Leveraging Industry 4.0 and Knowledge Management for Enhanced Innovation Performance: The Mediating Role of Organizational Learning

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ABSTRACT

This current article empirically examines the relationship between Knowledge Management (KM), Organizational Learning (OL), and Industry 4.0 (ID) in driving Innovative Performance (IP). Data was collected from (N=466) employees working at various levels in the manufacturing sector organizations of Pakistan through personally administered questionnaire. The findings validate KM as a primary driver of innovation ($\beta = 0.564$), with OL acting as a pivotal mediator. While OL partially mediates the KM-IP relationship, KM retains a stronger direct effect, underscoring the intrinsic value of knowledge assets beyond learning processes. Industry 4.0 exhibits a significant direct impact on OL ($\beta = 0.554$) but only a weak moderating effect on the KM-OL link ($\beta = 0.079$), suggesting its role is more additive than transformative. The moderated mediation effect is statistically negligible ($\beta = 0.028$), reinforcing those digital technologies enhance learning independently rather than amplifying KM's influence on innovation. KM's effectiveness grows with higher ID adoption, as advanced digital infrastructure improves knowledge capture and sharing. Practically, organizations should prioritize KM and OL foundations while selectively deploying ID as a secondary enabler. Theoretically, the results refine assumptions about Industry 4.0's disruptive potential, positioning it as a supportive rather than central force in innovation dynamics. Moreover, this article offers a nuanced framework for balancing knowledge, learning, and digitalization in innovation strategies, guiding both academic discourse and managerial decision-making.

Keywords**:** Knowledge Management, Organizational Learning, Industry 4.0, Innovation, Moderated Mediation, Digital Transformation

1. Introduction

Scientists have acknowledged that the arrival of Industry 4.0 has revolutionized industrial operations worldwide by incorporating sophisticated technologies like the Internet of Things (IoT), artificial intelligence (AI), big data analytics, and automation [1-3]. For developing nations such as Pakistan, adopting Industry 4.0 offers a pivotal chance to boost productivity, competitiveness, and innovation within its major industrial sectors: textiles, pharmaceuticals, and automobiles [4, 5]. These sectors are essential to Pakistan's economy, making substantial contributions to employment, GDP growth, and export revenues [6]. The textile industry, responsible for more than 60% of the country's total exports, serves as the cornerstone of industrial activity [7]. However, it contends with ongoing issues such as low productivity, dependence on obsolete technology, and intense competition from neighboring countries like Bangladesh and India [8].

Likewise, the Pharmaceutical and Health industry in Pakistan is seeing stable expansion because of the increasing need for healthcare at home [9]. However, it's dealing with slow-moving regulations and not enough money going into new research [10]. At the same time, the automobile industry is growing but relies too much on buying parts from other countries [11].

Even though Industry 4.0 technologies offer a lot of promise, most businesses in Pakistan's industrial sector haven't fully incorporated them [12]. They're still sticking to traditional manufacturing methods for the most part [13]. According to Rathore, Mahesar [14], this slow adoption of new technology has made it harder for Pakistani businesses to compete globally, led to less innovation, and caused inefficiencies in production and supply chains. While some big textile companies have started using automated looms and AI to check quality, most small and medium-sized businesses (SMEs) are still doing things the old way [15, 16]. In the pharmaceutical industry, fewer than 10% of companies have started using blockchain to make their supply chains more transparent [17]. And in the car industry, the heavy reliance on technology from other countries is hindering local innovation[18]. These issues show that there's a real need for research to figure out how Pakistani industries can use Industry 4.0 technologies in a way that fosters innovation and lasting growth. A crucial factor hindering the widespread embrace of Industry 4.0 in Pakistan boils down to a gap in comprehension. Many don't fully grasp how knowledge management practices and organizational learning play a vital role in smoothing the way for technological integration. When it comes to guiding a business through the difficulties of digital transformation, knowledge management which means that the careful and methodical management of information, know-how, and technological knowledge - is indispensable.

Likewise, organizational learning equips companies to keep pace with evolving technologies, nurturing a culture that values and drives innovation [19]. However, existing literature on Industry 4.0 predominantly focuses on developed economies [20, 21], leaving a significant research gap concerning its application in developing countries like Pakistan. Specifically, there is limited empirical evidence on how knowledge management practices influence Industry 4.0 adoption[22], the mediating role of organizational learning in enhancing innovative performance [23], and the sector-specific challenges faced by textiles, pharmaceuticals and health care, and automobiles in implementing smart technologies. Addressing these gaps is crucial for developing tailored strategies that align with Pakistan's industrial context.

Research from around the world highlights just how much Industry 4.0 can innovate products [24]. Manufacturing organizations that have effectively brought together IoT and AI see efficiency gains, and good knowledge management can speed up digital transformation [25, 26]. Plus, businesses that really focus on learning as an organization are three times more likely to successfully take on new technologies [27]. Even so, in Pakistan, adoption is still disturbingly slow. Only 15% of textile firms are using AI for predictive maintenance, and even fewer pharmaceutical and car companies are adopting advanced digital options[4]. The significant difference emphasizes the pressing requirement for research focused on specific regions. This research is necessary to pinpoint the obstacles and possibilities for Industry 4.0 adoption in Pakistan.

The goal of this study is to fill these vacuums by investigating the relationship among Industry 4.0, knowledge management methods, organizational learning, and innovative performance within Pakistan's crucial industrial areas. Through an examination of specific challenges and opportunities within each sector, this research strives to offer practical guidance for businesses and policymakers aiming to promote digital change. The results will lead to a more profound comprehension of how Pakistani companies can utilize Industry 4.0 technologies to boost innovation, increase competitiveness, and attain sustainable growth within a global economy that is becoming increasingly digital.

In conclusion, the literature review is the portion that comes after the introduction section of the paper. It is this section that sheds light on the empirical links between constructs and the theoretical reflections that lie behind the study model. Following the completion of the literature review, the methodology, and finally the analysis and findings of the results obtained using SMART PLS 4.0. The conclusion, discussion, implications, and recommendation for further research are all included in the final part.

2. Literature review

2.1 Innovation Performance

Innovation performance is all about how well a company can roll out new or much-improved products, processes [28], or even whole new ways of doing business that help them stay competitive and grow their market share [29]. It is also assumed that a company is innovative by looking at things like how many patents they file, how many new products they launch [30], the gains in efficiency they achieve, and the money they make from their innovative efforts [31]. There are two main ways to look at innovation performance: product innovation, which means coming up with new or better goods and services, and process innovation, which means finding ways to make production or delivery more efficient [32].

