Unlocking Innovation in Manufacturing: The Impact of Data Analytics Maturity and Knowledge-Oriented Leadership

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ABSTRACT

This study examines the impact of data analytics maturity on innovation capabilities in Pakistan's manufacturing sector, emphasizing the mediating role of knowledge-oriented leadership. It also investigates the distinct influence of data science skills and data analytical skills on explorative and exploitative innovation capabilities. This research fills a gap in the literature by exploring how organizations can leverage data competencies alongside leadership to drive innovation within a developing economy. A deductive methodology was adopted, with data collected from 354 respondents in manufacturing firms across Lahore, Faisalabad, Karachi, and Sialkot. Convenience sampling was employed, and Structural Equation Modeling (SEM) with Smart PLS 4.0 was utilized for data analysis. To ensure reliability, validity and robustness, the study assessed outer loadings, R-squared values and variance inflation factors. Results indicate that data analytical skills significantly influence both explorative and exploitative innovation capabilities, while data science skills have a stronger impact on explorative innovation. Knowledge-oriented leadership plays a crucial mediating role, reinforcing the importance of leadership in translating data competencies into innovation outcomes. The empirical findings confirm that knowledge-oriented leadership enhances both types of innovation, supporting theories of transformational leadership and organizational learning. The model exhibited strong explanatory power, with statistically significant path coefficients supporting the acceptance of all hypotheses. The study underscores that while data capabilities are essential, their impact on innovation is maximized when complemented by effective leadership. These findings contribute to research on digital transformation and innovation management, offering practical insights for manufacturing firms to integrate data-driven decision-making with leadership development. By fostering data analytics maturity and knowledge-oriented leadership, organizations can enhance their innovation capabilities, ensuring a sustainable competitive advantage in the era of Industry 4.0.

Keywords: Data analytics maturity, Knowledge-oriented leadership, Explorative innovation, Exploitative innovation, Manufacturing sector, Structural Equation Modeling (SEM)

1. Introduction

Worldwide, Digital technology and data analysis techniques interventions have fueled major increase in progress in manufacturing industries [1]. This sort of change is called as Industry 4.0 which makes organizations think about the utilizations of data, yield outputs and spark new ideas [2, 3]. Those manufacturers who are working in emerging markets are starting to look around for getting better ways to utilize the data analytics leading their selves to cutting-edge innovation [4]. This should help them to stay competitive in increasingly digitalized world[5].

Right people and right leaders governing those people really matter to direct and utilize the data effectively and this only happens if they know about the data analytics techniques [6]. This current study looks in to how good a manufacturing organization is in terms of utilizing the data analytical techniques which is driven by social sciences and analytical skills. According to ul Amin, Shehzad [7], Knowledge about the data analytical techniques really help leaders to innovate and explore new ideas in manufacturing industry of Pakistan. This would really help the manufacturing industries to innovate. *This current study delves into how knowledge-oriented leadership focuses on effective utilizations of knowledge which helps turn insights from data into lasting innovation*.

Although this is a fact that more and more practitioners working in, see data analytics as a major contributor to apply new ideas [8, 9], lots are having trouble to apply such data analytics and data science skills in to their advantage [10]. In the developed countries such as US, Japan, Germany have smoothly blended data driven techniques into their strategies for innovation in automotive making industries [11].

Businesses in developing nations are still facing lot of obstacles, like not having enough professional skilled workers, missing strong leadership and even though not having the right strategy to share organized knowledge[12]. Ever since, reaching up with new ideas is essential for a manufacturing organizations to be competitive and sustainable for a longer period of time in such as challenging world in chemical industry [12]. In addition to it, it is also necessary to drive out with the things that allow businesses to explore and exploit new innovations with the help of data science skills and data analytical techniques [13].

This current research article aims to examine the following objectives, 1) To examine the relationship between data analytics maturity such as data science skills (DS) and data analytical skills (DA) on explorative innovation capability (EXP) and exploitative innovation capability (EXI) in the manufacturing sector of Pakistan, 2) To examine the relationship amongst data science skills and data analytical skills on knowledge-oriented leadership of employees working in the manufacturing organizations of Pakistan, 3) To investigate the impact of knowledge-oriented leadership on explorative innovation capability, 4) To investigate the impact of knowledge-oriented leadership on exploitative innovation capability in the manufacturing sector context of Pakistan.5) To investigate the mediating impact of knowledge-oriented leadership between data analytics maturity i.e., data science skills and data analytics skills leading to innovation capabilities such as explorative innovation capability and, exploitative innovation capability in the manufacturing context of Pakistan.

The current research has its own significance and adding value in variety of ways both theoretically and in real-world scenarios. From a theoretical perspective, it is more focused on the manufacturing industry's utilization of data analytics capabilities leading to possessing an ability to innovate and investigate in the developing markets. It also makes leadership focused on the knowledge which connects the data utilization effectively leading to actual innovative results. On a practical level, these results can assist manufacturing organizations in Pakistan and in other like nations to raise a culture of giving value to the data, so that to improve their employee's skills and implement leadership typologies that encourage the sharing of knowledge and the development of innovative ideas.

Internationally, data science skills and data analytical skills have proven their worth in propelling innovation within the realm of Philippine manufacturing industry [14]. International manufacturing giants such as General Electric (GE) of United States of America (US), have harnessed the power of machine learning techniques and predictive analytics to fine-tune industrial processes, leading to a higher level of jumps in their efficiency and effectiveness [15, 16]. In Asia, China's "Made in China 2025" broader plan to chalk down not only but also implementing the big data analytics techniques in their smart manufacturing practices[17]. Furthermore, the utilization of big data analytical techniques, data science skills were also witnessed in the north Indian's manufacturing sector where data analytics techniques have been applied to boost innovation in supply chain processes and tailor products towards effectiveness[18].

This above comparative analysis of data analytics maturity techniques in the manufacturing sector across variety of regions revealed significant disparities in data analytical maturity and innovation performance [19]. In the developed world, such as USA and Germany, high level of data analytical maturity is witnessed which correlates with strong innovatory results as evidenced through the filing of over 150,000 patents respectively[20]. China with a medium to higher level of data analytics maturity, demonstrated a substantial innovation in terms of performance filing more than 120,000 patents [21]. In comparison, developing economies like India and Pakistan prove lower levels of data analytics adoption. India, with a medium maturity level, has a moderate innovation output, with over 80,000 patents filed, while Pakistan, with the lowest data analytics maturity, lags significantly behind, keeping only 10,000 patents[21].

This tendency underlines the crucial role of data analytics in driving innovation and highlights the need for developing economies to enhance their analytical capabilities to remain competitive in the global manufacturing view [22]. Pakistan's manufacturing industry gets itself at a critical point, where fully utilizing data analytics could completely revolutionize innovation [23]. Current research article strives to provide real-world proof of how data science and analytical skills boost exploratory innovation with prime focus on knowledge-oriented leadership in their processes [24].

To tackle current weaknesses in the manufacturing processes and provide actionable advice, this current study also hopes to equip manufacturing companies to employ their fullest innovation capabilities shaped by data based on the prior research undertaken by [25]. The manufacturing landscape is being transformed, largely driven by digital advancements and the potential of data analytics [26, 27]. As Industry 4.0 takes hold, manufacturers are finding innovative methods to polish their processes, improve efficiency and cultivate innovation in SME enterprises [28].

This digital revolution is specifically apparent in developing nations, where manufacturers recognize the advantage of leveraging data analytics to uncover novel concepts and maintain a competitive edge[27]. However, effective data utilization demands both competent technicians and leaders capable of making learned decisions derived from data insights [29]. *This study examines the impact of a manufacturing organization's data analytics proficiency specifically, their expertise in data science and analysis on their capacity for innovation within Pakistan's manufacturing sector. It further explores how leaders who prioritize knowledge contribute to translating data revelations into sustained innovation based on the prior works undertaken*. [30].

Finally, following the article's introduction section is the literature review which sheds light on empirical relationships between constructs and theoretical reflections behind the research model. After literature review, methodology and, then analysis and findings of the results conducted through SMART PLS 4.0. The final section is comprised of conclusion, discussion, implications and future research.

2. Literature Review

2.1 Innovation Capability

For a manufacturing company, being innovative is all about leveraging its knowledge, talents and sources to establish fresh, significant products in Vietnamese manufacturing sector organizations [30]. Manufacturing businesses must strike a balance between modification their current processes (recognized as exploitative innovation) and offering into unknown processes with entirely new concepts that could be central to different products or their entire business model (recognized as explorative innovation) [25]. Manufacturing organizations that are good at both sorts of innovation organization are dynamic organizations that really succeed and stay ahead in the long-term perspective [31].

Exploitative innovation boosts how completely things run and how dependable they are by modifying the ways businesses already operate [32]. It’s all about keeping products stable, making sure everyone involved is happy and saving money where possible. On the other side, explorative innovation is about existing adjustable and trying out innovative things to grow and reach new markets [33]. Manufacturing organizations that are really good at exploring are rapid to select up on innovations happening outside their walls, often pushing them ahead in today’s competitive world [34].

Researchers have extensively highlighted the requirement to reach a good equilibrium between exploiting innovatory ideas and exploring brand new ideas when it comes to innovation especially in the context of United Kingdom manufacturing firms [34]. But social scientists still don't have considerable concrete evidence viewing how a manufacturing company's level of data know-how shapes this equilibrium, especially in markets like Pakistan. Majority of the studies look at already well-off economies, leaving us in the dark about how going digital can spark innovation in places where resources are scarce[35].

If we can see across the world regarding the explorative and exploitative innovation, TESLA is a good example[36]. With the passage of time they are getting better and better in developing electric cars under the umbrella of exploring new products and also leading with an example in self-driving technology and energy storage which comes under the umbrella of exploitative innovation[36]. Toyota’s is applying technique such as *“Kaizen”* in their operations, being efficient[37]. At the same time, they are investing in making products with the assistance of artificial intelligence, which comes under the umbrella of exploring unique ideas[38]. In Pakistan, automation to develop new things and making environmental packaging is undertaken by Packages Limited[39].

2.2 Knowledge-Oriented Leadership

Leadership is fundamental when it comes to driving decisions based on data and accepting innovativeness through technologies [40]. Leaders who prioritize knowledge go beyond the old ways of managing, promoting both the discovery of new knowledge (exploration) and its practical use (exploitation)[41]. Good leaders make it easier to share data throughout the company, making sure that the insights gained from data analysis line up perfectly with the overall objectives [42]. While the link between leadership and digital transformation is a well-researched topic[43-45], there's a clear lack of deep dives into how this link plays out in specifically the manufacturing industries within developing countries.

