Digital Innovation, Digital Transformation, and Digital Platform Capability: Detrimental Impact of Big Data Analytics Capability on Innovation Performance

Jan Muhammad Sohu
School of Management, Jiangsu University, Zhenjiang, Jiangsu, China.

Tian Hongyun
School of Management, Jiangsu University, Zhenjiang, Jiangsu, China.

Ume Salma Akbar
Assistant Professor at Sukkur IBA University Sukkur, Sindh, Pakistan.
Email: u.salma@iba-suk.edu.pk

Fawad Hussain
Department of Management Sciences SZABIST Larkana, Pakistan.

Received on: 17-07-2023 Accepted on: 19-08-2023

Abstract

In the contemporary digital era, characterized by rapid technological advancements and the widespread utilization of big data analytics, concerns have emerged regarding the capacity of small and medium enterprises (SMEs) to maintain their competitiveness and enhance their innovation performance (IP). Addressing this research gap, this paper delves into the adverse role played by big data analytics capability (BDAC) in moderating the relationship between digital innovation (DI) and IP. The research methodology involved the analysis of data using structural equation models (SEM), employing the smartPLS-4. Data collected from manufacturing SMEs. The findings of this study reveal that digital platform capability (DPC) significantly mediates the connection between DI -> IP and digital transformation (DT) and IP. Additionally, DI, DT, DPC, and BDAC exert substantial, direct, and positive influences on IP. Moreover, BDAC emerges as a significant moderator in the relationships between DPC -> IP and between DT -> IP. The impetus for this research stems from its practical relevance, particularly in the context of supporting SMEs in their adoption of digital transformation and the Technology Acceptance Model (TAM). These findings not only enrich our understanding of the contributions of DT, DI, DPC, and BDAC to a firm's IP but also challenge the prevailing notion that BDAC invariably enhances performance, as it can also attenuate the relationship due to its 100% integration, leading to a reduction in DI and DPC

Keywords: Big Data Analytics Capabilities, Digital Innovation, Digital Transformation, Technology Acceptance Model, Digital Platform Capability

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

1. Introduction

In the contemporary era of digital innovation and transformation, businesses are engaged in a fervent race to integrate cutting-edge technologies into their operations. These transformative technologies have reshaped the landscape in which SMEs operate, influencing not only how they conduct business but also how individuals live and interact. For SMEs in developing countries, navigating this competitive digital terrain poses a formidable challenge. These enterprises are driven by a collective aspiration to harness digital technologies as a means to enhance their competitiveness, bolster sales figures, boost productivity levels, and ultimately elevate their IP. The digital age of innovation and transformation has ushered in a new competitive landscape, particularly challenging for SMEs in developing countries. These enterprises are driven to embrace digital technologies in their pursuit of greater competitiveness, increased sales, heightened productivity, and improved innovation performance. The adoption of such technologies, as emphasized by research, can yield substantial gains in productivity. However, it is crucial to recognize the dual role of Digital Innovation and Digital Transformation in this context, with the latter's impact on innovation performance hinging on the organization's level of digital maturity (Nousopoulou et al., 2022). Companies that want to survive in today's market must innovate both in process and product or risk falling behind the competition, they should adopt advanced technology, and learn to implement new business methods (Li et al., 2022). DI refers to producing, disseminating, and adding value to a novelty that is limitless in scope (such as a new product, service, operation, or business model). Adopting new digital technologies has drastically changed how SMEs innovate digitally and focus on right applicability of BDAC. DT is a complex and challenging process, but it can be successful if organizations focus on these eight building blocks. These blocks include leadership, culture, capabilities, processes, metrics, resources, partnerships, and governance (Vial et al., 2019).

Small and medium-sized enterprises (SMEs) play a crucial role in the development of economies like Pakistan. They drive economic growth, spark innovation, and generate employment opportunities. Despite their significance, SMEs in such countries often grapple with resource limitations, limited access to technology, inadequate government support, and a lack of expertise compared to larger corporations (Farhan et al., 2021). These challenges hinder their successful adoption of digital technologies. Our research aims to offer practical insights and recommendations to assist SMEs in navigating the digital landscape effectively. We bridge a gap in the existing literature by providing a comprehensive framework that links these variables and sheds light on how they collectively influence innovation performance.