Innovation comes in many forms, from big, groundbreaking changes to smaller, more gradual improvements [33]. Innovation is bringing together new elements into the way products are produced[34]. According to Du Plessis [35] viewed innovation as coming up with fresh knowledge and ideas that lead to new business results, mainly by improving how things are done and creating new products and services. Moreover, Lundvall and Nielsen [36], put it more in simple words that innovation is about something novel that adds value to what they already produce.

Scientists have also highlighted that innovation has two different dimensions: firstly, the traditional structuralist view, and secondly, the process-oriented perspective [37]. The traditional structuralist view sees innovation as a kind of product with set characteristics that external providers make and then hand over to users. On the other hand, the process-oriented perspective suggests that innovation is a multifaceted process, one that's shaped by political dynamics and decision-making, often involving various groups within organizations.

Furthermore, scientists have also categorized different kinds of innovation into two main groups: product innovation and process innovation [38]. This way of classifying things lines up with what had suggested earlier [39, 40]. When it comes to product innovation (PDI), it's all about how a company interacts with the outside world interms of making a product. This includes how brand new their products are, whether they're using cutting-edge tech, how many competitors they beat to market, and how many fresh products they launch. On the flip side, process innovation (PRI) is more about what's going on inside the company. It includes how quickly they embrace new technologies, how good they are at using tech compared to others, how new their process tech is, and how rapidly they adapt to technological shifts. A bunch of research has investigated how knowledge management (KM) affects what a company achieves, like how well it learns, the quality of its products, and its financial, economic, and operational success (Abubakar et al., 2019).

Tesla's electric cars and 3M's Post-it Notes are great examples of product-based innovation[41, 42]. When it comes to process-based innovation, Siemens' smart factories [43] and Toyota's Just-in-Time manufacturing [44]. Shifting our focus to Eastern countries, China stands out with Huawei's 5G technology [45] and Alibaba's AI-powered logistics [46]. In India, we see innovative efforts like Tata Motors' Nano [47] and Mahindra's adoption of lean production[48]. In Pakistan, examples of product innovation can be found in Suzuki's fuel-efficient cars[49] and Nishat Mills' high-performance fabrics [50].

As for process innovation, we can look at Lucky Cement's waste-heat recovery systems [51, 52] and Shan Foods' automated packaging solutions [53]. Pakistan does struggle with certain issues, including low investment in research and development (0.3% of GDP compared to China's 2.4%) [54], a lack of strong collaboration between industries and academia (Kamal et al., 2021), and regulatory hold-ups (PEC, 2022).

2.2 Knowledge Management Practices

Industry 4.0 has had a significant impact on how organizations handle knowledge [54, 55]. The management of knowledge (KM) involves capturing, storing, sharing, and utilizing knowledge [56, 57]. Knowledge management practices is a multidisciplinary method that helps organizations reach their goals by using knowledge effectively [58]. In the past, KM has improved because of the growing use of computers in the latter half of the 20th century. This allowed for the adoption of specific technologies like information repositories, intranets, and computer-aided cooperative work (Ruggles, 2009). Successful knowledge management (KM) also encompasses elements like human resources, organizational culture, and structure, all working in tandem with key mechanisms to ensure knowledge is used consistently [59].

The rise of Industry 4.0 (I4.0) has recently given KM practices a significant boost, thanks to digital applications that provide new and enhanced ways to generate, access, share, and utilize knowledge [60, 61]. Furthermore, the influence of I4.0 on KM can be seen in the embrace of design principles crucial for a successful digital transformation within organizations [62].

These principles often shape how people act and make choices, helping shift the organization's culture towards the Fourth Industrial Revolution [63]. Therefore, it's anticipated that blending good knowledge management practices with Industry 4.0 could create more innovative organizations (Cheah & Tan, 2021). But, without the right behaviors in place, efforts to digitalize probably won't do much to boost innovation performance.

2.3 Theoretical Justification

The close link between how companies handle knowledge and how well they innovate is deeply rooted in the Resource-Based View (RBV)[64] . This idea suggests that businesses get ahead by using their special, valuable, and hard-to-copy resources. Knowledge is a key resource here, driving creativity, problem-solving, and new technologies. When companies are organized about collecting, saving, and sharing databases, collections of best practices, or teamwork tools, they set the stage for new ideas to bloom. Take Google and 3M, for instance. They've made knowledge management a regular part of their work, with things like "20% time" (giving staff some hours to pursue their own projects) and brainstorms that bring together different teams. These approaches have paved the way for big innovations like Gmail and Post-it Notes.

Building on this connection is the Dynamic Capabilities Theory, initiated by [65]. This theory suggests that to thrive in fast-paced markets, companies need to constantly absorb, reshape, and utilize their knowledge. Toyota's "Just-in-Time" manufacturing approach serves as a prime example. This system depends on immediate information exchange between suppliers and the assembly line, significantly reducing waste and boosting efficiency. Toyota's skill in handling knowledge has cemented its status as a front-runner in process innovation within the industry. Research by (Darroch, 2005), among others, confirms this link, showing that businesses with robust Knowledge Management systems tend to secure more patents, bring products to market faster, and adjust to market shifts more effectively.

Knowledge Management (KM) directly fuels innovation, but there's a more nuanced story when Organizational Learning (OL) acts as the go-between. Think of it like this: OL uses KM as a raw material, helping organizations truly grasp and apply knowledge, rather than just stockpiling it. Pioneers like Argyris, Schön, and Senge showed us that companies learn by trying things out, seeing what works (and what doesn't), and adjusting accordingly. Take Amazon, for example. Even though ventures like the Fire Phone didn't pan out, the lessons they learned paved the way for the triumphs of Alexa and AWS. This shows how KM, when processed through the lens of learning, can truly power innovation.

The Absorptive Capacity Theory, proposed by Cohen and Levinthal in 1990 was also cited in the research by [66], adds another layer to our understanding of this process. It highlights that companies need to be able to identify, absorb, and then utilize external knowledge before they can truly innovate. Samsung's journey in the smartphone market is a perfect illustration of this. Starting as a competitor playing catch-up, Samsung made significant investments in knowledge management systems to soak up technological insights from rivals and research organizations. Gradually, this newfound knowledge became deeply embedded within the company through practices like dismantling competitor products to learn from them and partnering on research and development. This internalization of knowledge eventually empowered Samsung to surpass its rivals, introducing groundbreaking innovations such as foldable screens and cutting-edge semiconductor chips.