Additionally, past studies have often remained persistent on individual leadership traits rather than examining the formal organizational frameworks that encourage leadership procedures initiated with the knowledge [46-48]. Around the globe, manufacturing organizations such as General Electric (GE) are pioneers in this field, integrating AI and analytics into their decision-making, thus fostering a culture that prioritizes knowledge [49, 50]. In Asia, Samsung's leadership is strategically employing big data to spearhead breakthroughs in semiconductor technology [51]. Meanwhile, in Pakistan, the Fauji Fertilizer Company (FFC) is implementing a leadership style concentrated on knowledge to polish their supply chain management [52].

2.3 Theoretical Justification

Current research presents relationships between data science abilities, data analysis skills, leadership focused on knowledge and the capacity for innovation. These relationships can be backed up with established theories. When research discussed about direct effects, we mean the straight-up, immediate way one factor affects another. For example, leadership that emphasizes knowledge has a significant impact on the ability to innovate in an exploitative way [53, 54]. This aligns with the knowledge-based view proposed by [55], suggesting that leaders who make sharing knowledge a priority help bring about gradual improvements[56]. Also, skills in data science affect knowledge-focused leadership which is linked with upper echelons theory [57]. This theory suggests that a leader's actions are shaped by their specific expertise[58].

Data science skills really matter when it comes to a company's ability to innovate in a couple of key ways [59]. First, through what's called dynamic capabilities theory, as explained by [60], having strong analytical skills helps businesses improve the things they're already doing - this is known as exploitative innovation. Second, according to absorptive capacity theory, as put forward by [61], companies with top-notch data science skills are better at bringing in new ideas from outside and using them to come up with completely new innovations. Also, leaders who focus on knowledge, as suggested by transformational leadership theory [62], can really boost a company's ability to be a creatively innovative by being visionary and inspiring[63].

According to Barney [64], Data analytical skills can also influence knowledge-oriented leadership, as supported by the resource-based view. This perspective indicates that robust analytical abilities provide leaders with valuable strategic insights[64]. Furthermore, data analysis capabilities impact the ability to engage in exploitative innovation, a concept grounded in the technology-organization-environment framework [65, 66]. This framework posits that advanced analytics enhance operational efficiency. The capability for exploratory innovation is illuminated by disruptive innovation theory [67], which proposes that companies utilizing sophisticated data analytics can produce groundbreaking innovations.

The Phenomenon that indirect effects happen when an independent variable impacts a dependent variable through a mediating variable, specifically knowledge-oriented leadership. According to Fiedler [68], Data science skills enhance knowledge-oriented leadership, which subsequently increases the potential for exploitative innovation. This reverberates the leadership contingency theory [68], suggesting that leadership effectiveness relies on the availability of expertise and resources.

As per organizational learning theory, which underlines the role of leaders in fostering a learning culture that encourages innovation, data science skills affect explorative innovation capability via knowledge-oriented leadership [69, 70]. Data science skills can sway the capacity for explorative innovation[71].

Data analysis skills influence a leader's ability to drive exploratory innovation, a big thanks to knowledge-focused leadership. This idea is supported by the digital leadership model [72], which explains how leadership driven by data can enhance innovation within an organization. Likewise, the capacity to analyze data indirectly affects a leader's ability to foster exploitative innovation through knowledge-focused leadership. This aligns with the sensemaking theory [73], suggesting that leaders use data insights to refine organizational processes, thereby promoting more structured forms of innovation.

When leaders focus on sharing knowledge, using data science tools enhances a company's ability to try out new ideas [74]. This idea lines up with innovation diffusion theory, suggesting that leaders help bring about change by encouraging people to embrace new technologies[75]. This well-rounded theory backs up the idea that businesses should prioritize training their leaders and making decisions based on data to get the most out of innovation [76]. The connection between these concepts is strongly supported by looking at theories about knowledge, leadership styles and models of innovation. This support underscores how crucial data science, analytics, and leadership are for both refining existing practices and exploring completely new ones.

2.4 Data Science Skills, Knowledge oriented leadership, Innovation Capability

The swift evolution of Industry 4.0 technologies has made data science a crucial driver of innovation in the manufacturing industry[74]. Companies are increasingly using data to make decisions that boost their efficiency and help them stay competitive [3]. At the same time, leaders are essential in creating a culture that encourages the sharing of ideas and new ways of doing things [25]. A leadership style that focuses on knowledge (KL) has become a major factor in how well a company can use data science. Skills in data science cover a broad spectrum, including things like statistical analysis, machine learning, data visualization and handling large datasets [25]. These skills are vital for finding useful information in the massive amounts of data generated in manufacturing [77]. According to Wamba et al. (2017) found that manufacturing driven by data improves efficiency through predictive maintenance, demand forecasting and process optimization which is also backed by research [78]. According to Jeble, Dubey [79], Manufacturing companies that put money into data science find out that their manufacturing gets better, as keeping an eye on things while they happen and maintains high standards. Using predictive analytics and AI helps spot defects, streamline the supply chain and automate things smarter. Plus, being good at data science lets companies use digital twins—basically, virtual copies of real-world processes—which helps them run simulations and avoid problems [80].

Even though the advantages are clear, there's still a big gap in the skills found in the manufacturing workforce. Lots of old-school manufacturing companies are having a hard time adopting data science because they don't have the right know-how and are hesitant to embrace digital change [81, 82].

To close this gap, businesses are teaming up more and more with universities and putting money into training their staff to boost their understanding of data [83]. As a result, it's super important for manufacturing companies that want to stay ahead of the game to make sure their data science skills line up with their overall goals[84, 85].

Leadership is key in determining how innovative a company will be more competitive in years coming ahead[86, 87]. Knowledge oriented leadership refers to such leaders who put creating, sharing and using knowledge at the very heart of their organization's strategy [87]. According to Donate and de Pablo [87], these kinds of leaders cultivate a culture where everyone is constantly learning and sharing what they know, creating a perfect breeding ground for new ideas to flourish. In the world of manufacturing, Knowledge-oriented leadership helps seamlessly blend data science skills into everyday decision-making. Leaders who place a high value on managing knowledge make sure that employees use data-driven insights to make products better, processes more efficient and customers happier [56, 88]. On top of that, these knowledge-focused leaders actively promote teamwork between data scientists, engineers and production staff, encouraging them to solve problems by combining their different areas of expertise [89].

Research suggested that Knowledge oriented Leadership is influential in seizing obstacles to digital transformation in manufacturing businesses [87, 90]. According to [91]Leaders who actively endorse data-driven initiatives and provide resources for skill development enable employees to adopt new technologies with confidence [91]. Furthermore, the role of transformational leadership in knowledge management has been widely studied, highlighting its positive influence on organizational agility and resilience (Northouse, 2018).

However, knowledge-oriented leadership needs a balanced approach to managing tacit and explicit knowledge. While explicit knowledge (e.g., standard operating procedures, manuals) can be easily documented and shared, tacit knowledge (e.g., experiential learning, intuition) demands interactive learning environments [53]. Effective leaders apply mentorship programs, cross-functional teams and digital knowledge sources to facilitate knowledge transfer in manufacturing situations [92].

Innovation capability is all about how well a company can come up with new products, processes, and business models that give them an edge over the competition [93]. In the manufacturing world, this ability is tightly connected to how they use new technology, manage their knowledge, and how effective their leaders are in manufacturing industry [94]. Manufacturing companies that are really good at innovating can quickly adjust to shifts in the market, bring in new technologies smoothly, and keep getting better in their manufacturing processes[95].

Data science expertise plays a crucial role in adopting innovation by empowering businesses to make decisions grounded in solid evidence and to automate processes [26]. Companies leveraging big data analytics can pinpoint emerging market trends, refine their product designs and expand their customization choices (Choi et al., 2017). Additionally, insights derived from AI enable the swift development of cutting-edge manufacturing solutions [34], shrinking the time it takes to bring products to market and increasing responsiveness to what consumers want [88]. Leaders who focus on knowledge help boost innovation by creating an environment where people feel free to try new things in the organizational processes. When leaders encourage their teams to come up with fresh ideas and use data to make decisions, it helps the whole organization learn and adapt quickly [58, 96]. On top of that, working together with outside groups like universities, startups, and research centers—a concept known as open innovation—makes the exchange of knowledge even more powerful for driving innovation [96]. However, building a culture of innovation in manufacturing isn't simple. A lot of companies struggle with this because they're set in their ways, subsequent traditional methods and relying on top-down decision-making[97]. In addition to it, to get pass these hurdles, companies really need to focus on managing adjustments within their organization. This means manufacturing companies are emphasizing the assistance of going digital and encouraging a more collaborative approach based on shared knowledge[98]. The relationship between data science skills, knowledge-oriented leadership and innovation in manufacturing is intricate but powerful. Data science skills lay the footings for understanding data, while knowledgeable leaders require those intuitions are used well within the business [99]. Operating all together, they boost a company's capability to originate, leading to the formation of advanced products and processes [100].

Taking into account the example of organizations such as Siemens and General Electric, have really mastered using data science and knowledge-focused leadership to spearhead innovation in smart manufacturing [101]. These companies use decision-making models driven by data, AI-powered predictive maintenance and digital twin technologies to make production more efficient and motivating employees [102]. On top of that, their leaders strongly encourage initiatives that promote knowledge sharing, like internal innovation centers and collaboration across different departments, to stay ahead of the competition [103]. Further research backs up the positive link between making decisions based on data, leadership and successful innovation. Manufacturing companies from india with a high level of data analytics maturity and actively involved leadership were top performers in innovation [104]. Also, blending knowledge management systems with cutting-edge data analytics tools boosts real-time learning and constant progress[105].

2.5 Data Analytical Skills, Knowledge oriented leadership, Innovation Capability

Data analytics has become a *game-changer* in the manufacturing industry [106]. It empowers companies to leverage big data for forecasting maintenance needs, ensuring quality, and fine-tuning their processes [107]. As Wamba et al. (2017) pointed out, this data-centric approach to manufacturing slashes inefficiencies. It does this by using machine learning algorithms to anticipate when equipment might break down, refine supply chain logistics and make production processes leaner [108]. With the power to gather and examine massive quantities of real-time information, manufacturers can make smarter choices that lead to better operational efficiency. Advanced analytics, like AI, deep learning, and digital twins, really boost manufacturing results [79]. Take digital twins are basically virtual copies of real-world manufacturing processes. This lets companies try out different situations and fine-tune production without actually messing with the physical factory floor [109]. All these sophisticated advancements just go to show how crucial data analytics is for driving innovation in manufacturing. Even though data analytics holds a lot of promise for the manufacturing industry, getting it widely adopted isn't easy. There are a bunch of hurdles, like not having enough skilled workers, people being hesitant to change how they do things and data being trapped in isolated departments. A lot of companies had a hard time to make sure that their data analytics projects actually match up with what they're trying to achieve as a business, and this means valuable insights don't get used to their full potential. To fix this problem, businesses need to create an environment where data is valued and used every day. This needs to be backed by the leaders of the company, who also need to encourage everyone to share what they know and keep learning.