The existing literature often lacks in-depth exploration of the intricate relationships among DT, BDAC, DI, DPC, and their impact on IP. Drawing from the TAM, this study contributes significantly to the literature by examining the interplay between DI and DT. Furthermore, it addresses the research gap by expanding upon existing studies involving these variables, which still require further investigation when considered together. While these variables have been examined individually, systematic analyses that integrate them and assess their collective influence on SMEs operating in developing Asian countries are scarce. This research derives its motivation from both its practical relevance, aimed at supporting SMEs in their adoption of DT, and its theoretical significance in bridging the research gap pertaining to the

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

correlations among these factors. Additionally, it offers valuable insights that can inform the development of strategies, policies, and practices geared towards fostering innovation and digital growth within small and medium-sized enterprises.
This research focuses on analyzing new methods and tools for assessing the impact of BDAC on IP and understanding the factors influencing the success of BDAC implementation. Certain studies suggest relying only partially on digital technologies for innovation. Usai et al., (2021) claims that digital technology use had a negligible effect on IP while predicting innovation, organizations should consider investing in R&D. These results have changed the dilemma of only relying on digital technologies for innovation. This study investigates the relationship between DI, VCC, and DT, as well as the mediating and moderating impacts of DPC and big data analytics capabilities, respectively. This study addresses these research questions:

2. Theoretical support and hypothesis development

2.1 TAM theory

The TAM integration provides understandings of how SMEs can adopt digital technologies like BDAC, DT, and DI to enhance IP. The main goal of the TAM was to clarify the mechanisms that drive the adoption of technology, with the aim of forecasting behavior and furnishing a theoretical rationale for the effective integration of technology. In our study, TAM theory has been integrated to adopt the digital technology trough DT. Several studies used TAM theory to adopt digital technology but as per best of researcher's knowledge, literature missed the theoretical gap of integration TAM to in such a complex fusion of DI, DT, and BDAC, specifically in the context of SMEs operating in Pakistan. This study fills this gap and adds the literature by filling this theoretical gap.
The integration of the TAM offers valuable insights into how SMEs can successfully embrace digital technologies like BDAC, DT, and DI to enhance their IP. Originally conceived by (Davis, 1989), TAM was designed to elucidate the mechanisms driving technology adoption, aiming to predict behavior and provide a theoretical foundation for effective technology integration. In our study, we have employed TAM theory to guide the adoption of digital technology through DT. While previous research has applied TAM theory to digital technology adoption, our study stands out by addressing a notable gap in the literature. To the best of our knowledge, prior literature has overlooked the theoretical integration of TAM within the intricate fusion of DI, DT, and BDAC, particularly within the context of SMEs operating in Pakistan. Our research not only fills this critical theoretical gap but also contributes to the existing body of knowledge.

2.2 DI and DPC

In the digital age, DI and DPC emerge as pivotal concepts. DI involves the utilization of digital technologies to create something novel, whether it be a product or a service. This process of innovation is often intertwined with DT, as the advent of new technologies serves as a catalyst for innovation (Hadjielias et al., 2021; Robertsone et al., 2023). Research by Lee et al., (2019) has underscored the role of design science research in contributing to DI through the development of innovative IT artifacts. Conversely, DPC refers to the extent to which a company has embraced and effectively leveraged digital tools to enhance its operations (Khin et al., 2019a). Enterprises that have made substantial investments in their digital

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

infrastructure are better positioned for success in the realm of DI. DPC empowers organizations to identify digital opportunities, devise and implement digital solutions, and effectively manage digital risks (Tang et al., 2022). It represents an ongoing transformation that reshapes entire markets and positions businesses at the forefront of their respective fields. DI exerts a significant influence on organizational innovation, encompassing both opportunities and challenges (Tang et al., 2022). As highlighted by Khin & Ho, (2019a), DI is linked to improved and innovative organizational performance, manifesting in heightened efficiency and effectiveness through technology utilization.