Furthermore, Nonaka and Takeuchi's SECI Model, developed in 1995, illustrates the dynamic between tacit and explicit knowledge within companies, showing how this interplay drives learning and fuels innovation. Take NASA's "Lessons Learned" database, for instance. It distills the implicit knowledge gleaned from past missions like the setbacks experienced during the Apollo program and transforms it into well-defined educational resources. This ensures that subsequent endeavors, such as the Mars Rover missions, can draw upon this collective expertise. The ongoing cycle of knowledge management leads to organizational learning and subsequently to innovation clarifies why certain organizations consistently excel in research and development as well as in the creation of new products, surpassing their competitors.

The industry 4.0 shift, which includes things like the Internet of Things (IoT), Artificial Intelligence (AI), analyzing huge datasets, and smart manufacturing, changes how Knowledge Management (KM) and innovation are connected. It does this by speeding up the movement of information and making decisions based on data possible. The Technology-Organization-Environment Framework from Tornatzky and Fleischer (1990) helps us see this change, basically saying that new technologies alter the way companies use what they know and apply in the making of technologies [67]. A good example is Siemens. They use digital twins, which are basically virtual copies of real-world systems, to simulate and improve production processes as they happen, seriously cutting down on the time spent learning through trial and error. Without the tools that Industry 4.0 brings to the table, this kind of fast knowledge application just wouldn't be possible. Bharadwaj and colleagues (2013) put forth a theory on digital transformation, suggesting that digital infrastructure boosts the effectiveness of knowledge management by automating how data is collected and analyzed[68]. Take Tesla, for instance. Their over-the-air (OTA) software updates gather real-time performance data from a huge fleet of vehicles. This data then goes into AI-powered analytics platforms, allowing Tesla to roll out improvements without needing physical recalls. This kind of closed-loop system is a prime example of how Industry 4.0 tightens the bond between knowledge management and innovation by turning knowledge into action right away. On a larger scale, this research lines up with the Knowledge-Based View (KBV), as presented in the research papers by [69].

The KBV builds on the Resource-Based View (RBV) by proposing that knowledge is the most valuable strategic resource a company can have. This helps explain why companies like Apple and Microsoft are so dominant. It's not just their physical assets, but their unique knowledge ecosystems (think of Apple's iOS development frameworks or Microsoft's Azure AI tools) that give them their edge. Alongside the knowledge-based view (KBV) is Complex Adaptive Systems (CAS) Theory, proposed by (Holland, 1995). This theory sees organizations as dynamic entities that develop through learning and adaptation. In the Industry 4.0 landscape, CAS illuminates how real-time data flows and machine learning turn companies into "learning organisms." A prime instance is Netflix's recommendation algorithm, which perpetually learns from user interactions, refining its content suggestions in a self-improving cycle—this exemplifies CAS principles at work.

2.4 Knowledge Management Practices, Organizational learning and Innovation Performance

Knowledge acts as a valuable tool that can help organizations tackle the appropriate challenges, leading to better decisions and more effective use of resources. Collins [70] distinguished between two types of knowledge: tacit and explicit. Tacit knowledge is gained through hands-on experience and practical application, deeply rooted in an individual's personal journey. On the flip side, explicit knowledge refers to information documented in a structured, standardized format [71, 72]. These two forms of knowledge interact in a dynamic, cyclical process encompassing four stages: socialization, externalization, combination, and internalization [73].

The success of Knowledge Management (KM) can be affected by two main factors: (i) the environment and (ii) the processes, as suggested by [74, 75]. KM processes are often seen as crucial within organizations because they generate knowledge and persist even without formal organizational backing. However, KM processes can be categorized in various ways. One widely accepted method divides them into five stages: knowledge acquisition, creation, transfer, storage, and application, as outlined by Inkinen in 2016. KM helps knowledge flow through two key strategies: (i) codification and (ii) personalization. Codification involves extracting and storing explicit knowledge using information and communication technologies, while personalization focuses on human interaction as a method for sharing knowledge [76].

KM can also be categorized based on its actual practices [74]. Bawa, Attah [77] suggested sorting these practices into three groups: knowledge acquisition (KA), knowledge dissemination (KD), and responsiveness to knowledge (RK). KA covers finding, creating, or uncovering knowledge. KD involves the organized methods used to spread knowledge throughout a company. RK describes how an organization reacts to the different kinds of knowledge it can access. This way of classifying KM, along with its proven measurement scale, has been frequently used and cited in various studies [78]. Innovation comes in many forms, including both groundbreaking and more gradual changes. For example, J. Chen et al., (2004) described it as bringing together fresh combinations of key elements within a production system.

Scientists have categorized different kinds of innovation into two main groups: product innovation and process innovation[79, 80]. On the flip side, process innovation (PRI) is more about the internal culture of a company. It involves how quickly new technologies are adopted, how competitive the company is technologically, how new the process technologies are, and how rapidly technology is changing within the firm. There's been a lot of research on how knowledge management (KM) affects what happens in an organization. This includes things like how well the organization learns, the quality of its products, and its financial, economic, and operational performance. Knowledge Management (KM) is significant to innovation performance[81], this point is also backed by the research [82].

According to Du Plessis [35], actually stressed that the complexity of innovation has grown because organizations have access to so much knowledge, which underscores the need for well-managed KM [83]. Therefore, organizations focused on innovation need effective KM methods that thoughtfully deal with knowledge acquisition (KA), knowledge development (KD), and reusing knowledge (RK)[84, 85]. However, it's hard to get definitive answers from the current research on this link, as most studies are still in the early stages and use a variety of measures and scales [81, 85]. Additionally, Cabrilo and Dahms [86] claimed that it is hard to understand fully how a strategic approach to KM particularly impacts innovation performance.

2.5 Industry 4.0 Moderator

Industry 4.0 is Launched at the Hannover Fair in Germany back in 2011, Industry 4.0, or I4.0 for short, represents the current wave of digitalization [87], holding significant promise across a multitude of industries [88], including automotive [89], healthcare [90], food [91], public administration [58, 92, 93]. The adaptability of I4.0 has captured the interest of both professionals and scholars, who are now exploring the technological shift from embedded systems to cyber-physical systems, essentially bridging the gap between the digital realm and the real world [94].

Moreover, the fusion of digital and physical realms, propelled by groundbreaking technologies, sparked enthusiasm within organizations and supply chains, offering the potential for reduced expenses, greater adaptability and swiftness, and enhanced quality [95]. Consequently, several scholars [96-98] have chosen to implement Industry 4.0 through sophisticated industrial automation systems and supporting technologies. However, despite the extensive research dedicated to many of these technologies, their adoption fluctuates considerably among businesses and sectors, necessitating customized solutions that are frequently challenging to disseminate [58, 99].