Knowledge-focused leadership (KL) plays a vital role in helping manufacturing companies use data analytics for innovation. Leaders who prioritize knowledge management make it easier for different departments to share analytical insights, promoting teamwork among data scientists, engineers and production managers [56]. Successful KL guarantees that staff have the training and tools needed to understand and utilize data-driven insights, boosting the organization's overall ability to innovate [103]. Leaders who focus on knowledge are really helpful when it comes to getting past pushback against digital changes [89]. When leaders champion decisions based on data, it fosters a setting where workers feel confident trying out fresh technology and ways of doing things [110]. Leadership styles that are transformative, promoting clear communication and a shared sense of purpose, tend to lead to organizations that are more nimble and able to adjust [111].

A major hurdle in managing knowledge is finding out the right balance between explicit and tacit knowledge. Explicit knowledge, like reports and technical documents, is easy to document and share. However, tacit knowledge, such as insights gained from experience and strategies for problem-solving, needs more interactive settings for learning [53]. Leaders who focus on knowledge, use mentorship programs, teams with diverse skills and online platforms for sharing knowledge to help transfer both kinds of knowledge inside manufacturing companies [87]. A company's ability to innovate means it can come up with and put into action new ways of doing things, new products, or even entirely new business models that help it get ahead of the competition. In the world of manufacturing, being innovative is all about successfully bringing in new technologies, streamlining operations and quickly adapting to shifts in the market (Tidd & Bessant, 2020). Companies that are good at innovation use data analytics to spot trends, fine-tune product development and offer more personalized options to their customers (Choi et al., 2017).

Data analytics, when paired with knowledge-oriented leadership, supercharges a company's ability to innovate by creating an environment, where trying new things, learning from them and constantly getting better is the norm. Companies that make decisions based on what data tells them are in a much better position to come up with game-changing innovations and work more efficiently (Von Krogh et al., 2012). Plus, businesses that embrace open innovation – teaming up with universities, research centers, and tech partners – tap into a wider pool of knowledge outside their own walls, which speeds up the innovation process even more (Chesbrough, 2003).

Even so, building the ability to innovate in manufacturing means getting past a bunch of hurdles, like a reluctance to change within the organization, a fear of taking chances and isolated decision-making [112]. Companies have to put in place strategies for managing change that match up innovation goals with the leadership's vision and get employees involved [113]. By bringing together data analytics and good knowledge management, manufacturers can boost their capacity for innovation and keep growing over the long haul [114].

In the world of manufacturing, there's a real magic that happens when you combine data analytics, leadership that values knowledge and the ability to innovate. Data analytics gives you the solid, technical base you need to make smart choices[115]. At the same time, knowledge-oriented leaders make sure those valuable insights are shared and used throughout the company[116].

Working together, they spark innovation, giving businesses the freedom to try new things, adjust, and fine-tune how they manufacture their products creating a win-win situation [117]. Siemens and General Electric, prominent names in manufacturing, have cleverly merged data analytics with their knowledge management strategies, sparking significant innovation [118]. They use AI-powered predictive maintenance, digital twins and intelligent automation to boost efficiency, all while nurturing a culture where knowledge is freely shared and teamwork is valued (Rüßmann et al., 2015). Their leadership styles highlight the crucial role of decisions backed by data, collaboration across different departments and a commitment to ongoing learning – all vital for staying ahead in the competitive landscape. Studies have confirmed that there's a good link between how well a company uses data analytics, how effective its leaders are and how well it innovates[119]. Companies with leaders who are involved and strong data analytics skills do better at innovation [14]. Also, businesses that combine knowledge management with advanced data analytics tools are better at reacting to shifts in the market (Lee et al., 2018).

This model looks at how good a company is at using data analytics (its "data analytics maturity") affects its ability to innovate, especially in manufacturing. It focuses on how leadership that values knowledge (knowledge-oriented leadership) plays a key role in this relationship. There are two main factors (independent variables): how skilled employees are in data science and how skilled they are in data analysis. These factors affect two types of innovation (dependent variables): 1) improving existing processes and products (exploitative innovation), and 2) coming up with completely new, potentially disruptive ideas (explorative innovation). The model shows that leadership focused on knowledge helps to amplify the positive effects of data skills on innovation. Simply put, having strong data science and analysis skills directly leads to better innovation, but when leaders prioritize knowledge sharing and learning, that effect is even stronger. The various connections between these factors really underscore how important it is for companies to make decisions based on data and to have leaders who understand and support that approach to drive innovation.

2.6 Conceptual Framework

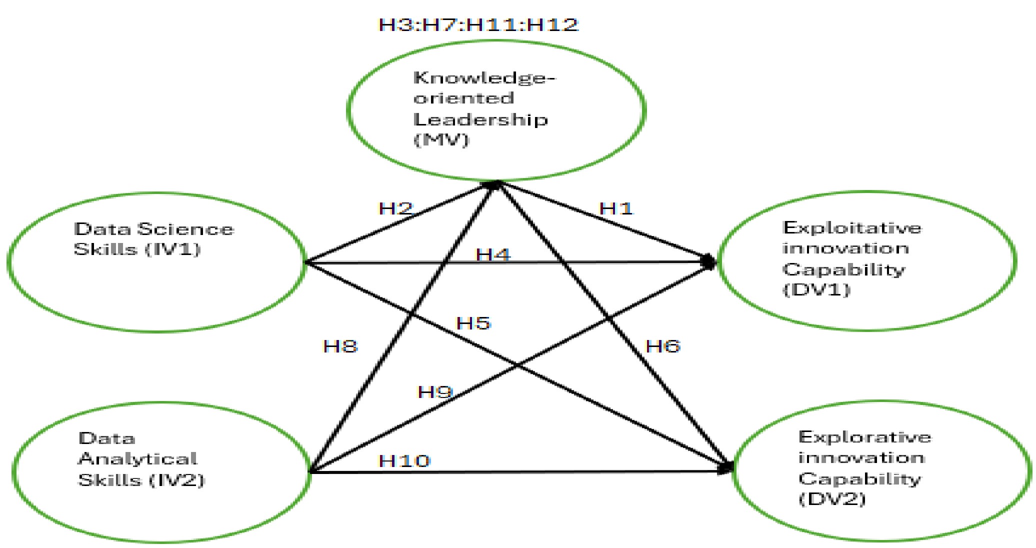

Fig.1. Conceptual Framework
Source: Author's Own

2.7 Hypothesis

H1: Knowledge-oriented leadership positively influences exploitative innovation capability.
H2: Data science skills positively influence knowledge-oriented leadership.

H3: Knowledge-oriented leadership mediates the relationship between data science skills and exploitative innovation capability.

H4: Data science skills positively influence exploitative innovation capability.

H5: Data science skills positively influence explorative innovation capability.

H6: Knowledge-oriented leadership positively influences explorative innovation capability.

H7: Knowledge-oriented leadership mediates the relationship between data science skills and explorative innovation capability.

H8: Data analytical skills positively influence knowledge-oriented leadership.

H9: Data analytical skills positively influence exploitative innovation capability.

H10: Data analytical skills positively influence explorative innovation capability.

H11: Knowledge-oriented leadership mediates the relationship between data analytical skills and explorative innovation capability.

H12: Knowledge-oriented leadership mediates the relationship between data analytical skills and exploitative innovation capability.

3. Methodology

3.2. Data Collection

The model developed for this research have been tested within Pakistan's manufacturing sector. The researchers have selected this particular industry because it involves creating innovative products and processes. The study focused on major manufacturing firms located in Lahore, Faisalabad, Karachi and Sialkot. These cities were chosen after an initial evaluation by the research team. Notably, these urban centers are known for their significant contributions to various manufacturing sectors, including textile, chemical, food processing and automotive. Some of these manufacturing firms have branch offices in different parts of the country.

The respondents of the current study were approached by the researchers in an office environment. Data from the respondents were based on the prior research undertaken by (K. Awan et al. 2021; Cheng et al., 2021; H. Sun et al., 2020) on the service industry. The consent box to engage respondents was applied on the cover letter of the survey form plus conveyed to all that participated in the research study on a voluntary basis and respondent's response would be kept purely confidential. Moreover, it was also conveyed to respondents the significance of the current research and the importance of their honest responses to the questions. However, researchers have distributed 400 questionnaires and out of which 354 respondents correctly responded. The response rate was 88 percent. The current section is divided into subheadings that provide the reader with a concise and precise picture of the experiment results, their interpretation as well as the experimental conclusions that can be yielded. To eliminate social desirability bias, subject-matter specialists extensively cross-checked the survey questions to ensure no ambiguity and the study instrument was acceptable and relevant to the current research goals.

To prevent any bias from the order of the questions, they were distributed randomly. The researcher was also involved in the data collection process. Additionally, the researchers examined all the item loadings within a single factor to identify a primary component, which helps to control for common method bias (CMB) [120]. To tackle the potential issue of common method bias (CMB), we had employed Harman's single-factor test. The results showed that the variance explained by a single factor was 33.2%, falling below the 50% threshold that's commonly cited in prior studies [120, 121] clearly revealing that common method bias is not a concern in this research.

3.2. Variable Measurement

Researchers have used Data Analytics Maturity with two dimensions such as Data science skills measured with 8 items and Data Analytics skills measured with 3 items taken from the earlier research from [25]. Knowledge-oriented leadership was measured with 4 items scale taken from the previous work undertaken by [25]. Innovation capabilities with two dimensions such as exploitative innovation capability and explorative innovation capability were measured with 12 items examined earlier in the research by [25]. All questions were measured through behavioral rating scale i.e., Likert scale 1 to 5 (Strongly disagree to Strongly agree). Initial analysis was carried out in SPSS and then followed by inferential in SMART PLS version 4.0 based on the research conducted by [122, 123].