2.3 DPC and IP

DPC serves as a vital component of a company's capacity to efficiently deliver digital services. For SMEs, embracing these digital services opens up new and innovative avenues to engage with customers through online platforms, mobile applications, and personalized digital experiences designed to meet their unique needs. This approach not only fosters customer loyalty but also drives increased sales and positive word-of-mouth recommendations (Peter et al. 2021; J. Su et al., 2023a). Moreover, DPC empowers SMEs to streamline internal processes and automate routine tasks. This operational efficiency, coupled with the utilization of data analytics, enables SMEs to allocate more time and resources toward innovation-focused endeavors such as research and development, product enhancements, and exploration of novel business models. By gaining access to new markets, SMEs can tap into global customer segments and offer niche products and services that were once beyond their reach, thus stimulating innovation by exposing them to fresh ideas and competitive dynamics. DPC also facilitates collaboration among SME stakeholders and research institutions, fostering open innovation, crowdsourcing, and partnerships (Xu et al., 2022). Such collaborations yield valuable insights, feedback, and ideas that enable SMEs to remain agile and responsive to changes in the market landscape. Furthermore, DPC empowers SMEs to leverage Big Data Analytics Capability (BDAC) by accumulating, analyzing, and harnessing vast volumes of data. This data-driven decision-making approach empowers SMEs to make informed choices, identify innovation gaps, and tailor their products and services to align with innovation performance and customer needs (Bagale et al., 2021; J. Su et al., 2023b).

2.4 DT and IP

DT within enterprises plays a pivotal and positive role in bolstering IP (Guo & Xu, 2021). Research outcomes indicate that two critical factors, namely digital mindset and digital competence, exert a direct and favorable impact on DT. Additionally, DT serves as a mediating force, enhancing corporate performance through digital orientation and improving revenue performance via digital capability (Iqbal et al., 2021; Naveed et al., 2023; Rupeika et al., 2022). In light of these findings, policymakers are urged to actively encourage DT initiatives and invest in Research and Development (R&D) activities aimed at enhancing innovation performance. Moreover, DT exhibits the potential to enhance corporate social sustainability by reducing environmental impact and increasing resource efficiency (Liang et al., 2022). However, it's worth noting that the influence of Digital Innovation (DI) on long-term company viability is not evenly distributed. Larger corporations and those located in more developed regions tend to reap greater benefits from DT. This underscores the importance of policymakers and managers alike in fostering DT to improve corporate sustainability and innovation. In particular, policymakers should prioritize initiatives that support the development and utilization of digital technology among SMEs and organizations operating in developing countries, thus ensuring a more equitable distribution of the benefits of DT (Zhang et al., 2022).

2.5 The Mediating Effect of DPC and DT

The impact of DT on innovation performance is strengthened when mediated by R&D capabilities within enterprises (Liang & Li, 2022) A systematic literature review conducted by Hausberg et al., (2019), analyzing over 1,054 research papers on DT and employing a citation network analysis, identified key research streams in DT research, emphasizing the roles of technology, organizations, and individuals. It posited that digital technologies hold the potential to enhance business performance and raised crucial questions about how organizations can adapt to the digital age and how individuals can develop the requisite skills and knowledge to thrive in the digital era, enabling digital capabilities.

Notably, there remains a research gap regarding the examination of the impacts of DT on various aspects such as the environment, employment, and inequality. The adoption of digital technologies empowers businesses to embrace digital methodologies, fundamentally reshaping their approach to market positioning. DT allows businesses to revolutionize their interactions and operational management (Vial et al., 2019). The rapid evolution of digital technologies has ushered in new challenges and opportunities for innovation, making it more accessible for firms to innovate. DT, in conjunction with service capability, has emerged as a pivotal driver of innovation. Consequently, organizations that effectively integrate DT and Digital Platform Capability (DPC) are more likely to foster innovation. Nonetheless, questions persist regarding the need for further investigation into the mediating effects of DPC and DT on innovation performance.

