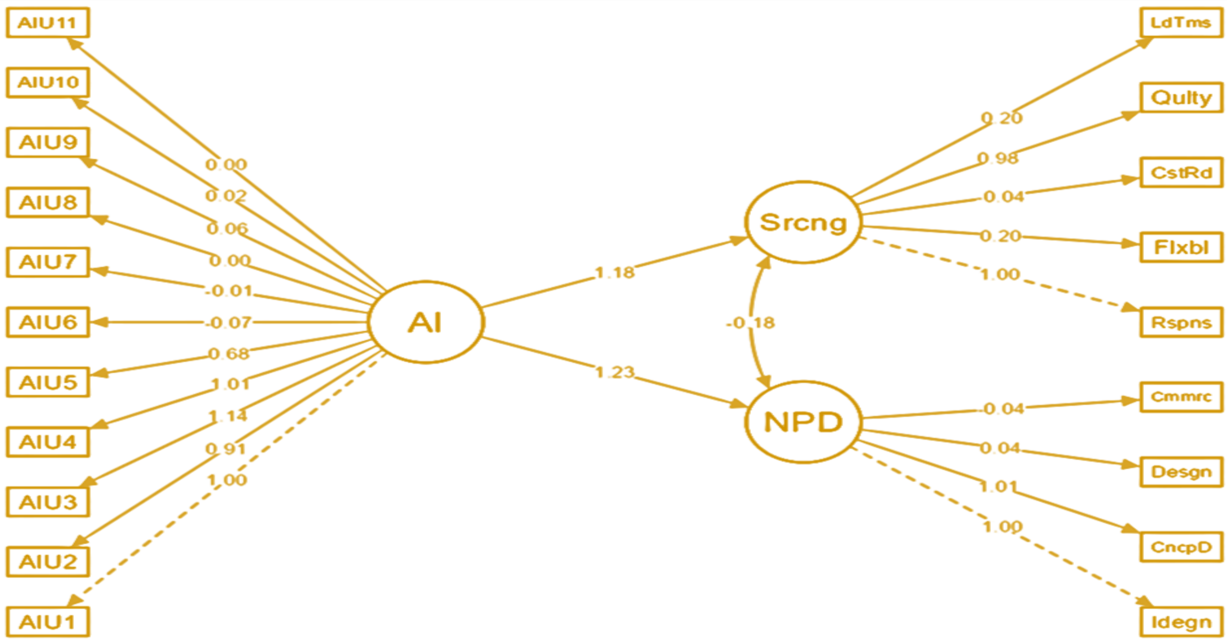

Table 5 - Measurement model

				95% Confidence Intervals				
Latent	**Observed**	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**z**	**p**
Artificial Intelligence (AI)	**AIU1**	1.00000	0.0000	1.0000	1.0000	0.66735		
	AIU2	0.91336	0.0588	0.7980	1.0287	0.67227	15.5225	<.001
	AIU3	1.13580	0.0724	0.9939	1.2777	0.68285	15.6875	<.001
	AIU4	1.00625	0.0654	0.8780	1.1344	0.66338	15.3838	<.001
	AIU5	0.67586	0.0517	0.5745	0.7772	0.51868	13.0745	<.001
	AIU6	-0.07058	0.0429	-0.1547	0.0136	-0.04665	-1.6441	0.100
	AIU7	-0.01439	0.0433	-0.0992	0.0704	-0.00939	-0.3326	0.739
	AIU8	0.00379	0.0392	-0.0731	0.0807	0.00273	0.0966	0.923
	AIU9	0.05631	0.0497	-0.0412	0.1538	0.03204	1.1324	0.257
	AIU10	0.02306	0.0431	-0.0614	0.1075	0.01511	0.5349	0.593
	AIU11	0.00211	0.039	-0.0755	0.0797	0.00150	0.0532	0.958

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			6					
New Product Development	**Idea Generation**	1.00000	0.0000	1.0000	1.0000	0.99111		
	Concept Development	1.00731	0.0101	0.9875	1.0271	0.98990	99.7042	<.001
	Product Designing	0.04253	0.0533	-0.0619	0.1470	0.03997	0.7979	0.425
	Commercialization	-0.03718	0.0515	-0.1380	0.0637	-0.03621	-0.7226	0.470
Strategic Sourcing Efficiency	**Responsiveness**	1.00000	0.0000	1.0000	1.0000	0.99338		
	Flexibility	0.20463	0.0498	0.1070	0.3022	0.20167	4.1084	<.001
	Cost Reduction	-0.04229	0.0507	-0.1416	0.0570	-0.04177	-0.8344	0.404
	Product Quality	0.97695	0.0111	0.9551	0.9988	0.98171	87.7974	<.001
	Lead Times	0.19730	0.0492	0.1009	0.2937	0.19717	4.0128	<.001