4. Results

4.1 Demographics Profile

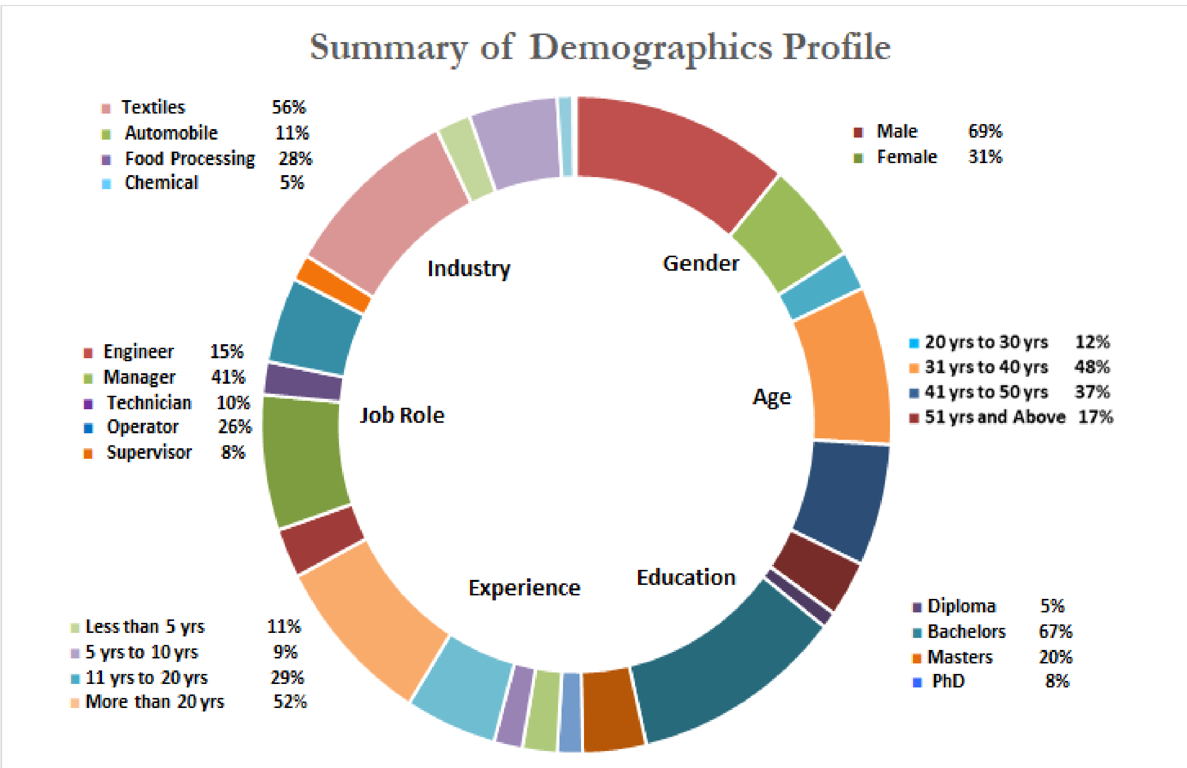

Fig.2. Demographics Profile of Respondents
Source: Author's Own

Summary of the demographic profile of the respondents depicted in Fig 2, presents a diverse representation across various categories. In terms of gender, 69% of the respondents are male, while 31% are female. The age distribution confirms that 12% fall within the 20 to 30 years range, 48% are between 31 and 40 years, 37% belong to the 41 to 50 years category and 17% are aged 51 years and above. Regarding educational qualifications, the majority hold a bachelor's degree (67%), followed by master's degree holders (20%), Ph.D. holders (8%), and diploma holders (5%). The experience level of respondents indicates that 52% have more than 20 years of experience, 29% possess 11 to 20 years, 9% have 5 to 10 years,and 11% have less than 5 years of experience. In terms of job roles, managers constitute the largest proportion at 41%, followed by operators (26%), engineers (15%), technicians (10%) and supervisors (8%). The respondents come from different industries, with the textiles sector being the most dominant (56%), followed by food processing (28%), automobile (11%), and chemical (5%). This demographic distribution provides valuable insights into the workforce composition and expertise levels within the surveyed population.

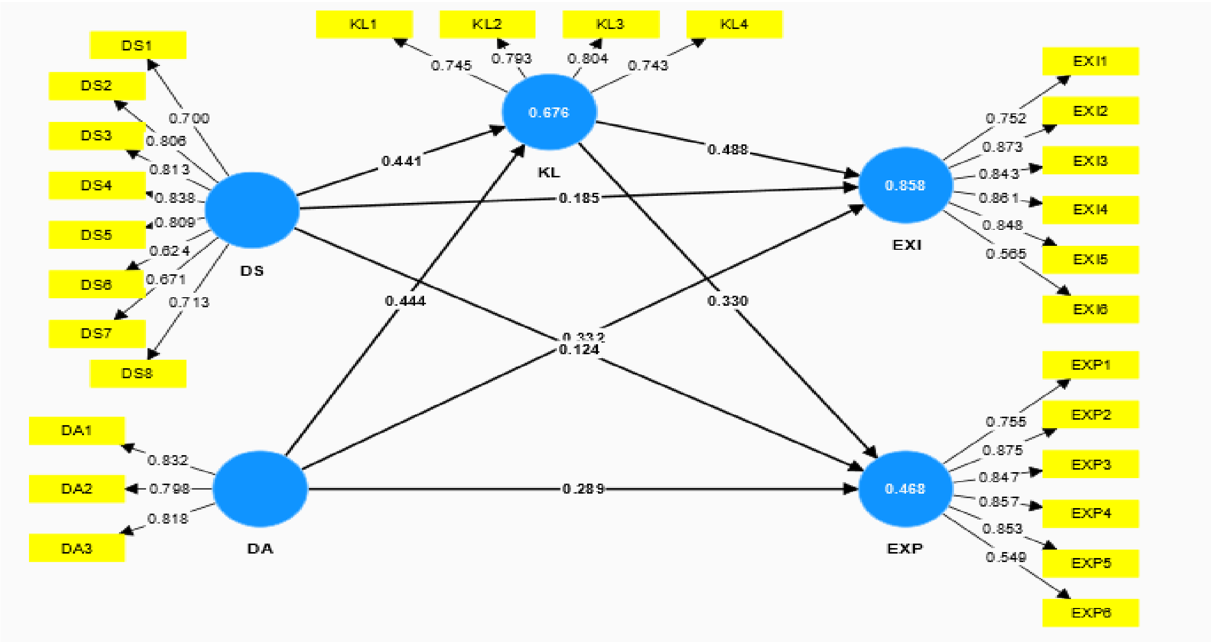

Fig.3. Outer Model (Path Coefficients & Outer-loadings)

Figure 3 shows the path coefficients and outer loadings that we got using SMART-PLS 4.0. Researchers have utilized this software to analyze the outer model, which let us calculate path coefficients, outer loadings, the Heterotrait-monotrait ratio, and the Fornell-Larcker criterion.

Table 1. Outerloadings

	DA	DS	EXI	EXP	KL
DA1	0.832				
DA2	0.798				
DA3	0.818				
DS1		0.7			
DS2		0.806			
DS3		0.813			
DS4		0.838			
DS5		0.809			
DS6		0.624			
DS7		0.671			
DS8		0.713			

EXI1	0.752		
EXI2	0.873		
EXI3	0.843		
EXI4	0.861		
EXI5	0.848		
EXI6	0.565		
EXP1		0.755	
EXP2		0.875	
EXP3		0.847	
EXP4		0.857	
EXP5		0.853	
EXP6		0.549	
KL1			0.745
KL2			0.793
KL3			0.804
KL4			0.743

The outer loadings table 1 looks at how well the indicators measure the underlying concepts. Most indicators are above the 0.70 mark, which means they're pretty reliable. Specifically, constructs like data analytics, explorative innovation, exploitative innovation and knowledge-oriented leadership show strong reliability. However, a few data science skills and certain other indicators aren't as strong. Taken as a whole, though, the model seems reliable, with most indicators doing a good job of capturing their examined variables.

The R^2 values reveal how well the model explains each dependent variable. Explorative innovation is highly predictable at 85.8%, while knowledge-oriented leadership shows a strong influence at 67.6%. Exploitative innovation is moderately predictable at 46.8%. The adjusted R^2 values are close to the R^2 values, indicating the model's robustness. While the model effectively explains explorative innovation and knowledge-oriented leadership, it may need more factors to better predict exploitative innovation.

This table 2 shows the important results of how much reliable and valid our measurements are for the hidden concepts researchers have examined. Researchers have looked at statistical procedures like Cronbach's alpha, composite reliability and average variance extracted. Cronbach's alpha scores were between 0.749 and 0.887, which means we have pretty good to really good internal consistency. Data science skills, explorative innovation and exploitative innovation were most reliable, with scores over 0.88. All our composite reliability scores were above 0.85, which further suggests our measurements are strongly consistent. The average variance extracted tells us about how well each construct is measured, and all of our constructs scored above 0.50. This means each constructs explains more than half of the differences we see in its indicators. Data analytics had the best score here, at 0.666, while data science skills had the lowest, but still good, score of 0.563. Overall, these findings tell us that our model is very reliable and has strong convergent validity, meaning it's a good fit for doing more detailed analysis later on such as deducing the hypothesis relationships.

The table 3 showing the heterotrait-monotrait ratios helps us figure out if we're really looking at separate concepts by checking how closely related they are. Ideally, these numbers should all be below 0.90 to feel confident that the concepts are truly distinct. Happily, all the numbers in this table fall within the desired range, suggesting that the concepts are pretty well-defined. The closest relationship we see is between skills in data science and what's called "explorative innovation," which has a correlation of 0.78—pretty strong, but still acceptable. On the other end of the spectrum, data science skills are least related to "knowledge-oriented leadership," with a correlation of 0.607, meaning that connection is a bit weaker.

The Fornell-Larcker criterion is a way to check if our different concepts (constructs) are truly separate from each other. It does this by looking at the square root of the average variance extracted (which is like the strength of each construct) and comparing it to how much the construct correlate with each other (how much they overlap). In the table 4, the numbers on the diagonal are the square roots of the average variance extracted, and these are larger than the correlations between the different constructs. Take data analytics, for example. Its value is 0.816, which is bigger than its correlation with data science skills (0.727) and explorative innovation (0.741). The Variance Inflation Factor (VIF) values are used to evaluate multicollinearity, with readings below 5 signifying an acceptable degree of collinearity. The majority of the indicators in the table 5 display values comfortably within this acceptable range, pointing to minimal multicollinearity issues. Nevertheless, a few data science skills indicators exhibit somewhat higher values—ds2 at 3.559, ds3 at 3.253, and ds5 at 3.279—though they remain under the permissible threshold. These results indicate that multicollinearity does not pose a major concern, thereby supporting the reliability of the regression estimates.