2.6 The moderating effect of BDAC

Big data has emerged as a potent tool for catalyzing transformation in small and medium-sized enterprises (SMEs). Through the collection and analysis of vast data sets, SMEs can uncover valuable insights into their customer base, market dynamics, and internal operations, leading to enhancements in efficiency, profitability, and innovation. SMEs adept at harnessing the potential of big data enjoy a substantial competitive advantage (Khan et al, 2022; Lytras et al., 2023). The adoption of Big Data Analytics Capability (BDAC) is on the rise among both small and large companies, including SMEs, as they recognize its potential to elevate Innovation Performance (IP). However, there remains a research gap in understanding the precise conditions under which BDAC exerts a significantly positive impact on IP (Bhatti et al., 2022a; Mikalef et al., 2020). BDAC plays a pivotal role in nurturing innovation capabilities (Tongtong et al., 2022). In conclusion, BDAC holds immense potential to revolutionize business operations. By fostering innovation in products, processes, and systems, the use of BDAC can enhance overall operations and position businesses competitively within their industries. It is evident that the foundation of big data analytics (BDA) plays a significant role in shaping Organizational IP (Tempini et al., 2017).

2.7 Conceptual Framework

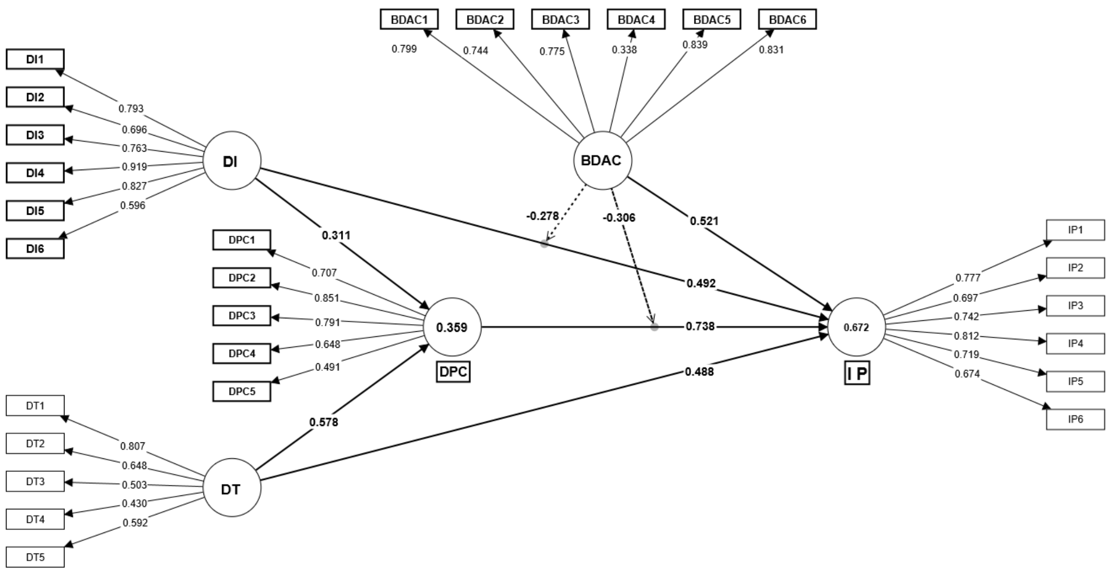

Figure 1: Conceptual Framework

3. Methodology

3.1 Research samples and data collection

The study's primary objective is to analyze the relationship between DT and DI on IP through DPC. This paper also investigates the role of BDAC in moderating the relationship between DI and IP. The study employed a quantitative approach which fits the current research objectives and scope. Data collected from different manufacturing sectors of SMEs by distributing online and off-line questionnaires. The two experts from industry and academia revised the questionnaire to make it reliable and understandable for the respondents with the help of pilot test. Around 846 questionnaires were distributed in November 2022 and researchers get complete responses in the May 2023. Interviews were conducted from CEOs and managers as they are the most relevant respondents for the nature of study regarding use of digital technologies. After getting 516 (61%) responses back, 110 responses were further excluded based on missing and improper data and remaining 406 responses were considered valid for further analysis. As per the selected sample meet the minimum sample selection criteria.