Table 5 of Measurement Model is a more in-depth estimation of the correlation between the latent constructs which are Artificial Intelligence (AI), New Product Development and Strategic Sourcing Efficiency and the observed indicators. In the case of the Artificial Intelligence (AI) construct, the base variable is AIU1, which is set at 1.000, and its standardised loading (867) is the reference variable. The five indicators (AIU2 to AIU5) have strong and statistically significant positive loadings (0.518 to 0.683, all p <.001), which validates them as effective measures of the AI construct. The following indicators (AIU6 to AIU11) however, have non-significant loadings (p > 0.05) which implies that they hardly contribute to the latent construct or are negligible. Idea Generation is configured as the reference indicator in the New Product Development dimension (= 0.991), and also, the relationship between Concept Development is strong and significant (= 0.990, p <.001). On the contrary, the loadings of Product Designing and Commercialization are non-significant and low (p > 0.05), implying that they do not affect the overall construct to a large degree. To achieve Strategic Sourcing Efficiency, Responsiveness is the reference indicator (= 0.993) and Flexibility, Product Quality and Lead Times have significant and high positive loadings (= 0.197 to 0.982 all with p <.001), showing that they contribute a significant amount to the construct. Non-significant relationship, however, is exhibited by Cost Reduction (p = 0.404). Generally, the model suggests that, although some of the indicators, especially AIU2 to AIU5, Concept Development, and Product Quality strongly depict their latent constructs, some indicators have weak or no significant associations, and as such, they can be refined or eliminated to enhance measurement validity of the model.

Table 6 - Variances and Covariances

	95% Confidence Intervals	

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Variable 1	Variable 2	Estimate	SE	Lower	Upper	β	z	p
AIU1	AIU1	0.73092	0.04150	0.64958	0.8123	0.5546	17.61	<.001
AIU2	AIU2	0.59372	0.03365	0.52777	0.6597	0.5481	17.64	<.001
AIU3	AIU3	0.86660	0.04893	0.77069	0.9625	0.5337	17.71	<.001
AIU4	AIU4	0.75610	0.04300	0.67183	0.8404	0.5599	17.59	<.001
AIU5	AIU5	0.72841	0.04411	0.64197	0.8149	0.7310	16.51	<.001
AIU6	AIU6	1.34022	0.09451	1.15499	1.5255	0.9978	14.18	<.001
AIU7	AIU7	1.37835	0.09734	1.18757	1.5691	0.9999	14.16	<.001
AIU8	AIU8	1.13360	0.08006	0.97669	1.2905	1.0000	14.16	<.001
AIU9	AIU9	1.81106	0.12781	1.56055	2.0616	0.9990	14.17	<.001
AIU10	AIU10	1.36691	0.09652	1.17773	1.5561	0.9998	14.16	<.001
AIU11	AIU11	1.15410	0.08151	0.99436	1.3139	1.0000	14.16	<.001
Idea Generation	Idea Generation	0.01322	0.00195	0.00941	0.0170	0.0177	6.79	<.001
Concept Development	Concept Development	0.01528	0.00204	0.01128	0.0193	0.0201	7.48	<.001
Product Designing	Product Designing	0.82965	0.05859	0.71481	0.9445	0.9984	14.16	<.001
Commercialization	Commercialization	0.77322	0.05461	0.66619	0.8802	0.9987	14.16	<.001
Responsiveness	Responsiveness	0.00872	0.00142	0.00594	0.0115	0.0132	6.14	<.001
Flexibility	Flexibility	0.64460	0.04554	0.55535	0.7339	0.9593	14.16	<.001
Cost Reduction	Cost Reduction	0.66771	0.04716	0.57529	0.7601	0.9983	14.16	<.001
Product Quality	Product Quality	0.02343	0.00206	0.01940	0.0275	0.0362	11.39	<.001
Lead Times	Lead Times	0.62815	0.04437	0.54118	0.7151	0.9611	14.16	<.001
Artificial Intelligence (AI)	Artificial Intelligence (AI)	0.58690	0.07110	0.44755	0.7262	1.0000	8.25	<.001
New Product Development	New Product Development	-0.15640	0.01112	-0.17820	-0.1346	-0.2130	-14.06	<.001