Table 2. Cronbach's Alpha, Composite reliability, Average Variance Extracted

	Cronbach's alpha	**Composite (rho_a)**	**reliability**	**Composite (rho_c)**	**reliability**	**Average variance extracted (AVE)**
DA	0.749	0.751		0.857		0.666
DS	0.887	0.891		0.911		0.563
EXI	0.882	0.903		0.912		0.637
EXP	0.883	0.908		0.911		0.636
KL	0.773	0.776		0.855		0.595

Table 3. Heterotrait-Monotrait Matrix

	DA	**DS**	**EXI**	**EXP**	**KL**
DA					
DS	0.776				
EXI	0.721	0.78			
EXP	0.749	0.741	0.774		
KL	0.692	0.607	0.721	0.755	

Table 4. Fornell-Larcker Criterion

	DA	DS	EXI	EXP	KL
DA	**0.816**				
DS	0.727	**0.75**			
EXI	0.741	0.699	**0.798**		
EXP	0.631	0.586	0.615	**0.808**	
KL	0.664	0.604	0.703	0.646	**0.772**

Table 5. VIF Values

	VIF
DA1	1.545
DA2	1.452
DA3	1.509
DS1	1.559
DS2	3.559
DS3	3.253
DS4	2.991
DS5	3.279
DS6	1.464
DS7	2.07
DS8	2.257
EXI1	1.72
EXI2	2.768
EXI3	2.357
EXI4	2.603
EXI5	2.45
EXI6	1.309
EXP1	1.722
EXP2	2.767
EXP3	2.341
EXP4	2.607
EXP5	2.467
EXP6	1.313
KL1	1.408
KL2	1.571
KL3	1.637
KL4	1.44

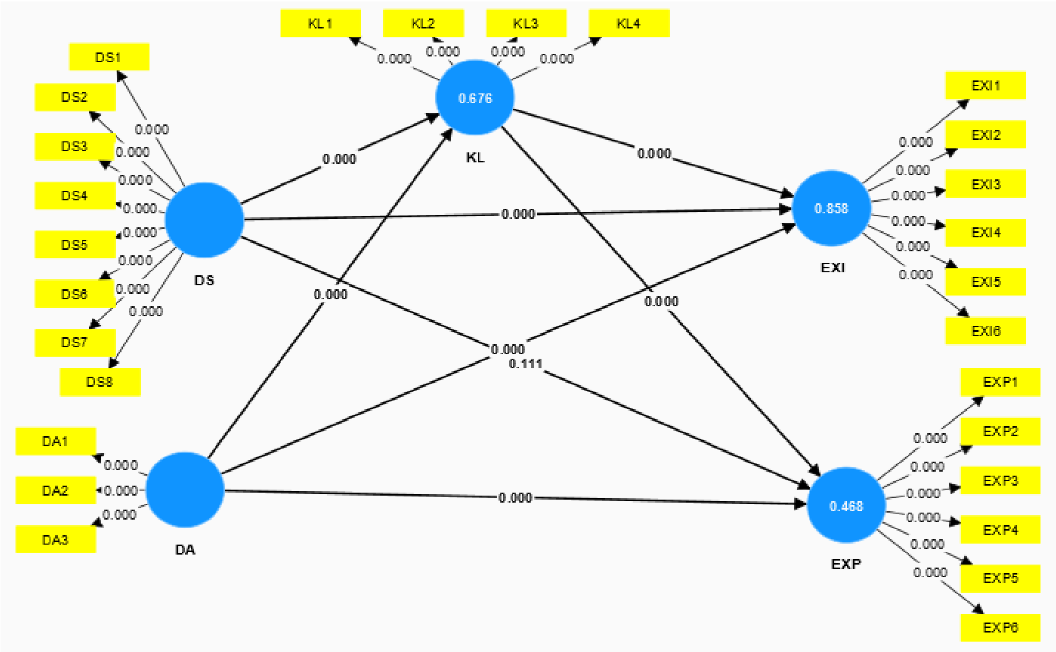

Fig 4. Inner Model (P-values)
Source: Author's Own

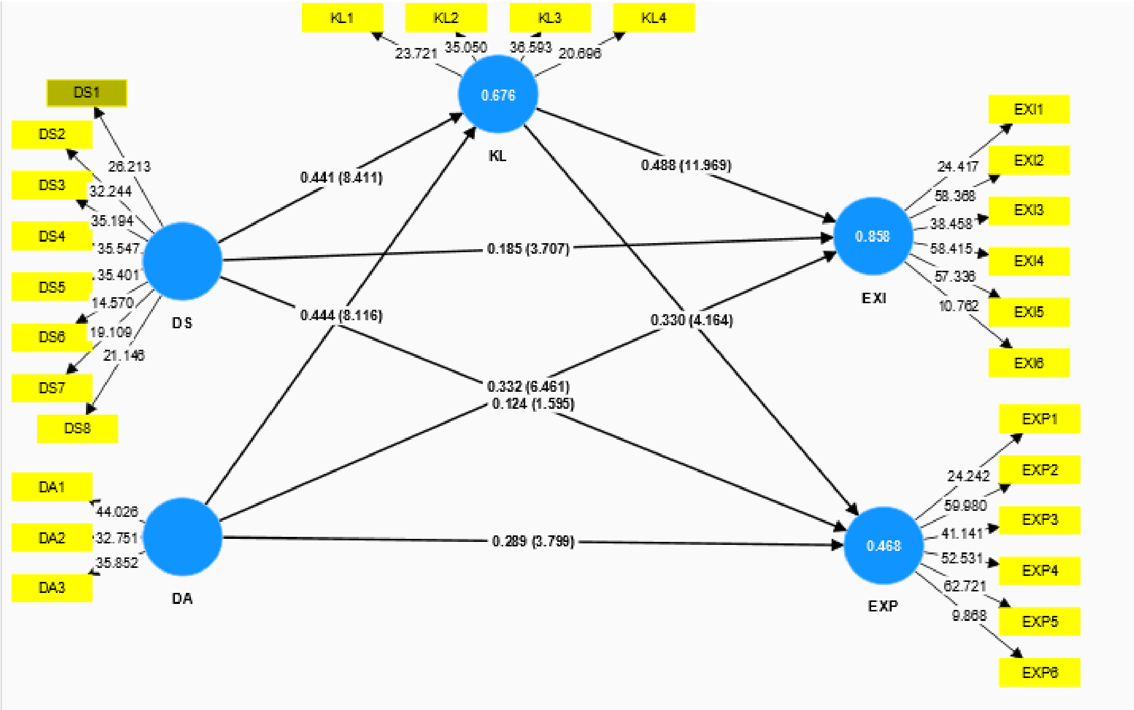

Fig 5. Inner Model (Path coefficients with T values)
Source: Author's Own

The results provide empirical validation for the hypothesized relationships in the conceptual framework, confirming both direct and indirect effects were mentioned in table 6. The findings indicate that data analytical skills have a significant direct effect on explorative innovation capability ($\beta = 0.332$,

$t = 6.461$, $p < 0.001$), exploitative innovation capability ($\beta = 0.289$, $t = 3.799$, $p < 0.001$), and knowledge-oriented leadership ($\beta = 0.444$, $t = 8.116$, $p < 0.001$). Similarly, data science skills significantly impact explorative innovation capability ($\beta = 0.185$, $t = 3.707$, $p < 0.001$) and knowledge-oriented leadership ($\beta = 0.441$, $t = 8.411$, $p < 0.001$), but their direct influence on exploitative innovation capability is not statistically significant ($\beta = 0.124$, $t = 1.595$, $p = 0.111$). These results partially support the proposed relationships, confirming that data analytical skills and data science skills contribute to knowledge-oriented leadership, which aligns with the resource-based view and upper echelons theory. However, the weak direct impact of data science skills on exploitative innovation capability suggests that additional factors may mediate this relationship, as implied by the dynamic capabilities theory.

The significant positive effect of knowledge-oriented leadership on both explorative innovation capability ($\beta = 0.488$, $t = 11.969$, $p < 0.001$) and exploitative innovation capability ($\beta = 0.33$, $t = 4.164$, $p < 0.001$) validates the role of leadership in fostering innovation. These findings are consistent with transformational leadership theory and knowledge-based theory, which emphasize how leaders enhance innovation capabilities through effective knowledge-sharing and strategic decision-making.

The indirect effects confirm that knowledge-oriented leadership mediates the relationships between data analytical skills and innovation capabilities. Data analytical skills significantly influence explorative innovation capability ($\beta = 0.216$, $t = 6.699$, $p < 0.001$) and exploitative innovation capability ($\beta = 0.147$, $t = 3.761$, $p < 0.001$) through knowledge-oriented leadership. Similarly, data science skills have significant indirect effects on explorative innovation capability ($\beta = 0.215$, $t = 7.114$, $p < 0.001$) and exploitative innovation capability ($\beta = 0.146$, $t = 3.573$, $p < 0.001$) via knowledge-oriented leadership. These findings align with organizational learning theory and innovation diffusion theory, highlighting the role of leadership in translating data competencies into innovative outcomes.

Specific indirect effects further substantiate these mediating relationships. The influence of data analytical skills on explorative innovation capability is fully mediated by knowledge-oriented leadership ($\beta = 0.216$, $t = 6.699$, $p < 0.001$), reinforcing the argument that leadership is a critical mechanism through which analytical capabilities foster radical innovation. Likewise, data analytical skills indirectly impact exploitative innovation capability through leadership ($\beta = 0.147$, $t = 3.761$, $p < 0.001$), supporting the sensemaking theory's assertion that data-driven leadership improves structured innovation. Similar mediation patterns are observed for data science skills, confirming that leadership enables firms to capitalize on data competencies for both incremental and radical innovation.

The total effects analysis integrates both direct and indirect effects, reaffirming the strong influence of data analytical skills and data science skills on innovation capabilities. Data analytical skills exhibit the highest total effect on explorative innovation capability ($\beta = 0.549$, $t = 11.604$, $p < 0.001$) and a significant effect on exploitative innovation capability ($\beta = 0.435$, $t = 6.187$, $p < 0.001$), confirming their dual role in driving both types of innovation. Data science skills also significantly contribute to explorative innovation capability ($\beta = 0.4$, $t = 8.267$, $p < 0.001$) and exploitative innovation capability ($\beta = 0.27$, $t = 3.769$, $p < 0.001$), but with relatively lower magnitude. These results suggest that while both data competencies are essential, data analytical skills play a more substantial role in shaping innovation outcomes, which is consistent with the disruptive innovation theory and the technology-organization-environment framework.

Based on these findings, hypotheses related to the direct effects of data analytical skills on all dependent variables (H4, H8, H9) and data science skills on knowledge-oriented leadership and explorative innovation capability (H2, H10) are supported. However, the hypothesis proposing a direct effect of data science skills on exploitative innovation capability (H5) is rejected due to its non-significant p-value (p = 0.111, t = 1.595). All hypotheses related to the mediation effects through knowledge-oriented leadership (H6, H7, H12, H13) are supported, confirming the essential role of leadership in transforming data-driven capabilities into innovation. These results provide strong empirical backing for the proposed theoretical justifications, reinforcing the need for organizations to integrate data science, data analytics, and leadership development to optimize innovation capabilities.