Meanwhile, the design principles of Industry 4.0 clearly lay out the foundation for understanding the different parts of this trend (Hermann et al., 2016). These principles are thought to help professionals foresee possible organizational problems when putting Industry 4.0 into practice, thus influencing the choices and actions that drive the technological progress (Gilchrist, 2016; Vogel-Heuser & Hess, 2016). Because of this, some scholars (like Cañas et al., 2021; Ghobakhloo, 2018; Hermann et al., 2016; Herrmann et al., 2015; Lu, 2017) have centered their research on the core design principles that encourage widespread adoption of Industry 4.0.

Even though there might be slight differences in how we refer to these concepts, the core design principles of Industry 4.0 can be summarized like this: (i) connecting machines, devices, sensors, and people through digital means, (ii) making information readily available to everyone who needs it, (iii) using technology to aid in decision-making and problem-solving, such as employing digital twins, (iv) enabling systems to operate as independently as possible with the help of cyber-physical systems, (v) collecting, storing, and analyzing data in real time, and (vi) rapidly adapting to shifts in the market, facilitated by information and communication technologies. When we think about bringing Industry 4.0 into knowledge management (KM) practices, it seems like a natural fit, as earlier research Capestro & Kinkel (2020), Lee et al., (2013), and Li et al. (2019) has already pointed out that improvements in information and communication technologies have fundamentally changed the part knowledge plays in our economy.

Digital transformation has made it possible for everyone to easily access all kinds of information, which in turn helps us handle knowledge acquisition, knowledge development, and knowledge retention more effectively. This connection is so widely stressed that some scholars even think of knowledge management mainly as using cutting-edge technologies, turning implicit knowledge into explicit form, and exchanging knowledge through information systems [36]. The main benefit of Industry 4.0 for businesses is that it allows them to use data, information, and knowledge in a more efficient way for various decision-making processes. AI actually generates valuable insights from data, which could possibly result in more informed forecasts and choices, identification of significant opportunities and risks, and can inspire and aid creative processes that serve as a crucial starting point for innovation across various fields [100] . Cloud computing, on the other hand, provides access to information and knowledge, often at a reduced cost, leading to enhanced customer experiences, more informed employee decisions, and broader knowledge sharing among all stakeholders (AlEmran et al., 2018; Pagliosa et al., 2019). These examples are all incorporated within the broader framework of Industry 4.0 design principles, which theoretically offer companies a competitive edge [101].

Essentially, while traditional Knowledge Management (KM) has historically relied on searchable, and sometimes intelligent, databases, Industry 4.0 offers a potentially robust set of tools that can allow KM to be more actively involved in various facets of organizational effectiveness, including, notably, innovation effectiveness. However, the widespread digitalization of organizations might bring about intricate and contradictory outcomes that could ultimately undermine the influence of KM practices on innovation effectiveness [102]). For example, a significant repercussion of digitalization is the increasing scarcity of tacit knowledge, which consequently intensifies the challenges associated with managing this form of knowledge. On top of that, integrating Industry 4.0 (I4.0) speeds up shifts in processes, products, and services. This means organizations have to learn new things more quickly, which could make it harder for them to gather and share knowledge effectively [103, 104].

Looking at it through a sociotechnical systems (STS) lens, how a company manages knowledge (KM) can reflect the concrete, technical parts of the equation [85, 105]. Meanwhile, the guiding ideas behind I4.0 can stand for the less tangible, social and cultural factors (Cañas et al., 2021; Tortorella et al., 2021a). These are all important for a company to be really innovative. We believe that both the technical and the social/cultural sides need to be developed at the same time to boost both process innovation readiness (PRI) and product development improvement (PDI) within organizations. In the light of above discussion, Knowledge management practices is taken as independent variable (IV) and Innovative performance is dependent variable (DV) and organizational learning is a mediating variable (MV) illustrated in the figure 1. Moreover, conceptual framework also illustrates the role of moderating variable industry 4.0 principles between Knowledge management practices and organizational learning leading to innovative performance.

2.6 Conceptual Framework

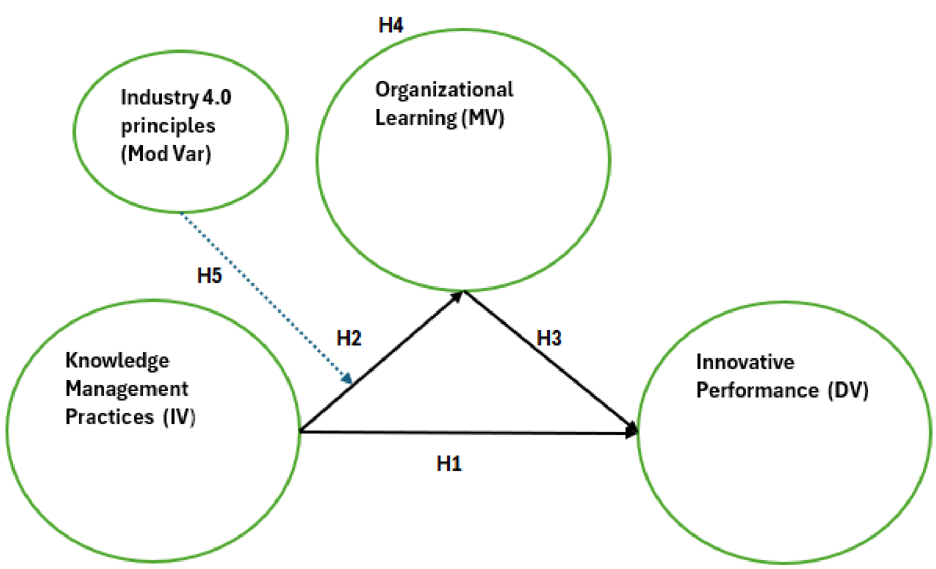

Fig 1. Conceptual Framework

2.7 Hypothesis

H1: There is a significant positive relationship between Knowledge Management Practices (KMP) and Innovative Performance (IP).

H2: Organizational Learning (OL) has a significant positive effect on Innovative Performance (IP).

H3: Organizational Learning (OL) mediates the relationship between Knowledge Management Practices (KMP) and Innovative Performance (IP).

H4: Industry 4.0 Technologies (I4.0) moderate the relationship between Knowledge Management Practices (KMP) and Innovative Performance (IP).

3. Methodology

This research uses a quantitative approach and deductive reasoning, based on the positivist philosophy that values objective measurements and statistical analysis. This method tests hypotheses developed from established theories. The study zeroes in on four main sectors: Healthcare & Pharmaceutical, Automobile, Textile, and Information Technology. It investigates the connections among Knowledge Management Practices, Organizational Learning, Industry 4.0 adoption, and Innovative Performance. The study focuses on mid-career and first-line managers, recognizing their crucial role in putting into action knowledge-based strategies and fostering innovation in their companies. To ensure a diverse range of regions and industries were represented, data was gathered from 466 employees across five of Pakistan's major cities: Karachi, Lahore, Peshawar, Gujranwala, and Faisalabad. Convenience sampling was used because it was a practical way to reach people who were available and willing to take part. Face-to-face surveys were the main method of collecting data, as they tend to result in more responses and clearer answers. A standard survey was used to collect the responses, and it included tried-and-tested scales to measure the main concepts being studied.