Strategic Sourcing Efficiency	Strategic Sourcing Efficiency	-0.16050	0.00943	-0.17899	-0.1420	-0.2459	-17.01	<.001
New Product Development	Strategic Sourcing Efficiency	-0.17640	0.00977	-0.19554	-0.1572	-1.1134	-18.06	<.001

In table 6 The estimates of variability within and between the measured and unmeasured variables in the model, the standard errors of both (SE), the confidence interval, the standardised coefficients (ο), the z-values, and the level of significance (p-values) are presented in the table named Variances and Covariances. In the case of the Artificial Intelligence (AI) indicators (AIU11), the estimates of the variances are all statistically significant ($p < .001$), with the number of the estimations ranging between 0.5937 and 1.8111, which implies that the amount of unique variance in each of the observed variables is significant. The coefficients of these indicators (which are standardised) are have a range of between 0.53 to 1.00 implying moderate to high reliability between items. The same applies to the New Product Development as the variables Idea Generation and Concept Development have a small but significant variance (0.013222 and 0.01528 respectively) whereas Product Designing and Commercialization are also at a higher variance (0.82965 and 0.77322 respectively) and significant at $p <.001$. All indicators, such as Responsiveness, Flexibility, Cost Reduction, Product Quality, and Lead Times, in the case of Strategic Sourcing Efficiency demonstrate considerable variance estimates (0.0087 to 0.6677), which proves the consistency of measurement reliability. The latent variables variances also present some important outcomes Artificial Intelligence (AI) has a high estimate of variance (0.5869, $p <.001$), and New Product Development (-0.1564) and Strategic Sourcing Efficiency (-0.1605) have negative covariance values, which means that the constructs are inversely correlated. Moreover, the covariance between New Product Development and Strategic Sourcing Efficiency (-0.1764, $p <.001$) shows that these two constructs are strongly negatively correlated such that the higher the performance of one construct, the lower the performance of the other. Comprehensively, the table suggests that all the variances and covariances are significant, which means that measurement items are internally consistent, and at the same time, the negative associations between major latent constructs are significant.

Table 7 - Intercepts

			95% Confidence Intervals			
Variable	**Intercept**	**SE**	**Lower**	**Upper**	**z**	**p**
AIU1	3.711	0.057	3.598	3.823	64.730	<.001
AIU2	3.845	0.052	3.744	3.947	73.983	<.001
AIU3	3.411	0.064	3.287	3.536	53.612	<.001
AIU4	3.883	0.058	3.769	3.997	66.910	<.001
AIU5	3.810	0.050	3.713	3.908	76.439	<.001
AIU6	3.077	0.058	2.964	3.191	53.172	<.001
AIU7	3.910	0.059	3.795	4.025	66.692	<.001
AIU8	4.032	0.053	3.928	4.137	75.841	<.001

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AIU9	3.788	0.067	3.656	3.920	56.337	<.001
AIU10	3.880	0.058	3.766	3.995	66.454	<.001
AIU11	4.022	0.054	3.917	4.128	74.979	<.001
Idea Generation	3.728	0.043	3.643	3.812	86.346	<.001
Concept Development	3.711	0.044	3.625	3.796	85.228	<.001
Product Designing	3.664	0.046	3.575	3.753	80.492	<.001
Commercialization	3.716	0.044	3.630	3.802	84.563	<.001
Responsiveness	3.737	0.041	3.658	3.817	92.021	<.001
Flexibility	3.740	0.041	3.660	3.820	91.369	<.001
Cost Reduction	3.748	0.041	3.668	3.828	91.760	<.001
Product Quality	3.738	0.040	3.659	3.817	93.110	<.001
Lead Times	3.735	0.040	3.656	3.814	92.521	<.001
Artificial Intelligence (AI)	0.000	0.000	0.000	0.000		
New Product Development	0.000	0.000	0.000	0.000		
Strategic Sourcing Efficiency	0.000	0.000	0.000	0.000		