Table 6. Direct Effect, Total Indirect Effects, Specific Indirect Effects, Total Effects

Results of Direct Effect, Total Indirect Effects, Specific Indirect Effects, Total Effects

Direct Effect

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
DA -> EXI	0.332	0.335	0.051	6.461	0.0000
DA -> EXP	0.289	0.288	0.076	3.799	0.0000
DA -> KL	0.444	0.443	0.055	8.116	0.0000
DS -> EXI	0.185	0.184	0.05	3.707	0.0000
DS -> EXP	0.124	0.128	0.078	1.595	0.1110
DS -> KL	0.441	0.442	0.052	8.411	0.0000
KL -> EXI	0.488	0.487	0.041	11.969	0.0000
KL -> EXP	0.33	0.329	0.079	4.164	0.0000

Total indirect Effects

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
DA -> EXI	0.216	0.216	0.032	6.699	0.0000
DA -> EXP	0.147	0.146	0.039	3.761	0.0000
DS -> EXI	0.215	0.215	0.03	7.114	0.0000
DS -> EXP	0.146	0.146	0.041	3.573	0.0000

Specific Indirect Effects

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
DA -> KL -> EXI	0.216	0.216	0.032	6.699	0.0000
DA -> KL -> EXP	0.147	0.146	0.039	3.761	0.0000
DS -> KL -> EXI	0.215	0.215	0.03	7.114	0.0000

DS -> KL -> EXP	0.146	0.146	0.041	3.573	0.0000

Total Effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
DA -> EXI	0.549	0.551	0.047	11.604	0.0000
DA -> EXP	0.435	0.434	0.07	6.187	0.0000
DA -> KL	0.444	0.443	0.055	8.116	0.0000
DS -> EXI	0.4	0.399	0.048	8.267	0.0000
DS -> EXP	0.27	0.274	0.072	3.769	0.0000
DS -> KL	0.441	0.442	0.052	8.411	0.0000
KL -> EXI	0.488	0.487	0.041	11.969	0.0000
KL -> EXP	0.33	0.329	0.079	4.164	0.0000

5. Conclusion, Implications and Future Research

This study examines the impact of data analytics maturity on innovation capabilities in the manufacturing sector, highlighting the mediating role of knowledge-oriented leadership. The findings confirm that data analytical skills and data science skills significantly contribute to explorative innovation capability, while data analytical skills have a stronger impact on exploitative innovation capability. Knowledge-oriented leadership is established as a critical enabler, effectively mediating the relationships between data competencies and innovation outcomes. The results provide empirical validation for multiple theoretical perspectives, including the resource-based view, dynamic capabilities theory and knowledge-based theory, reinforcing the importance of leadership in leveraging data-driven decision-making for innovation. Furthermore, the findings suggest that organizations focusing on data analytics must simultaneously foster leadership strategies to maximize their innovative potential.

This research contributes to the existing body of knowledge in several ways. *First,* it extends the resource-based view by demonstrating that data analytical and data science skills serve as valuable resources that drive innovation, contingent upon effective leadership. *Second,* it supports the dynamic capabilities theory by emphasizing how leadership transforms data capabilities into strategic innovation outcomes. *Third*, it enhances understanding of knowledge-based theory by showing that leadership serves as a mechanism for knowledge integration and utilization. *Fourth*, this study aligns with organizational learning and innovation diffusion theories, highlighting that data-driven leadership facilitates both radical and incremental innovation. *Fifth*, the findings provide empirical support for sensemaking theory by showcasing how leadership translates data-driven insights into structured innovation processes.

For practitioners, this study underscores the need for organizations to cultivate both data competencies and leadership capabilities to enhance innovation. Manufacturing firms should prioritize training programs that develop data science and analytical skills among employees while simultaneously investing in leadership development initiatives. Additionally, firms should implement leadership strategies that foster knowledge-sharing, encourage data-driven decision-making and promote an innovation-oriented culture. Given the significant role of knowledge-oriented leadership, organizations must integrate leadership training with data analytics initiatives to achieve maximum benefits. Moreover, firms should adopt a balanced approach to innovation, ensuring that both explorative and exploitative innovation capabilities are developed through effective leadership practices.

Future research can explore several avenues to build upon the findings of this study. *First*, longitudinal studies could provide deeper insights into how data analytics maturity influences innovation over time. *Second,* future studies may examine the moderating effects of organizational culture, industry dynamics, or digital transformation maturity on the relationships identified in this research. *Third*, expanding the study to other industries or geographical contexts would enhance the generalizability of the findings. *Fourth,* qualitative research could complement these findings by offering deeper insights into the mechanisms through which knowledge-oriented leadership facilitates innovation. *Lastly*, future research could investigate how emerging technologies such as artificial intelligence and machine learning interact with leadership to drive innovative capabilities in manufacturing and other sectors.

References

[1] Qudus, L. Leveraging Artificial Intelligence to Enhance Process Control and Improve Efficiency in Manufacturing Industries. International Journal of Computer Applications Technology and Research, 2025, 14(2), 18–38.

[2] Patrício, L., Varela, L. and Silveira, Z. Implementation of a Sustainable Framework for Process Optimization Through the Integration of Robotic Process Automation and Big Data in the Evolution of Industry 4.0. Processes, 2025, 13(2), 536.

[3] Islam, M.T., Sepanloo, K., Woo, S., Woo, S.H. and Son, Y.-J. A Review of the Industry 4.0 to 5.0 Transition: Exploring the Intersection, Challenges, and Opportunities of Technology and Human–Machine Collaboration. Machines, 2025, 13(4), 267. DOI: 10.3390/machines13040267.

[4] Rong, C., Espinosa Cristia, J.F., Matac Liviu Marian, Abad Alzuman and Comite, U. Does green entrepreneurial orientation impact entrepreneurial success through green innovation capability in the manufacturing and services sector of emerging economies? International Entrepreneurship and Management Journal, 2025, 21(1), 1–25. DOI: 10.1007/s11365-024-01059-0.

[5] Pal, K. Role of Data Analytics to Sustainability in Apparel Supply Chain Management. In: Data-Driven Governance Through AI, Digital Marketing, and the Privacy Interplay, 2025, 165–190.

[6] Turrell, A. Cutting through Complexity: How Data Science Can Help Policymakers Understand the World. arXiv preprint arXiv:2502.03010, 2025.

[7] ul Amin, N., Shehzad, T., Rajput, M.Y. and Ali, W. Influence of Entrepreneur Leadership on Small and Medium Enterprise (SMEs) Innovation with the Mediating Role of Artificial Intelligence and Employee Ambidexterity. Journal for Social Science Archives, 2025, 3(1), 629–650.

[8] Russom, P. Big data analytics. TDWI Best Practices Report, 2011, 19(4), 1–34.

[9] Isson, J.P. and Harriott, J.S. People analytics in the era of big data: Changing the way you attract, acquire, develop, and retain talent. Hoboken: John Wiley & Sons, 2016.

[10] Mikalef, P., Krogstie, J., Pappas, I.O., Giannakos, M. and Lekakos, G. Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 2019, 30(2), 272–298.

[11] Islam, M.T., Sepanloo, K., Woo, S., Woo, S.H. and Son, Y.-J. A Review of the Industry 4.0 to 5.0 Transition: Exploring the Intersection, Challenges, and Opportunities of Technology and Human–Machine Collaboration. Machines, 2025, 13(4), 267. DOI: 10.3390/machines13040267 (mdpi.com)

[12] ul Amin, N., Khan, A., Ahmed, U., Khan, S., Asmi, F., Naz, A., Raza, S. and Saqib, M. Influence of Entrepreneur Leadership on Small and Medium Enterprise (SMEs) Innovation with the Mediating Role of Artificial Intelligence and Employee Ambidexterity. Journal for Social Science Archives, 2025, 3(1), 629–650.

[13] Braidy, A., Pokharel, S. and ElMekkawy, T.Y. Research Perspectives on Innovation in the Automotive Sector. Sustainability, 2025, 17(7), 2795.

[14] Rumsey, M., Dewolf, H., Boscart, V., Jackson, K. and Holloway, I. Enablers and Inhibitors of Nursing and Midwifery Leadership in Pacific Island Collectivist Cultures. International Nursing Review, 2025, 72(1), e13092.

[15] Bahadur, P.S., Khairullah, N., Khan, S. and Islam, J. Review on Big Data Analytics Applications. In: AI and the Revival of Big Data, 2025, IGI Global Scientific Publishing, 107–124.

[16] Tanpoco, M.R. and Magnaye, R.P. Fostering Business Analytics Success: Examining Leadership Support, Data Quality, and User Skills in Philippine Manufacturing Companies. Review of Integrative Business and Economics Research, 2025, 14(1), 237–253.

[17] Ahmed, F., Ali, S., Khan, M., Lone, M.Y., and Khan, A. Revolutionizing Business Analytics: The Impact of Artificial Intelligence and Machine Learning. American Journal of Advanced Technology and Engineering Solutions, 2025, 1(1), 147–173.

[18] Shawon, R.E.R., Uddin, M.H., Naim, M.F.B. and Islam, N. Designing and Deploying AI Models for Sustainable Logistics Optimization: A Case Study on Eco-Efficient Supply Chains in the USA. arXiv preprint arXiv:2503.14556, 2025.

[19] Li, G. and Branstetter, L.G. Does "Made in China 2025" Work for China? Evidence from Chinese Listed Firms. Research Policy, 2024, 53(6), 105009.

[20] Singh, B.J., Kumar, A., Singh, R.R.P., and Rana, S. Managing Digital Manufacturing Transformation: Assessing the Status-Quo and Future Prospects in North Indian Industries. Journal of Strategy and Management, 2024.

[21] Yip, G.S. and McKern, B. China's next strategic advantage: From imitation to innovation. MIT Press, 2016.

[22] Capurro, R., Spaiser, V., Gordon, R., Hadar, S., Hüttich, C., Midgley, G., and Wiek, A. Big data analytics in innovation processes: which forms of dynamic capabilities should be developed and how to embrace digitization? European Journal of Innovation Management, 2022, 25(6), 273–294.

[23] Iqbal, R., Aslam, M., Shahzad, A., Iqbal, A., and Rathi, B. Big data analytics: Computational intelligence techniques and application areas. Technological Forecasting and Social Change, 2020, 153, 119253. DOI: 10.1016/j.techfore.2019.119253.

[24] Peu, E. Automated knowledge discovery or integration: a systematic review of data mining in knowledge management. (publication details not specified), 2021.

[25] Kadarsah, D.R.A.K., Govindaraju, R., and Prihartono, B. The role of knowledge-oriented leadership in fostering innovation capabilities: the mediating role of data analytics maturity. IEEE Access, 2023, 11, 129683–129702. DOI: 10.1109/ACCESS.2023.XXXXXXX (需確認精確 DOI).