We used descriptive statistics like averages, standard deviations, and frequency distributions to get a general sense of the data trends. We also used inferential statistics, specifically structural equation modeling, to test out the relationships we thought we might find. For the structural equation modeling, we chose SMART PLS 4.0, a tool that's particularly good for making predictions and exploring complicated models. However, there's a known issue with survey research called common method bias, which can be a problem when both the independent and dependent variables come from the same source (as described by Kock, Berbekova, and Assaf in 2021). To try to reduce this bias, we ran Harman's single-factor test in SPSS 25.0. In this test, we put all our variables through an unrotated factor analysis.

The results indicated that only 33% of the variance was explained by a single factor, which is below the 50% threshold (Jordan & Troth, 2020), confirming that common method bias was not a significant concern in this study. Knowledge management practices (KM) was comprised of two dimensions i.e., Knowledge management acquisition, Knowledge management dissemination and measured through twelve items scale examined in the earlier studied by Tortorella, Prashar [58], Organizational learning (OL) was examined with five items by the earlier research conducted by Jerez-Gomez, Céspedes-Lorente [106]. Innovation Performance was comprised of two dimensions product innovation and process innovation performance, examined through five items by Wang and Ahmed [107], and with four items by Terziovski [108] and Damanpour and Gopalakrishnan [109]. Industry 4.0 was measured with six items examined Tortorella, Prashar [58].

3.1 Analysis

As per table 1, the research included a total of 466 people working in Pakistan's manufacturing sector. Men made up 65% of the group (303 individuals), while women accounted for 35% (163 individuals). Most of the participants (49%) were between 31 and 40 years old, and a significant portion (40%) fell between 41 and 50 years old. A smaller number of people were aged 21 to 30 (8%), very few were under 20 (2%), and only 1% were over 50. When it came to their education, the majority had a bachelor's degree (59%), followed by 23% who had completed postgraduate studies. A smaller number had finished higher secondary education (9%), matriculation (7%), or just primary education (1%). The automobile industry had the strongest showing among participants (45%), with pharmaceuticals and healthcare following closely at 37%. Textiles contributed 14%, while information technology had a smaller presence at 3%. In terms of job titles, 32% of the respondents were in supervisory positions, 29% identified as engineers, 17% as technicians, and managers and those in other roles each made up 11% of the group. This wide range of respondents, varied across gender, age, education, industry, and job level, gives us a comprehensive view that enhances the reliability and broader applicability of the results within Pakistan's manufacturing landscape.

Table 1. Demographics Profile

Gender		
Male	303	65%
Female	163	35%
Age		
less than 20 yrs	7	2%
21 yrs to 30 yrs	39	8%
31 yrs to 40 yrs	228	49%
41 yrs to 50 yrs	186	40%
51 yrs to 60 yrs	6	1%
Education		
Primary	5	1%
Matric	33	7%
Higher Secondary School	44	9%
Bachelors	229	59%
Post Graduate	108	23%
Industry		
Textiles	67	14%
Pharmaceutical & Health	174	37%
Automobile	210	45%
Information Technology	15	3%
Managerial Role		
Manager	51	11%
Supervisor	151	32%
Engineer	137	29%
Technician	78	17%
Others	49	11%

The analysis of the relationships between two variables at a time shows some notable connections among the key concepts of this study (table 2). The extent to which Industry 4.0 is embraced (ID) is strongly and positively linked to both how well an organization learns (OL; $r = .788$, $p < .01$) and how innovative it is (IP; $r = .698$, $p < .01$). This lines up with what's been written about digital transformations, where technology is emphasized to boost learning abilities [110] and bring about better innovation results

[111]. The especially tight bond between how knowledge is managed (KM) and innovation performance ($r = .809, p < .01$) backs up the idea that organizations are fundamentally about knowledge management practices (Grant, 1996). It confirms that having a well-organized approach to knowledge is important for successful innovation, just as earlier research has shown [112].

Organizational learning has strong connections with all the variables studied (with correlation coefficients ranging from .680 to .788). This suggests that it plays a key role in converting knowledge and digital skills into innovation. This finding aligns with [113] idea that learning acts as a link between knowledge resources and the creation of competitive innovations. The interaction between Industry 4.0 (ID) and Knowledge Management (KM) shows a more modest correlation (ranging from .505 to .568), hinting at a noticeable but weaker moderating impact. This aligns with theories that emphasize the contingency nature of integrating technology and knowledge (Bharadwaj et al., 2013). Although statistically significant (with a p-value less than .01), these moderating effects seem less influential than the direct relationship between KM and Innovation Performance (IP). This could mean that the way Industry 4.0 boosts knowledge management practices might vary depending on the situation, which calls for a deeper exploration using conditional process analysis [114].

It's worth pointing out that all the correlations are under 0.85, which means we don't have to worry too much about multicollinearity when we do our regression modeling in previous research [115]. Overall, our results support the main ideas of our theoretical model and really drive home how important knowledge management and organizational learning are in the whole innovation process. These results build on what others have found about what helps innovation along by measuring the strength of these relationships in the context of Industry 4.0. This has real implications for where to focus knowledge management investments as we move into the digital transformation era.

Table 2 Bivariate correlations

	ID	**IP**	**KM**	**OL**	**ID x KM**
ID	1				
IP	0.698	1			
KM	0.602	0.809	1		
OL	0.788	0.744	0.68	1	
ID x KM	0.565	0.505	0.523	0.568	1