The main objective of this study is to examine the relationship between DT and DI on IP through the mediation of DPC. Additionally, the research delves into the moderating role of BDAC in the relationship between DI and IP. A quantitative research approach was employed, aligning with the research objectives and scope. Data was gathered from various SMEs in the manufacturing sector through the distribution of both online and offline questionnaires. To ensure the reliability and comprehensibility of the questionnaires, they underwent revision by two experts from both industry and academia, with the assistance of a pilot test. The data collection process spanned from November 2022 to May 2023, involving the distribution of 846 questionnaires. Subsequently, complete responses were obtained, and after excluding

110 responses due to missing or improper data, 406 responses were deemed suitable for further analysis. It's worth noting that, in accordance with guidelines provided by Hair et al., (2014), the selected sample size meets the minimum criteria for valid statistical analysis.

3.2 Variables and measurement.

This study used adapted all measure from top reputable journals. To measure DI, six items were adapted from, while DPC is measured by using five items of. DT were measured using 5 items adopted from. Six items derived from and utilized to evaluate BDAC. Lastly, IP is measure by six items derived from.

In this study, well-established measures from respected journals were adapted to assess the key constructs. To gauge Digital Innovation (DI), a set of six items were adapted from a study by Xu et al., (2022). Digital Platform Capability (DPC) was evaluated using five items originally developed by (Liu et al., 2023). The measurement of Digital Transformation (DT) drew from five items adopted from the work of (AlNuaimi et al., 2022). For Big Data Analytics Capability (BDAC), a set of six items was derived from the research conducted by (Al-Khatib, 2022). Lastly, Innovation Performance (IP) was assessed using six items, sourced from studies by (Carrasco-Carvajal et al., 2023; Espasandín-Bustelo et al., 2023).

3.3 Data analysis

To validate the connections between multiple constructs in the newly proposed theoretical framework, PLS-SEM method is selected for statistical analysis (Hair et al., 2019). In order to investigate the causal relationships between independent and dependent variables and determine the extent to which the theories are supported or refuted, the advantages of Partial Least Squares Structural Equation Modelling (PLS-SEM) are being considered.

4. Results

4.1 Testing for convergent and discriminant validity

1.4.1 Measurement model

In the measurement model, to validate the reliability and validity of data, the values of outer loadings, Cronbach alpha (α), composite reliability, average variance extracted (AVE), and variance inflation factor (VIF) have met the defined thresholds by (Hair et al., 2019; Kock, 2017; Sarstedt, 2019)(see Table 1).

Table 1: Reliability and Validity

Items	*loadings*	*Variables*	*Alpha*	*Rho_a*	*CR*	*AVE*	*Outer VIF*
BDAC1	0.799	BDAC	0.824	0.887	0.874	0.550	1.700
BDAC2	0.744						1.806
BDAC3	0.775						2.915
BDAC4	0.738						1.114
BDAC5	0.839						3.502
BDAC6	0.831						2.337
DI1	0.793	D I	0.861	0.896	0.897	0.596	3.032
DI2	0.796						1.635
DI3	0.763						2.573
DI4	0.919						4.444

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

DI5	0.827						3.133
DI6	0.706						1.491
DPC1	0.707	DPC	0.751	0.802	0.830	0.502	1.429
DPC2	0.851						1.858
DPC3	0.791						1.706
DPC4	0.748						1.441
DPC5	0.701						1.250
DT1	0.807	DT	0.715	0.741	0.739	0.522	1.095
DT2	0.718						2.109
DT3	0.703						1.714
DT4	0.703						1.716
DT5	0.712						1.539
IP1	0.777	I P	0.834	0.845	0.877	0.545	2.315
IP2	0.797						1.780
IP3	0.742						4.401
IP4	0.812						2.035
IP5	0.719						4.271
IP6	0.774						1.514

The assessment of discriminant validity involved Heterotrait-Monotrait (HTMT), cross loading, and Fornell-Larcker Criterion. According to (Hair et al., 2019), there was a lack of collinearity for all HTMT ratios that were lower than the cutoff value of 0.90. In Table 2 and 3 HTMT, cross loadings, and Fornell-Larcker Criterion values are below the threshold (Hair et al., 2019).