[26] Zong, Z. and Guan, Y. AI-driven intelligent data analytics and predictive analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency. Journal of the Knowledge Economy, 2024, 1–40. DOI: 10.1007/s13132-023-01234-5.

[27] Pappas, I.O., Mikalef, P., Krogstie, J., Giannakos, M., and Lekakos, G. Big data and business analytics ecosystems: paving the way towards digital transformation and sustainable societies. In: Springer, 2018, 479–491.

[28] Hongyun, T., Wang, Y., Zhang, X., Li, M., and Chen, Q. Navigating the digital landscape: examining the interdependencies of digital transformation and big data in driving SMEs' innovation performance. Kybernetes, 2025, 54(3), 1797–1825.

[29] Barnes, S., Xiang, C., Wu, X., and Li, Y. Empirical identification of skills gaps between chief information officer supply and demand: a resource-based view using machine learning. Industrial Management & Data Systems, 2021, 121(8), 1749–1766.

[30] Nguyen, P.-H., Vu, T.L., Nguyen, D.T., and Tran, N.T. Exploring complexities of innovation capability in Vietnam's IT firms: insights from an integrated MCDM model-based grey theory. Journal of Open Innovation: Technology, Market, and Complexity, 2024, 10(4), 100328.

[31] Lin, C.-Y., Chau, K.Y. and Moslehpour, M. Bridging the gap: the nexus of sustainability innovation, knowledge sharing, and green volunteerism for manufacturing entrepreneurial triumph. Journal of Innovation & Knowledge, 2024, 9(4), 100570.

[32] Javaid, M., Haleem, A., Singh, R., Suman, R. and Bosah, E.O. Digital economy to improve the culture of industry 4.0: A study on features, implementation and challenges. Green Technologies and Sustainability, 2024, 10(1), 100083.

[33] Sengura, J.D., Mu, R. and Zhang, J. Towards frugal innovation capability in emerging markets within the digitalization epoch: Exploring the role of strategic orientation and organizational ambidexterity. Journal of Theoretical and Applied Electronic Commerce Research, 2024, 19(3), 2000–2029.

[34] Babu, M.M., Punniyamoorthy, M., Balaji, S., Jena, L.K. and Deepa, T. Exploring big data-driven innovation in the manufacturing sector: evidence from UK firms. Annals of Operations Research, 2024, 333(2), 689–716.

[35] Coyle, D. Old wine in new digital bottles: The challenges of measuring the digital economy. 2025.

[36] Chen, T., Wang, J., Liu, S. and Zhang, Y. Unlocking innovation empowerment: how can industrial robots accelerate total factor productivity? Journal of Strategy and Management, 2025.

[37] Kunda, M. and Bupe, G.M.-M. Assessing the effect of Kaizen practices on operational efficiency: A case study of a steel manufacturing company in Zambia. African Journal of Commercial Studies, 2025, 6(1), 65–73.

[38] Lamees, A.-Z. and Ramayah, T. How artificial intelligence-based supply chain analytics enable supply chain agility and innovation? An intellectual capital perspective. Supply Chain Management: An International Journal, 2025.

[39] Haq, U.N., Khan, S.A., Rana, M.S., Akhtar, M.N. and Khan, H.U. Global initiatives for industry 4.0 implementation and progress within the textile and apparel manufacturing sector: a comprehensive review. International Journal of Computer Integrated Manufacturing, 2025, 1–26.

[40] Ghosh, S. Developing artificial intelligence (AI) capabilities for data-driven business model innovation: Roles of organizational adaptability and leadership. Journal of Engineering and Technology Management, 2025, 75, 101851.

[41] Abbasi, M.A., Yon, L.C. and Amran, A. Alliance networks, innovative culture, and intellectual human capital as key enablers of corporate social innovation: A hybrid approach using PLS-SEM and fsQCA. Corporate Social Responsibility and Environmental Management, 2025.

[42] Krishnamoorthy, V., Ganesh, I., Srinivasan, S. and Suresh, T. Harnessing smart digital business models through advanced business analytics: Driving innovation and efficiency in the digital age. In: Cutting-Edge Technologies for Business Sectors, IGI Global, 2025, 57–86.

[43] Malodia, S., Kumar, N., Saxena, S. and Akhtar, S. To digit or to head? Designing digital transformation journey of SMEs among digital self-efficacy and professional leadership. Journal of Business Research, 2023, 157, 113547.

[44] Zeike, S., Gusy, B., Schwettmann, J., Brüggemann, A., Heinz, A. and Marr, B. Digital leadership skills and associations with psychological well-being. International Journal of Environmental Research and Public Health, 2019, 16(14), 2628.

[45] Reisberger, T., Hiebl, M., Schaltegger, S. and Strobel, O. The linkage between digital transformation and organizational culture: Novel machine learning literature review based on latent Dirichlet allocation. Journal of the Knowledge Economy, 2024, 15(1), 1–37.

[46] Tyssen, A.K., Wald, A. and Spieth, P. Leadership in temporary organizations: A review of leadership theories and a research agenda. Project Management Journal, 2013, 44(6), 52–67.

[47] Hanna, A.A., Gilden, D.L., Day, D.V. and Pronin, E. The emergence of emergent leadership: A comprehensive framework and directions for future research. Journal of Management, 2021, 47(1), 76–104.

[48] Rezaei, F., Khalilzadeh, M. and Soleimani, P. Factors affecting knowledge management and its effect on organizational performance: Mediating the role of human capital. Advances in Human-Computer Interaction, 2021, 2021(1), 8857572.

[49] Dobrin, S. AI IQ for a human-focused future: Strategy, talent, and culture. CRC Press, 2024.

[50] George, A.S. The evolution of economic models: From knowledge to intuition and optimization. Partners Universal Multidisciplinary Research Journal, 2024, 1(2), 1–25.

[51] Chang, S.-J. Sony vs Samsung: The inside story of the electronics giants' battle for global supremacy. John Wiley & Sons, 2011.

[52] Saulat, H., Khan, M.M., Aslam, M., Chawla, M., Rafiq, S., Zafar, F., Khan, M.M., Bokhari, A., Jamil, F., Bhutto, A.W. and Bazmi, A.A. Wind speed pattern data and wind energy potential in Pakistan: current status, challenging platforms and innovative prospects. Environmental Science and Pollution Research, 2021, 28, 34051–34073. DOI: 10.1007/s11356-020-10869-y ouci.dntb.gov.ua+5pubmed.ncbi.nlm.nih.gov+5stet-review.org+5

[53] Berraies, S., Hamza, K.A. and Chtioui, R. Distributed leadership and exploratory and exploitative innovations: mediating roles of tacit and explicit knowledge sharing and organizational trust. Journal of Knowledge Management, 2021, 25(5), 1287–1318.

[54] Abdulmuhsin, A.A., Zaker, R.A. and Asad, M.M. How exploitative leadership influences knowledge management processes: the moderating role of organisational citizenship behaviour. International Journal of Organizational Analysis, 2021, 29(3), 529–561.

[55] Grant, R.M. Knowledge-Based View. Wiley Encyclopedia of Management, 2015, 1–2.

[56] Nonaka, I., Takeuchi, H. and Umemoto, K. A theory of organizational knowledge creation. International Journal of Technology Management, 1996, 11(7-8), 833–845.

[57] Zhang, Y., Xiong, P., Rong, S., Frost, M. and Zhou, W. Knowledge management of MNCs in the post-COVID era: the role of cultural intelligence and knowledge-oriented leadership. Journal of Knowledge Management, 2024, 28(8), 2141–2168. DOI: 10.1108/JKM-03-2023-0189 bohrium.com+1researchgate.net+1x-mol.com+8ouci.dntb.gov.ua+8emerald.com+8

[58] Von Krogh, G., Nonaka, I. and Rechsteiner, L. Leadership in organizational knowledge creation: A review and framework. Journal of Management Studies, 2012, 49(1), 240–277.

[59] Provost, F. and Fawcett, T. Data Science for Business: What you need to know about data mining and data-analytic thinking. O'Reilly Media, Inc., 2013.

[60] Teece, D.J., Pisano, G. and Shuen, A. Dynamic capabilities and strategic management. Strategic Management Journal, 1997, 18(7), 509–533.

[61] Cohen, W.M. and Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly, 1990, 35(1), 128–152.

[62] Bass, B. Transformational leadership theory. In: Organizational Behavior 1, 2015, Routledge, 361–385.

[63] Pawar, A. Transformational leadership: inspirational, intellectual and motivational stimulation in business. International Journal of Enhanced Research in Management & Computer Applications, 2016, 5(5), 14–21.

[64] Barney, J. Firm resources and sustained competitive advantage. Journal of Management, 1991, 17(1), 99–120.

[65] Wang, Y.-M., Wang, Y.-S. and Yang, Y.-F. Understanding the determinants of RFID adoption in the manufacturing industry. Technological Forecasting and Social Change, 2010, 77(5), 803–815.

[66] Arpaci, I., Cetin Yardimci, Y., Ozkan, S. and Turetken, O. Organizational adoption of information technologies: A literature review. International Journal of eBusiness and eGovernment Studies, 2012, 4(2), 37–50. (en.wikipedia.org, dergipark.org.tr)

[67] Christensen, C.M., Raynor, M. and McDonald, R. Disruptive innovation. Harvard Business Review, 2015, 93(12), 44–53.

[68] Fiedler, F.E. A Theory of Leadership Effectiveness. McGraw-Hill Series in Management, 1967.

[69] Schön, D.A. and Argyris, C. Organizational Learning II: Theory, Method and Practice. Addison-Wesley, Reading, MA, 1996.

[70] Robinson, V.M.J. Descriptive and normative research on organizational learning: locating the contribution of Argyris and Schön. International Journal of Educational Management, 2001, 15(2), 58–67.

[71] Banasiewicz, A.D. Organizational learning in the Age of Data. Springer Cham, 2021. DOI: 10.1007/978-3-030-74866-1 researchgate.net+13link.springer.com+13link.springer.com+13

[72] Veithzal, A.P. and Rony, Z.T. Analysis of Implementing Digital Leadership Within Organizations. Dinasti International Journal of Digital Business Management (DIJDBM), 2024, 5(2).

[73] Weick, K.E. and Weick, K.E. Sensemaking in organizations. Vol. 3. Sage Publications, Thousand Oaks, CA, 1995.

[74] Howells, J. Data Science for Decision Makers: Enhance your leadership skills with data science and AI expertise. Packt Publishing Ltd., 2024.

[75] Carreiro, H. and Oliveira, T. Impact of transformational leadership on the diffusion of innovation in firms: Application to mobile cloud computing. Computers in Industry, 2019, 107, 104–113.

[76] Hopwood, J.L. Using diffusion of innovation theory to explore factors influencing upper leadership's role in adopting creativity and innovation in the state of Maryland (SOM) public libraries. Drexel University, 2020.