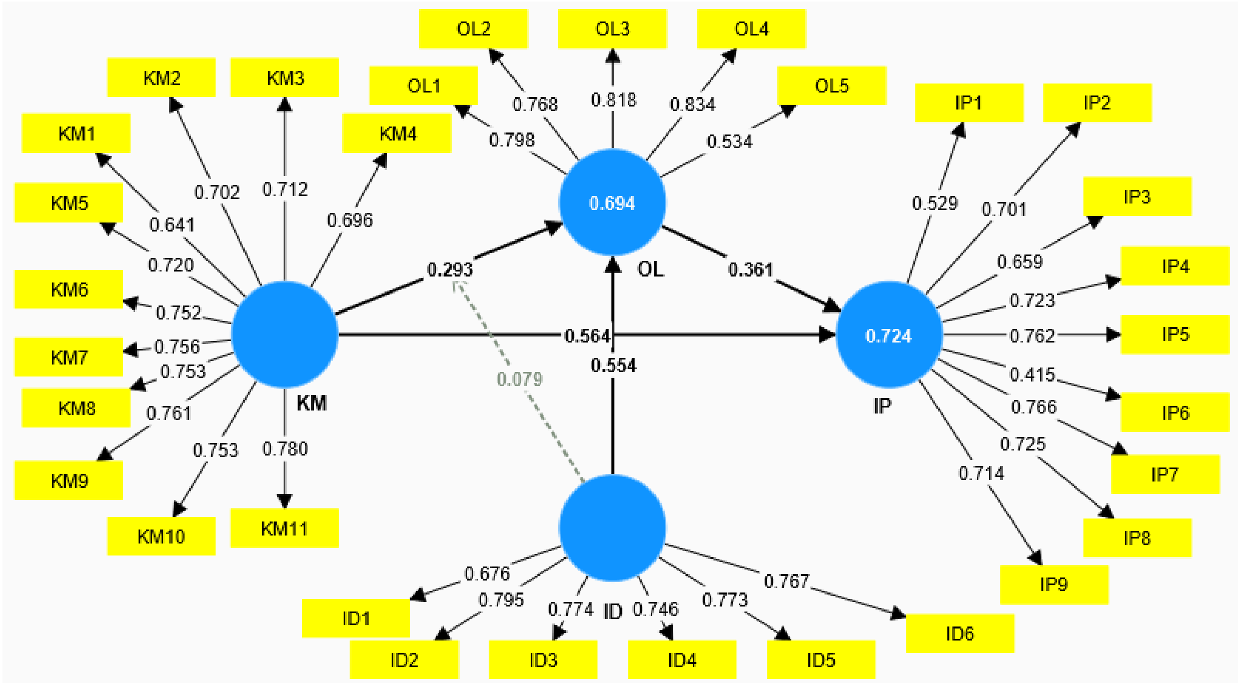

Fig 2. Measurement Model

Source: Author’s Own

Table 3 reveals that the measurement model mostly exhibits satisfactory psychometric qualities across the various constructs, even though there's some room for improvement. The Industry 4.0 adoption (ID) scale demonstrates strong reliability, with a Cronbach's alpha of 0.85 and a Composite Reliability of 0.854. Its convergent validity is somewhat acceptable, with an Average Variance Extracted (AVE) of 0.572. All Outerloadings are depicted in Fig2. However, the outer loading for ID1 is 0.676, which is below the commonly recommended 0.7 cutoff (Hair et al., 2019). This suggests that removing ID1 might enhance the overall construct. Regarding innovation performance (IP), the scale shows good internal consistency, evidenced by a Cronbach's alpha of 0.84 and a Composite Reliability of 0.86. Nevertheless, two items, namely IP1 (0.529) and IP6 (0.415), exhibit relatively low loadings. These low loadings likely explain the IP scale's AVE of 0.501, which is only just above the generally accepted threshold. To adhere to standard validity guidelines [116], it would be advisable to eliminate these two items.

Knowledge management (KM) really shines here, showing itself to be the strongest concept with good reliability ($\alpha = 0.912$, CR = 0.914), and all its parts connecting well above 0.64. While already good, reducing KM1 (0.641) could slightly boost its acceptable AVE (0.534).

Organizational learning (OL) also looks strong in terms of reliability ($\alpha = 0.808$, CR = 0.833), but one piece (OL5 = 0.534) isn't pulling its weight and should be dropped to improve its overall validity (AVE = 0.575). This all lines up with standard quality checks [117] and indicates that with a little fine-tuning, our concepts will be ready to test the ideas in your Industry 4.0 innovation model.

3.2 Outer loadings, Cronbach’s Alpha, Composite Reliability, Average Variance Extracted

Table 3. Outerloadings, Cronbach's Alpha, Composite Reliabilities, Average Variance Extracted

Variables/Constructs	Items	Outer loadings	Cronbach's Alpha	Composite Reliability(CR)	Average Variance Extracted(AVE)
Industry 4.0 Principle (ID)					
	ID1	0.676			
	ID2	0.795	0.85	0.854	0.572
	ID3	0.774			
	ID4	0.746			
	ID5	0.773			
	ID6	0.767			
Innovative Performance(IP)					
	IP1	0.529			
	IP2	0.701	0.84	0.86	0.501
	IP3	0.659			
	IP4	0.723			
	IP5	0.762			
	IP6	0.415			
	IP7	0.766			
	IP8	0.725			
	IP9	0.714			
Knowledge Management Practices (KM)					
	KM1	0.641			
	KM2	0.702	0.912	0.914	0.534
	KM3	0.712			
	KM4	0.696			
	KM5	0.72			
	KM6	0.752			
	KM7	0.756			
	KM8	0.753			
	KM9	0.761			
	KM10	0.753			
	KM11	0.78			
Organizational Learning (OL)					
	OL1	0.798			
	OL2	0.768	0.808	0.833	0.575
	OL3	0.818			

OL4	0.834
OL5	0.534

The evaluation of discriminant validity demonstrates that the constructs are distinct from one another based on empirical evidence. As shown in Table 3, all the Heterotrait-Monotrait (HTMT) ratios are below the stringent cutoff point of 0.85, as recommended by Gold et al. (2001); the highest ratio is 0.811, observed between Industry 4.0 (ID) and Innovation Performance (IP). This implies that discriminant validity is acceptable, although the correlation between ID and IP is nearing the threshold, which suggests some conceptual similarity between these two constructs while they still remain distinct statistically. Furthermore, Table 5 presents the Fornell-Larcker criterion, which further substantiates the discriminant validity: the square root of the Average Variance Extracted (AVE) for each construct (displayed on the diagonal) surpasses their correlations with other constructs, in line with Fornell and Larcker's (1981) guidelines. A case in point is Organizational Learning (OL), which has a diagonal value of 0.858, significantly higher than its strongest correlation with another construct, which is 0.721 (with KM).

Table 6 really highlights how well this model predicts things. It turns out that Innovation Performance (IP) is accounting for a substantial 72.4% of the variance ($R^2 = 0.724$). Organizational Learning (OL) is also a strong predictor, explaining nearly as much at 69.4% ($R^2 = 0.694$). The fact that the R^2 and adjusted R^2 values are so close together suggests the model is just right – not too complicated and not overfitted, as per study by [118].