Table 7 named Intercepts shows the estimated mean of the observed and the latent variables, which are the expected scores of the variables when all the predictors are kept constant. The intercept value of the Artificial Intelligence (AI) indicators (AIU1-AIU11) is between 3.077 and 4.032 with highly significant z-values (between 53.172 and 76.439) and p-values of less than.001, which means that they are statistically significant and that the observed variables are consistently a part of the AI construct. AIU8 (4.032) and AIU11 (4.022), among them, have the biggest intercepts implying that these indicators have better baseline levels in comparison with others. The Intercepts of Idea Generation, Concept Development, Product Designing, and Commercialization in the New Product Development construct fall within a very strong range of 3.664 to 3.728 all significant at p =.001 suggesting that the contribution of these indicators to the construct is stable and equal. On the same note, the Strategic Sourcing Efficiency dimension, consisting of Responsiveness, Flexibility, Cost Reduction, Product Quality, and Lead Times, also exhibits a strong conformity between intercept values of 3.735- 3.748 and very high z-values (above 91) and p <.001. Latent constructs Artificial Intelligence (AI), New Product Development and Strategic Sourcing Efficiency intercepts are all set to 0.000, which is a usual convention of structural equation modelling, to act as a reference point to calculate observed means of variables. On the whole, all the measured indicators in the three constructs indicate highly significant and positive intercepts, which demonstrate good performance at the baseline and inter-measurement consistency throughout the model.

Discussion and Conclusion

This paper set out to examine the effects of artificial intelligence (AI) on the development of new products and efficiency in strategic sourcing. The results were very informative in terms of how AI-powered technologies can achieve products innovation and optimization of procurement. The impact of AI on the new product development was demonstrated in its capability to simplify the Product Designing processes, improve the prototyping and provide the data-driven decision making. Machine learning and generative AI were instrumental in the quickening of innovations, and helped companies discover any new trends in the market, optimise Product Designing s, and shorten development periods (Bilgram and Laarmaan, 2023). Predictive analytics also contributed to the creation of AI, which made the companies more responsive to any alterations in consumer preferences (Columbus, 2020). The findings can be compared to the existing studies stressing the transformative power of AI in efficient management of innovation and product development (Brem et al., 2023). The research on AI-enhanced prototyping also showed how corporations like General Electric have cut their product development time by a significant margin using AI-enhanced simulations and digital twins, which confirmed the findings of this research (Bogaisky, 2019).

Within the framework of strategic sourcing, the findings were used to identify the presence of AI in the automation of procurement decisions, enhancing supplier selection, and optimising contract negotiation. The AI-powered systems reviewed large data volumes to obtain cost-saving opportunities, increase risk management, and enhance supply chain transparency (Handfield et al., 2019). The adoption of AI-based predictive analytics has enabled companies to make more knowledge-based decisions in sourcing, thus making procurement more effective and efficient. These findings were aligned with previous reports that highlighted how AI can transform procurement processes by reducing manpower, maximising accuracy, and streamlining relationships with suppliers (Kosmol et al., 2019). In addition, the potential of AI to enhance cost efficiency in the procurement process has been highlighted in the previous literature, and researchers report that AI-driven procurement models are becoming more and more popular in the global supply chain (Loureiro et al., 2021). The research also supported the statements of Hallikas et al. (2021) who opined that digital procurement improves the performance of the supply chain using AI to make real-time decisions and analyse data.

All in all, the current study made a contribution to the increased literature on the transformative nature of AI in the functioning of businesses. Although AI has already proven to be a great way of product development and procurement, the possibility in this area has not yet been fully exploited. Subsequent studies ought to examine the possible long-term consequences of AI implementation in other sectors with regard to ethical issues, the difficulties in the implementation process, and the changing aspects of technology. The results highlighted the strategic significance of AI, which beats it an essential instrument of organisations that aim to gain efficiency, innovation, and competitiveness in a digitalized business environment.

Study Implications

This paper offers an important understanding of how AI can be used to improve the product development and has contributed to optimising strategic sourcing, to enable organisations to harness the power of AI to become innovative and efficient. Companies are able to combine AI-based predictive analytics to automate decision-making, decrease the time required to develop a product, and enhance the accuracy of procurement. The conclusions provide some practical implication to managers that may be willing to use AI solutions in supply chain management and new product Product Designing. These insights can guide policymakers to formulate the regulations that favour AI implementation and curb the risks of AI implementation. The future of research should be based on the long-term effects of AI on business sustainability and competitive advantage.