Table 2: HTMT Ratio and Fornell-Larcker Criteria

HTMT					
Items	BDAC	D I	DPC	DT	I P
BDAC					
D I	0.214				
DPC	0.718	0.380			
DT	0.239	0.337	0.542		
I P	0.595	0.568	0.872	0.468	
Fornell-Larcker Criterion					
Items	BDAC	D I	DPC	DT	I P
BDAC	***0.742***				
D I	0.162	***0.772***			
DPC	0.504	0.311	***0.709***		
DT	0.107	0.277	0.578	***0.610***	
I P	0.521	0.492	0.738	0.488	***0.758***

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

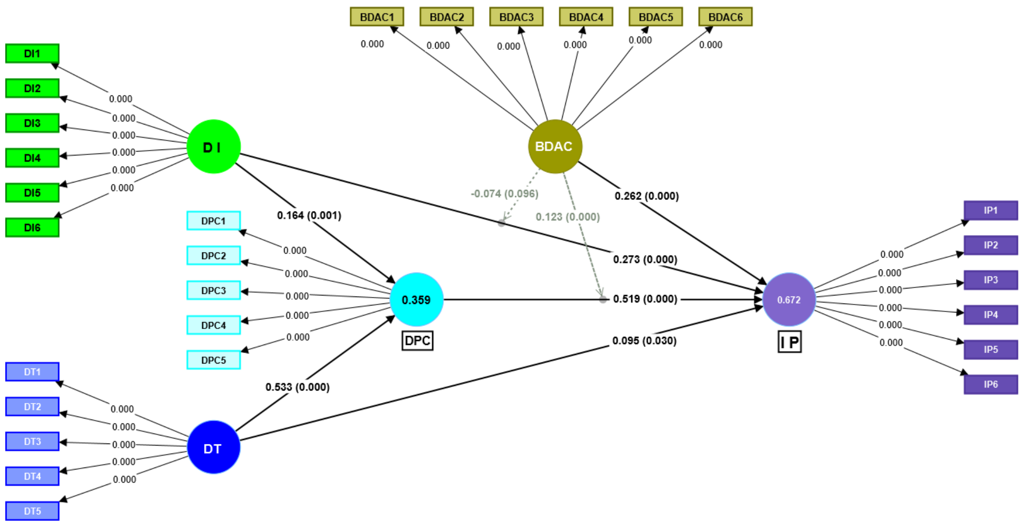

Figure 2: Structural Model

Table 3: Cross Loadings

Items	BDAC	D I	DPC	DT	I P
BDAC1	**0.799**	0.208	0.381	0.158	0.567
BDAC2	**0.744**	0.082	0.423	0.113	0.348
BDAC3	**0.775**	0.034	0.481	0.128	0.378
BDAC4	**0.738**	-0.009	0.136	-0.064	0.163
BDAC5	**0.839**	0.131	0.422	0.026	0.346
BDAC6	**0.831**	0.176	0.327	0.000	0.355
DI1	-0.005	**0.793**	0.324	0.343	0.395
DI2	0.199	**0.696**	0.209	0.244	0.353
DI3	0.072	**0.763**	0.254	0.194	0.309
DI4	0.174	**0.919**	0.318	0.270	0.517
DI5	0.171	**0.827**	0.184	0.167	0.342
DI6	0.167	**0.596**	0.077	-0.038	0.312
DPC1	0.170	0.156	**0.707**	0.504	0.574
DPC2	0.405	0.343	**0.851**	0.592	0.633
DPC3	0.371	0.315	**0.791**	0.341	0.619
DPC4	0.299	0.123	**0.648**	0.321	0.300
DPC5	0.710	0.054	**0.791**	0.149	0.384
DT1	0.158	0.268	0.648	**0.807**	0.451
DT2	0.080	0.187	0.228	**0.648**	0.324
DT3	-0.123	0.006	0.055	**0.503**	0.040
DT4	0.041	-0.012	0.110	**0.430**	0.155
DT5	-0.120	0.148	0.170	**0.592**	0.200
IP1	0.335	0.542	0.482	0.351	**0.777**
IP2	0.299	0.330	0.399	0.247	**0.697**
IP3	0.444	0.289	0.464	0.346	**0.742**
IP4	0.350	0.356	0.702	0.589	**0.812**

IP5	0.409	0.275	0.454	0.357	**0.719**
IP6	0.478	0.376	0.604	0.197	**0.674**

5. Discussions Results

5.1 Structural Measurement Model

The structural equation model has been shown in figure 2. The model goodness is indicated by the beta coefficient value of latent variables and R^2 (Briones et al., 2018). Better model fitness requires higher values of R-squared (Hair et al., 2019). To further validate the model, structural model has been tested at 10,000 bootstrap sample rotations for the significance levels of the estimates (t-statistics) and R^2 values (Hair et al., 2019). Results show that R^2 has explained 24.5% and 36.3% variance for DPC and IP respectively.