Table 7 shows that multicollinearity isn't a major concern. None of the Variance Inflation Factor (VIF) values exceed the strict limit of 3.3, as suggested by [119]. Although KM7 (3.081), KM8 (3.174), and KM10 (3.054) are close to this limit, their values still don't signal a problematic level of collinearity. Most items have moderate VIFs between 1.5 and 2.5, indicating a healthy level of correlation between items without being repetitive. The consistently low VIFs for the rest of the constructs, like the ID items ranging from 1.546 to 2.183, further support the measurement model's reliability for structural analysis.

Table 4. Heterotrait-Monotrait (HTMT) Ratio

	ID	**IP**	**KM**	**OL**	**ID x KM**
ID					
IP	0.811				
KM	0.675	0.793			
OL	0.748	0.781	0.777		
ID x KM	0.609	0.543	0.548	0.633	

Table 5. Fornell-Larcker Criterion

	ID	**IP**	**KM**	**OL**
ID	**0.756**			
IP	0.698	**0.775**		
KM	0.602	0.709	**0.831**	
OL	0.688	0.704	0.721	**0.858**

Table 6. R-square & Adjusted R-Square

	R-square	R-square adjusted
IP	**0.724**	**0.723**
OL	**0.694**	**0.692**

Table 7. VIF values

	VIF
ID1	1.546
ID2	2.183
ID3	2.042
ID4	1.966
ID5	2.146
ID6	1.689
IP1	1.383
IP2	2.269
IP3	2.163
IP4	2.066
IP5	2.19
IP6	1.311
IP7	2.307
IP8	1.925
IP9	1.792
KM1	1.979
KM10	3.054
KM11	2.386
KM2	2.168
KM3	1.903
KM4	1.827
KM5	1.931
KM6	2.487
KM7	3.081
KM8	3.174
KM9	2.702
OL1	2.21
OL2	2.139
OL3	1.983

OL4	2.037
OL5	1.212

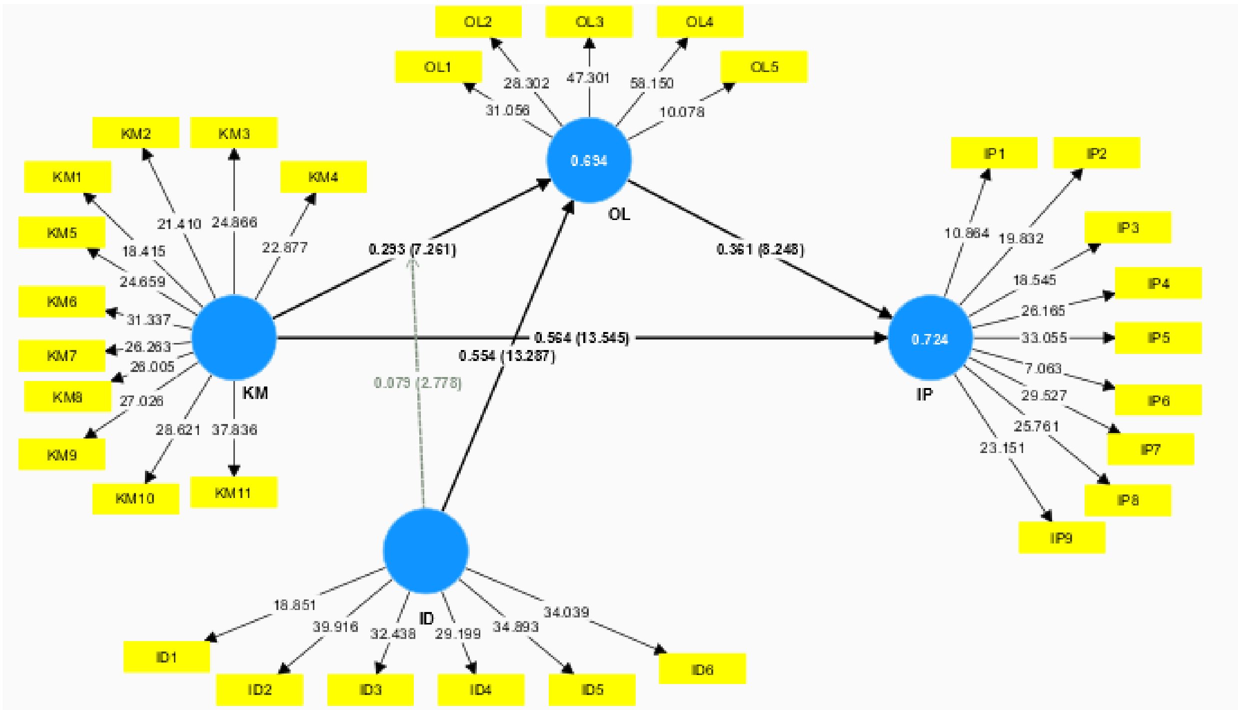

Fig 3. Structural Model

Source: Author's Own

According to the structural model extracted from smart PLS shown in fig3, it is yielded that our research strongly supports the idea that managing knowledge well is the key to being innovative. It is also found out that learning organization plays a big role in this, and that Industry 4.0 makes a real difference too. All the paths with their respective hypothesis (from H1 to H7) were significant statistically ($p< 0.01$), even if their real-world effects differed in table 8. The most powerful effects were especially striking: Industry 4.0 really boosts organizational learning (H1, with a coefficient of 0.554), and good knowledge management directly and strongly improves innovative performance (H2, coefficient of 0.564). Also, while organizational learning helps knowledge management drive innovation (H3 and H4), knowledge management's direct effect is still the most important.

However, the moderation and mediated effects were showing that ID does amplify KM's role in fostering OL (H5: β = 0.079 with t significant and $p<0.001$), the effect is marginal, suggesting that Industry 4.0 operates more as an independent driver rather than a strong enhancer of KM. The mediation pathway (H6: β = 0.106) was significant, reinforcing OL's critical bridging role. The moderated mediation effect (H7: β = 0.028) was also confirmed but proved negligible in practical terms.

Table 8. Direct, Total Indirect, Specific Indirect and Total Effects.