Future Scope of the Study

The study can be furthered in the future to examine how AI use in product development and procurement would affect different industries in the long run. It is possible to study the ethical, regulatory, and security issues that relate to the AI-driven decision-making. There is an opportunity of research on the integration of AI and emerging technologies such as blockchain and IoT in supply chains. The future studies regarding the role of AI in sustainable procurement and its contribution to environmental and social governance (ESG) should be conducted. The growth of AI usage in the fluid market setting has the potential to give more accurate insights into its versatility and potential in future.

References

[1] Akter, S., Bandara, R., Hani, U., Wamba, S. F., Foropon, C., & Papadopoulos, T. (2023). Artificial intelligence in business: From research and innovation to market deployment. Journal of Business Research, 144, 657–669. https://doi.org/10.1016/j.jbusres.2022.12.085

[2] Applied Marketing Science. (2023). Machine learning uncovers key insights for snow removal. Retrieved from https://ams-insights.com/case-study/machine-learning-uncovers-key-insights-for-snow-removal/

[3] Bag, S., Wood, L. C., Mangla, S. K., & Luthra, S. (2020). Procurement 4.0 and its implications on business process performance in a circular economy. Resources, Conservation and Recycling, 152, 104502. https://doi.org/10.1016/j.resconrec.2019.104502

[4] Barrad, S., Gagnon, S., & Valverde, R. (2020). An analytics architecture for procurement. International Journal of Information Technology & Systems Approach (IJITSA), 13(2), 73-98. https://doi.org/10.4018/IJITSA.2020070104

[5] Baryannis, G., Dani, S., & Antoniou, G. (2019a). Predicting supply chain risks using machine learning: The trade-off between performance and interpretability. Future Generation Computer Systems, 101, 993-1004. https://doi.org/10.1016/j.future.2019.07.059

[6] Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019b). Supply chain risk management and artificial intelligence: State of the art and future research directions. International Journal of Production Research, 57(7), 2179-2202. https://doi.org/10.1080/00207543.2018.1530476

[7] Bienhaus, F., & Haddud, A. (2018). Procurement 4.0: Factors influencing the digitisation of procurement and supply chains. Business Process Management Journal, 24(4), 965-984. https://doi.org/10.1108/BPMJ-06-2017-0139

[8] Bilgram, V., & Laarmaan, F. (2023). Accelerating innovation with generative AI: AI-augmented digital prototyping and innovation methods. IEEE Engineering Management Review, 51(2), 18–25. https://doi.org/10.1109/EMR.2023.3272799

[9] Bogaisky, J. (2019, March 9). GE says it's leveraging artificial intelligence to cut product Product Designing times in half. Forbes. Retrieved from https://www.forbes.com/sites/jeremybogaisky/2019/03/06/general-electric-ge-artificial-intelligence/?sh=20c1d115d881

[10] Brem, A., Giones, F., & Werle, M. (2023). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. https://doi.org/10.1109/TEM.2021.3109983

[11] Brossard, M., Gatto, G., Gentile, A., Merle, T., & Wlezien, C. (2020, February 5). How generative Product Designing could reshape the future of product development. McKinsey. Retrieved from https://www.mckinsey.com/capabilities/operations/our-insights/how-generative-Product Designing -could-reshape-the-future-of-product-development

[12] Brynjolfsson, E., & McAfee, A. (2017). Machine, platform, crowd: Harnessing our digital future. W.W. Norton & Company.

[13] Chehbi-Gamoura, S., Derrouiche, R., Damand, D., & Barth, M. (2020). Insights from big data analytics in supply chain management: An all-inclusive literature review using the SCOR model. Production Planning & Control, 31(5), 355-382. https://doi.org/10.1080/09537287.2019.1639839

[14] Chen, J., Reilly, R. R., & Lynn, G. S. (2010). The efficiency of firms' product development processes: The moderating role of knowledge management. R&D Management, 40(5), 484–497. https://doi.org/10.1111/j.1467-9310.2010.00610.x