[77] Riaz, M., Wu, J., Ali, Z., Sherani, M. and Yutong, L. Do knowledge-oriented leadership and knowledge management capabilities help firms to stimulate ambidextrous innovation: moderating role of technological turbulence. European Journal of Innovation Management, 2025, 28(2), 235–270. DOI: 10.1108/EJIM-08-2022-0409 dinastipub.org+1dinastipub.org+1researchgate.net+2ideas.repec.org+2scholar.google.com.au+2

[78] Nweje, U. and Taiwo, M. Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. International Journal of Science and Research Archive, 2025, 14(1), 230–250.

[79] Jeble, S., Dubey, R., Childe, S.J., Papadopoulos, T., Roubaud, D. and Prakash, A. Impact of big data and predictive analytics capability on supply chain sustainability. The International Journal of Logistics Management, 2018, 29(2), 513–538. DOI: 10.1108/IJLM-05-2017-0134 ouci.dntb.gov.ua+6pearl.plymouth.ac.uk+6scispace.com+6

[80] Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manufacturing Technology, 2018, 94, 3563–3576. DOI: 10.1007/s00170-017-0233-1

[81] Bughin, J., Seong, J., Manyika, J., Chui, M. and Joshi, R. Notes from the AI frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute Discussion Paper, 2018, 4(1). junioreconomist.org+9mckinsey.com+9nist.gov+9

[82] Bughin, J., Catlin, T., Hirt, M. and Willmott, P. Why digital strategies fail. McKinsey Quarterly, 2018, 1(1), 14–25. strategicreading.uk+5mckinsey.com+5consejerosmasdigitales.com+5

[83] Gandomi, A. and Haider, M. Beyond the hype: Big data concepts, methods, and analytics. International Journal of Information Management, 2015, 35(2), 137–144.

[84] Marr, B. Big data in practice: how 45 successful companies used big data analytics to deliver extraordinary results. John Wiley & Sons, 2016.

[85] Bose, S., Dey, S.K. and Bhattacharjee, S. Big data, data analytics and artificial intelligence in accounting: An overview. In: Handbook of Big Data Research Methods, 2023, 32–51.

[86] Schoemaker, P.J.H., Heaton, S. and Teece, D.J. Innovation, dynamic capabilities, and leadership. California Management Review, 2018, 61(1), 15–42.

[87] Donate, M.J. and de Pablo, J.D.S. The role of knowledge-oriented leadership in knowledge management practices and innovation. Journal of Business Research, 2015, 68(2), 360–370.

[88] Abdelmoteleb, A.A.S., Kamarudin, S. and Noohuddin, P.N.E. Data driven customer experience and the roadmap to deliver happiness. Marketing and Branding Research, 2017, 4, 236–248.

[89] Thomas, A. Knowledge Management, Leadership, and Innovation in Digital Transformation: Navigating the Future of Organizations. Taylor & Francis, 2024.

[90] Singh, S.K., Gupta, S., Busso, D., Kamboj, S. and Singh, R. Top management knowledge value, knowledge sharing practices, open innovation and organizational performance. Journal of Business Research, 2021, 128, 788–798. DOI: 10.1016/j.jbusres.2019.04.040

[91] Birasnav, M. Knowledge management and organizational performance in the service industry: The role of transformational leadership beyond the effects of transactional leadership. Journal of Business Research, 2014, 67(8), 1622–1629.

[92] Alshurideh, M.T., Al-Kurdi, B. and Akour, I.A. Nexus between Knowledge Management and Creative Organizational Climate on Smart Organizations: Case of the Manufacturing Industry. International Journal of Theory of Organization and Practice, 2023, 3(1), 143–157.

[93] Tidd, J. Managing innovation. In: IEEE Technology and Engineering Management Society Body of Knowledge (TEMSBOK), 2023, 95–108.

[94] Oztemel, E. and Gursev, S. Literature review of Industry 4.0 and related technologies. Journal of Intelligent Manufacturing, 2020, 31(1), 127–182.

[95] Steenhuis, H.-J. and Pretorius, L. The additive manufacturing innovation: a range of implications. Journal of Manufacturing Technology Management, 2017, 28(1), 122–143.

[96] Chesbrough, H. The logic of open innovation: managing intellectual property. California Management Review, 2003, 45(3), 33–58.

[97] Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L. and Canhoto, A. Big data, big decisions: The impact of big data on board level decision-making. Journal of Business Research, 2018, 93, 67–78. DOI: 10.1016/j.jbusres.2018.08.029 ideas.repec.org+5ideas.repec.org+5pureportal.coventry.ac.uk+5

[98] Wu, L., Sun, L., Chang, Q., Zhang, D. and Qi, P. How do digitalization capabilities enable open innovation in manufacturing enterprises? A multiple case study based on resource integration perspective. Technological Forecasting

and Social Change, 2022, 184, 122019. DOI: 10.1016/j.techfore.2022.122019 sciencedirect.com+5ideas.repec.org+5scribd.com+5

[99] Lin, H. and Li, M. Practitioner's guide to data science. Chapman & Hall/CRC, 2023.

[100] Moro-Visconti, R. Digital Networking and Artificial Intelligence-Driven Startups. In: Startup Valuation: From Strategic Business Planning to Digital Networking, Springer, 2025, 241–291.

[101] Wang, X. Industry Innovation in the Era of Artificial Intelligence: The AI Compass. CRC Press, 2025.

[102] Siddiqui, N.N. Effective Leadership Strategies for Enhancing Employee Motivation and Reducing Turnover in Distributed Energy Conversion Companies. In: Hybrid Electric Vehicles and Distributed Renewable Energy Conversion: Control and Vibration Analysis, IGI Global Scientific Publishing, 2025, 337–364.

[103] Phookan, H. and Sharma, R.R. Cross-border interpersonal knowledge sharing within the MNE: does intra-MNE competition hinder or facilitate it? Journal of Knowledge Management, 2025.

[104] Manigandan, R., Raghuram, J.N.V. and Venugopal, P. Supply chain strategic shielding: an IPMA approach to unveiling the serial mediating effects of risk management and resilience in the entrepreneurial orientation-firm performance relationship in Indian manufacturing SMEs. International Journal of Procurement Management, 2025, 22(4), 421–449.

[105] Yoshikuni, A.C., Gómez, J.L., García-Marzá, D.J., da Silva, R.V., Maciel, C.R. and Da Silva, J.N. The role of IT governance and organizational agility in enhancing firm performance: a study of Asian and Latin American firms. Industrial Management & Data Systems, 2025.

[106] Kshetri, N., Voas, J., Tan, J., Hart, A. and Wu, S. Harnessing Generative Artificial Intelligence: A Game-Changer for Small and Medium Enterprises. IT Professional, 2025, 26(6), 84–89.

[107] Selvakumar, P., Ramamoorthy, V., Balaji, M., and Ravi, V. The role of artificial intelligence in business model innovation: overview of AI technologies. In: AI-Driven Business Model Innovation, IGI Global, 2025, 219–246.

[108] Shaikh, Z.P. and Shah, N. Supply chain processes through artificial intelligence and machine learning: application of demand planning, reinforcement learning, and product clustering. In: Supply Chain Transformation Through Generative AI and Machine Learning, IGI Global Scientific Publishing, 2025, 379–408.

[109] Tao, F., Qi, Q., Liu, A. and Kusiak, A. Digital twin in industry: state-of-the-art. IEEE Transactions on Industrial Informatics, 2018, 15(4), 2405–2415. DOI: 10.1109/TII.2018.2819141

[110] Li, C. Open leadership: How social technology can transform the way you lead. John Wiley & Sons, 2010.

[111] Rathore, S. and Chauhan, S. Navigating leadership and management styles: strategies for organizational success. [Chapter 8] 2024.

[112] Drucker, P.F. Entrepreneurial strategies. California Management Review, 1985, 27(2).

[113] Waseel, A.H., Zhang, J., Khan, S. and Malik, H. Does empowering leadership help firms to establish collaborative culture and organizational commitment to stimulate frugal innovation? Kybernetes, 2025, 54(2), 1289–1318. emerald.com+8ingentaconnect.com+8emerald.com+8

[114] Iqbal, S., Bashir, M., Bureš, V., Zanker, M., Ullah, S. and Rizwan, A. Impact of knowledge sharing and innovation on performance of organization: evidence from the pharmaceutical industry of Pakistan. Cogent Business & Management, 2025, 12(1), 2471536. sciencedirect.com+4researchgate.net+4tandfonline.com+4

[115] Guadalupe, D. Smart Contracts to Smart Decisions: How AI is Shaping Blockchain Technology. AMBCrypto, 2025.

[116] Ghlichlee, B., Bayat, F. and Hatami, A. Knowledge-oriented leadership and business performance: the mediating role of intellectual capital and sustainable competitive advantage in the knowledge-intensive service industry. Journal of Intellectual Capital, 2025, 26(1), 152–173.

[117] Bhalla, R., Singh, R., Sharma, K. and Singh, P. Empowering Small and Medium Enterprises Through Smart Technology and Talent Management. In: Designing Sustainable Internet of Things Solutions for Smart Industries, IGI Global, 2025, 351–380.

[118] Whig, P., Madavarapu, J.B., Yathiraju, N. and Thatikonda, R. Managing Knowledge in the Era of Industry 4.0: Challenges and Strategies. In: Knowledge Management and Industry Revolution 4.0, Wiley, 2024, 239–273. novel-coronavirus.onlinelibrary.wiley.com+7researchgate.net+7scholar.google.com+7

[119] Saefullah, A., Hidayatullah, S., Fadli, A. and Candra, H. The impact of transformational leadership on energy innovation: a review from the viewpoint of the consumer. International Journal of Artificial Intelligence Research, 2025, 8(1.1). DOI: 10.29099/ijair.v8i1.1.1357 core.ac.uk+5ijair.id+5ijair.id+5

[120] Aguirre-Urreta, M.I. and Hu, J. Detecting common method bias: performance of the Harman's single-factor test. ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 2019, 50(2), 45–70.

[121] Sreeram, A., Kesharwani, A. and Desai, S. Factors affecting satisfaction and loyalty in online grocery shopping: an integrated model. Journal of Indian Business Research, 2017, 9(2), 107–132.

[122] Rizvi, R.A. and Ali, N.W. The synergistic consequence of knowledge management and artificial intelligence on technological innovation in manufacturing firms of developing country. Journal of Intelligence Technology and Innovation, 2024, 2(4), 86–105.

[123] Yu, T., Li, F., Wang, Y. and Chen, X. Role of environment-driven CSR, green servant leadership, and green dynamic capabilities in firm green innovation: evidence from manufacturing industry. Environment, Development and Sustainability, 2024, 26(9), 1–27.