Direct Effect (Mean, SD, T-Values, P-values)

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ID -> OL	0.554	0.553	0.042	13.287	0.0000
KM -> IP	0.564	0.567	0.042	13.545	0.0000
KM -> OL	0.293	0.295	0.04	7.261	0.0000
OL -> IP	0.361	0.359	0.044	8.248	0.0000
ID x KM -> OL	0.079	0.08	0.028	2.778	0.0050
Total Indirect Effect (Mean, SD, T-Values, P-values)					
	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
KM -> IP	0.106	0.106	0.018	5.768	0.0000
ID x KM -> IP	0.028	0.028	0.01	2.809	0.0050
Specific Indirect Effects (Mean, SD, T-Values, P-values)					
	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
ID -> OL -> IP	0.2	0.199	0.032	6.194	0.0000
KM -> OL -> IP	0.106	0.106	0.018	5.768	0.0000
Total Effect (Mean, SD, T-Values, P-values)					
	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
ID -> OL	0.554	0.553	0.042	13.287	0.0000
KM -> IP	0.669	0.672	0.033	20.391	0.0000
KM -> OL	0.293	0.295	0.04	7.261	0.0000
OL -> IP	0.361	0.359	0.044	8.248	0.0000
ID x KM -> IP	0.028	0.028	0.01	2.809	0.0050
ID x KM -> OL	0.079	0.08	0.028	2.778	0.0050

4. Discussion

The findings of this study offer significant empirical validation for the proposed theoretical framework, demonstrating how Knowledge Management (KM) serves as a primary driver of Innovative Performance (IP), with Organizational Learning (OL) acting as a mediator and Industry 4.0 (ID) functioning as a moderating factor. The results strongly support KM's direct positive impact on innovation (β = 0.564), consistent with established literature emphasizing knowledge as a critical resource for competitive advantage. This relationship is further enhanced through OL, which plays a pivotal mediating role, suggesting that effective knowledge utilization requires institutionalized learning processes to fully translate into innovative outcomes. However, the study reveals that while OL partially mediates this relationship, KM maintains a stronger direct effect, indicating that knowledge assets retain intrinsic value beyond their contribution to learning capabilities.

Industry 4.0 emerges as a significant but somewhat limited factor in this dynamic. While ID demonstrates a substantial direct effect on OL (β = 0.554), its moderating influence on the KM-OL relationship proves relatively weak (β = 0.079). This suggests that digital transformation technologies enhance organizational learning independently rather than dramatically amplifying the impact of existing knowledge management practices. The moderated mediation effect, though statistically significant, is practically negligible (β = 0.028), reinforcing the conclusion that ID's primary value lies in its standalone contribution to learning rather than in transforming how knowledge management drives innovation.

The moderation interaction plot which is shown as figure 4 that the effectiveness of Knowledge Management (KM) on organizational outcomes is significantly influenced by the level of Industry 4.0 adoption. At low adoption levels, KM has minimal impact due to the lack of digital infrastructure. With moderate adoption, KM's benefits become more noticeable. At high adoption levels, KM's impact is strongly amplified, as advanced digital technologies enhance knowledge capture, processing, and sharing. This highlights the technological complementarity between KM and Industry 4.0, where digital maturity boosts the value of KM practices.

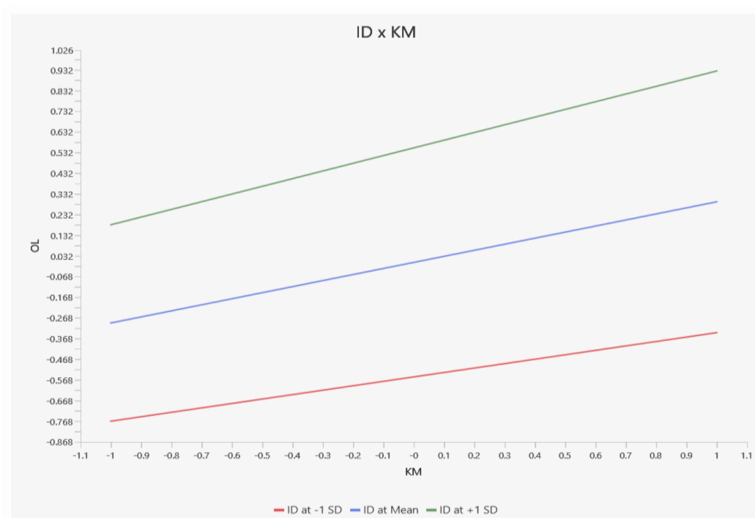

Fig 4. Moderation Interaction Plot

These findings carry important implications for both theory and practice. They contribute to ongoing academic discussions by clarifying the distinct yet complementary roles of KM, OL, and ID in innovation processes, challenging some assumptions about the transformative potential of digital technologies in knowledge-intensive contexts. For practitioners, the results suggest a strategic approach that prioritizes robust knowledge management systems while viewing digital transformation as an important but secondary enabler. Organizations would benefit from focusing first on developing strong KM foundations and learning cultures, then selectively implementing Industry 4.0 technologies to support these existing capabilities rather than expecting digital tools to fundamentally reshape their knowledge and innovation dynamics.

Several limitations of the current study point to valuable directions for future research. The cross-sectional design prevents definitive causal conclusions, suggesting the need for longitudinal studies. Additionally, industry-specific analyses could reveal important variations in how these relationships manifest across different sectors. Potential moderators such as leadership styles or organizational culture might further refine our understanding of the conditions under which these factors interact most effectively. Despite these limitations, the study provides compelling evidence for a nuanced understanding of innovative drivers, where knowledge management remains central, organizational learning serves as a crucial amplifier, and digital technologies play a supporting rather than revolutionary role. This balanced perspective offers both theoretical clarity and practical guidance for organizations navigating the complex interplay of knowledge, learning, and technology in their innovation strategies.

5. Conclusion and Future Research

This study provides compelling evidence that Knowledge Management serves as the cornerstone of organizational innovation, with Organizational Learning acting as a crucial bridge that translates knowledge assets into innovative outcomes. While Industry 4.0 technologies demonstrate significant potential to enhance learning capabilities, their role as a moderator of the KM-innovation relationship appears more limited than often assumed. The findings collectively suggest that organizations stand to gain most by prioritizing robust knowledge management systems and fostering a culture of continuous learning, with digital transformation initiatives playing a supporting rather than central role in innovation strategies. These insights contribute to theoretical discourse by clarifying the distinct yet interconnected roles of knowledge, learning, and technology in driving innovation, while offering practical guidance for managers seeking to allocate resources effectively in an increasingly digital business environment.

Future research should build on these findings through longitudinal studies that can better establish causal relationships and track the evolution of these dynamics over time. Investigations across different industries could reveal important contextual variations, particularly in comparing manufacturing with service sectors or examining knowledge-intensive versus capital-intensive industries. Additional studies might explore how organizational factors such as leadership styles, corporate culture, or incentive systems influence the effectiveness of these innovation drivers. There is also potential to examine more nuanced aspects of digital transformation, such as how specific Industry 4.0 technologies (e.g., AI, IoT, or blockchain) differentially impact knowledge management and learning processes. Finally, research could benefit from incorporating more objective performance measures alongside perceptual data to strengthen the validity of findings. These future directions would collectively enhance our understanding of how organizations can best leverage their knowledge resources, learning capabilities, and technological investments to sustain innovation in an increasingly complex and competitive business landscape.

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