[15] Collins, H., Evans, R., & Gorman, M. (2021). The origins of AI research: The Dartmouth Conference, 1956. In History of Artificial Intelligence (pp. 10–30). Springer.
[16] Columbus, L. (2020, July 9). 10 ways AI is improving new product development. Forbes. Retrieved from https://www.forbes.com/sites/louiscolumbus/2020/07/09/10-ways-ai-is-improving-new-product-development/?sh=27a90ce45d3c
[17] Cooper, R. G. (1983). A process model for industrial new product development. IEEE Transactions on Engineering Management, EM-30(1), 2–11. https://doi.org/10.1109/TEM.1983.6447467
[18] Cooper, R. G. (1990). Stage-Gate systems: A new tool for managing new products. Business Horizons, 33(3), 44–54. https://doi.org/10.1016/0007-6813(90)90040-I
[19] Cooper, R. G. (2019). Agile–Stage-Gate for Manufacturers: Changing the Way New Products Are Developed. Research-Technology Management, 62(1), 12–19. https://doi.org/10.1080/08956308.2018.1544985
[20] Dahan, E., & Hauser, J. R. (2000). The virtual customer. The Journal of Product Innovation Management, 17(4), 275–279. https://doi.org/10.1016/S0737-6782(00)00031-5
[21] Deeb, G. (2023, September 6). Artificial intelligence is taking over marketing. Forbes. Retrieved from https://www.forbes.com/sites/georgedeeb/2023/09/06/artificial-intelligence-is-taking-over-marketing/?sh=4e82c8c15588
[22] Eastwood, B. (2023, March 6). Artificial intelligence can help Product Designing more appealing cars. MIT Management Sloan School. Retrieved from https://mitsloan.mit.edu/ideas-made-to-matter/artificial-intelligence-can-help-Product Designing -more-appealing-cars
[23] Euchner, J. (2023). ChatGPT and generative AI. Research Technology Management, 66(3), 71–74. https://doi.org/10.1080/08956308.2023.2188861
[24] Forsey, C., & Mishra, D. (2023, June 28). How AI will revolutionize product development and how to prepare [insights from AWS' senior advisor to startups]. HubSpot. Retrieved from https://blog.hubspot.com/marketing/how-ai-will-revolutionize-product-development
[25] Giunipero, L. C., Hooker, R. E., & Denslow, D. (2012). Purchasing and supply management sustainability: Drivers and barriers. Journal of Purchasing and Supply Management, 18(4), 258-269. https://doi.org/10.1016/j.pursup.2012.06.003
[26] Glas, H. A., & Kleemann, C. F. (2016). The impact of Industry 4.0 on procurement and supply management: A conceptual and qualitative analysis. International Journal of Business and Management Invention, 5(6), 55-66.
[27] Griffin, A. (1997). The effect of project and process characteristics on product development cycle time. Journal of Marketing Research, 34(1), 24–35. https://doi.org/10.1177/002224379703400103
[28] Guo, Z. X., & Wong, W. K. (2013). Fundamentals of artificial intelligence techniques for apparel management applications. In Optimizing Decision Making in the Apparel Supply Chain Using Artificial Intelligence (AI): From Production to Retail (pp. 13-40). https://doi.org/10.1533/9780857097842.13
[29] Guszcza, J., Mahoney, S., Koo, A., & Moodie, S. (2017). The power of people in the AI era. Deloitte Review, 20, 1–16.
[30] Hallikas, J., Immonen, M., & Brax, S. (2021). Digitalizing procurement: The impact of data analytics on supply chain performance. Supply Chain Management: An International Journal, 26(5), 629-646. https://doi.org/10.1108/SCM-05-2020-0201
[31] Handfield, R., Jeong, S., & Choi, T. (2019). Emerging procurement technology: Data analytics and cognitive analytics. International Journal of Physical Distribution & Logistics Management, 49(10), 972-1002. https://doi.org/10.1108/IJPDLM-11-2017-0348

[32] Helfrich, T. (2022, August 12). 10 ways to use AI for a successful product launch. Forbes. Retrieved from https://www.forbes.com/sites/forbestechcouncil/2022/08/12/10-ways-to-use-ai-for-a-successful-product-launch/?sh=3e7ae39274b1
[33] Huo, B., Zhao, X., Zhou, H., & Zhao, J. (2020). Role of artificial intelligence applications in new product development: A resource-based perspective. IEEE Transactions on Engineering Management, 67(3), 793–804. https://doi.org/10.1109/TEM.2019.2909593
[34] Jaggaer. (2019). Digital transformation in procurement: How close are we? - A study based on the complete results of the Global JAGGAER Digital Procurement Survey.
[35] Jha, S., & Topol, E. J. (2016). Adapting to artificial intelligence: Radiologists and pathologists as information specialists. JAMA, 316(22), 2353–2354. https://doi.org/10.1001/jama.2016.17438
[36] Kahn, K. B., Barczak, G., Moss, R., & Leon, J. (2012). Perspectives on new product development research: A status report. Journal of Product Innovation Management, 29(4), 659–671. https://doi.org/10.1111/j.1540-5885.2012.00924.x
[37] Kakatkar, C., Ferreira, J. J., Nobre, H., & Ali, M. (2020). The role of AI in new product development: Implications for innovation management. Technological Forecasting and Social Change, 151, 119784. https://doi.org/10.1016/j.techfore.2019.119784
[38] Kosmol, T., Reimann, F., & Kaufmann, L. (2019). You'll never walk alone: Why we need a supply chain practice view on digital procurement. Journal of Purchasing and Supply Management, 25(4), 100553. https://doi.org/10.1016/j.pursup.2019.100553
[39] Lee, I., Lee, K., & Park, H. (2019). AI-enabled smart services for business and society. The Journal of Open Innovation: Technology, Market, and Complexity, 5(2), 28. https://doi.org/10.3390/joitmc5020028
[40] Lorentz, H., Aminoff, A., Kaipia, R., Pihlajamaa, M., Ehtamo, J., & Tanskanen, K. (2020). Acquisition of supply market intelligence – An information processing perspective. Journal of Purchasing and Supply Management, 26(5), 100649. https://doi.org/10.1016/j.pursup.2020.100649
[41] Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2021). Artificial intelligence in business: State of the art and future research agenda. Journal of Business Research, 129, 911-926. https://doi.org/10.1016/j.jbusres.2020.11.001
[42] Luzzini, D., Amann, M., Caniato, F., Essig, M., & Ronchi, S. (2015). The path of innovation: Purchasing and supplier involvement into new product development. Industrial Marketing Management, 47, 109-120. https://doi.org/10.1016/j.indmarman.2015.02.034
[43] Marr, B. (2023, July 25). The future of manufacturing: Generative AI and beyond. Forbes. Retrieved from https://www.forbes.com/sites/bernardmarr/2023/07/25/the-future-of-manufacturing-generative-ai-and-beyond/?sh=7cdfd45051fa
[44] Marshall, D., McCarthy, L., Heavey, C., & McGrath, P. (2015). Environmental and social supply chain management sustainability practices: Construct development and measurement. Production Planning & Control, 26(8), 673-690. https://doi.org/10.1080/09537287.2014.963726
[45] McGrath, R. G., & Lánszti, A. (1998). Innovation in project-based firms: The case of new product development. Organization Science, 9(3), 345–366. https://doi.org/10.1287/orsc.9.3.345
[46] Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. International Journal of Logistics Research and Applications, 13(1), 13-39. https://doi.org/10.1080/13675560902736537
[47] Moretto, A., Ronchi, S., & Patrucco, A. S. (2017). Increasing the effectiveness of procurement decisions: The value of big data in the procurement process. International Journal of RF Technologies: Research and Applications, 8(3), 79-103. https://doi.org/10.3233/RFT-171670

[48] Mugurusi, G., & Oluka, P. N. (2021). Towards explainable artificial intelligence (XAI) in supply chain management: A typology and research agenda. In IFIP International Conference on Advances in Production Management Systems (pp. 32-38).
[49] Nambisan, S. (2003). Information systems as a reference discipline for new product development. MIS Quarterly, 27(1), 1–18. https://doi.org/10.2307/30036535
[50] Naveh, E. (2005). The effect of process management on product development performance: The mediating role of innovation and efficiency. International Journal of Production Research, 43(16), 3437–3454. https://doi.org/10.1080/00207540500142482
[51] Nieto-Rodriguez, A., & Vargas, R. V. (2023, February 2). How AI will transform project management. Harvard Business Review. Retrieved from https://hbr.org/2023/02/how-ai-will-transform-project-management
[52] Palzer, S. (2022). Meaningful innovation to unlock growth. Nestlé Investors Seminar, Barcelona, Spain. Retrieved from https://www.nestle.com/sites/default/files/2022-12/investor-seminar-2022-innovation-transcript.pdf
[53] Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. Information Systems Research, 17(3), 198–227. https://doi.org/10.1287/isre.1060.0094
[54] Ponce, P., Rodríguez, C., & Gómez, A. (2022). Analytical AI frameworks for smart business systems. Information Systems Frontiers, 24(1), 111–130. https://doi.org/10.1007/s10796-021-10182-5
[55] Prem, R. (2019). The AI revolution and its impact on customer service. Journal of Business and Management, 11(4), 15–28.
[56] Procter and Gamble. (2022, March 1). Leveraging technology to improve the lives of P&G consumers. Retrieved from https://us.pg.com/blogs/executive-talks-innovation-vittorio-cretella/
[57] PwC. (2019). Artificial intelligence is here: How AI is changing business. PricewaterhouseCoopers. Retrieved from https://www.pwc.com/gx/en/issues/data-and-analytics/artificial-intelligence.html
[58] Schnellbächer, W., Weise, D., Tevelson, R., & Högel, M. (2018). Jump-starting the digital procurement journey. Boston Consulting Group. Retrieved from https://www.bcg.com/publications/2018/jump-starting-digital-procurement-journey
[59] Schütz, K., Kässer, M., Blome, C., & Foerstl, K. (2020). How to achieve cost savings and strategic performance in purchasing simultaneously: A knowledge-based view. Journal of Purchasing and Supply Management, 26(2), 100553. https://doi.org/10.1016/j.pursup.2019.04.002
[60] Siemens. (2023). Airplane manufacturer uses Siemens solutions to reduce product development time for all-electric composite aircraft. Retrieved from https://resources.sw.siemens.com/en-US/case-study-bye-aerospace?bc=eyJwYWdlIjoiMjhSa2ZFOEtnaFpiSlhXajllMUR6UCIsInNpdGUiOiJkaXN3IiwibG9jYWxlIjoiZW4tVVMifQ
[61] Simon, H. A. (1995). Artificial intelligence: An empirical science. Artificial Intelligence, 77(1), 95–127.
[62] Stafford, T. F., Jackson, K. C., & Thorne, M. (2020). Artificial intelligence applications in business: A review of current practice and future opportunities. Journal of Business Research, 116, 274–287. https://doi.org/10.1016/j.jbusres.2020.05.024
[63] Tang, L., Weng, W., & Chen, L. (2020). Transforming business with AI: Challenges and opportunities. Management Decision, 58(9), 1883–1898. https://doi.org/10.1108/MD-06-2019-0827

[64] Tao, F., Zhang, M., Liu, Y., & Nee, A. Y. C. (2023). Digital twin driven smart manufacturing: Pathways to dynamic new product development. Computers in Industry, 138, 103683. https://doi.org/10.1016/j.compind.2022.103683
[65] Uber. (2023). Using data predictions to apply Uber-like dynamic pricing. Retrieved from https://www.obviously.ai/post/using-data-predictions-to-apply-uber-like-dynamic-pricing
[66] Van Houtven, C., & ChatGPT. (2023, May 5). How artificial intelligence is accelerating digital product development. LinkedIn. Retrieved from https://www.linkedin.com/pulse/how-artificial-intelligence-accelerating-digital-van-houtven
[67] van Weele, A. J., & van Raaij, E. M. (2014). The future of purchasing and supply management research: About relevance and rigor. Journal of Supply Chain Management, 50(1), 56-72. https://doi.org/10.1111/jscm.12042
[68] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain Product Designing and management. Journal of Business Logistics, 34(2), 77-84. https://doi.org/10.1111/jbl.12010
[69] Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2016). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. International Journal of Production Economics, 176, 98-110. https://doi.org/10.1016/j.ijpe.2016.03.014
[70] Wind, Y., Robertson, T. S., & Tashchian, A. (1997). Marketing research and new product development in the 1990s. Marketing Science Institute Report No. 97-103.
[71] Wu, D., Olson, D. L., & Dolgui, A. (2017). Artificial intelligence in engineering risk analytics. Engineering Applications of Artificial Intelligence, 65, 433-435. https://doi.org/10.1016/j.engappai.2017.09.001
[72] Zhang, Y., Huang, G. Q., & Qu, T. (2021). Revisiting the stages of new product development: An integrated framework for idea development to operations management. Journal of Engineering and Technology Management, 60, 101622. https://doi.org/10.1016/j.jengtecman.2021.101622