The outcomes of the study's hypothesis tests are presented in Table 4. According to the findings, both the beta and p values of direct path for the standardized coefficient of DI, DPC, DT, and BDAC are found significant with IP. This suggests that SMEs who are actively adopting and implementing digital technologies, must have a greater chance of effectively transforming digital initiatives. SMEs which collaborate with external partners and incorporate their feedback into the DT process are more likely to obtain the benefits of digital technology. Having direct, positive, and significant effect of DI on DPC establishes that businesses that prioritize and invest in technological initiatives like DI, are more likely to develop and refine their digital service capabilities. Furthermore, DI and DT has positive, direct, and significant impact over DPC. Therefore, these hypotheses for direct effect are accepted with significant p value at 0.01***, at 0.05**, and at 0.10*, respectively.

Table 4: Path Analysis

	Direct Path Analysis						
	Hypotheses	Beta	Mean	SD	T value	P value	*Dec*
H1a	*D I -> DPC*	0.164	0.164	0.051	3.220	0.001**	*Acc*
H1b	*D I -> I P*	0.273	0.277	0.040	6.786	0.000***	*Acc*
H2	*DPC -> I P*	0.519	0.518	0.048	10.793	0.000***	*Acc*
H3a	*DT -> DPC*	0.533	0.540	0.044	12.247	0.000***	*Acc*
H3b	*DT -> I P*	0.095	0.095	0.044	2.184	0.030**	*Acc*
H4	*BDAC -> I P*	0.262	0.260	0.033	7.948	0.000***	*Acc*
	Indirect Path Analysis/Mediation						
	Hypotheses	Beta	Mean	SD	T value	P value	*Dec*
H5	*D I -> DPC -> I P*	0.085	0.084	0.026	3.281	0.001**	*Acc*
H6	*DT -> DPC -> I P*	0.276	0.280	0.041	6.775	0.000***	*Acc*
	Total indirect Path Analysis						
	Hypotheses	Beta	Mean	SD	T value	P value	*Dec*
	D I -> I P	0.085	0.084	0.026	3.281	0.001**	*Acc*
	DT -> I P	0.276	0.280	0.041	6.775	0.000***	*Acc*
	Moderation						
	Hypotheses	Beta	Mean	SD	T value	P value	*Dec*
H7	*BDAC x D I -> I P*	-0.074	-0.076	0.044	2.012	0.096*	*Acc*
H8	*BDAC x D T -> I P*	0.123	0.132	0.024	2.906	0.000***	*Acc*

DI = Digital Innovation, DT = Digital Transformation, DPC = Digital Platform Capability,

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

BDAC = Big Data Analytics Capability, IP = Innovation Performance

5.2 Path Analysis

The findings reveal that DI, DT, DPC, and BDAC have positive, significant and direct impact on IP. To explain H1a: DI positively influences DPC with beta coefficient of 0.164, which is statistically significant ($p < 0.001$). This suggests that as DI increases, DPC also increases. All other direct path are shown in Table 4. This study uses mediation model where DPC is mediating the relationship between DI _> IP and DT _> IP. This shows that DPC is important for transforming DI and adopting DT into tangible results, such as improved IP. H5 explains DI indirectly influences IP through DPC with beta coefficient of 0.085, which is statistically significant ($p < 0.001$). This suggests that DPC partially mediates the relationship between DI and IP. This implies for SMEs to develop, prioritize, and enhance their DPC to improve SMEs' overall IP. In addition to that, results reveal that DPC significantly and partially mediates the relationship between DT and IP. All indirect mediating hypotheses are partially mediated and accepted.

Nevertheless, the moderating effect of BDAC between DI and the statistical significance but detrimental effect on IP occurs at p value < 0.10 at (T value = 2.012, P value < 0.096) and BDAC also has positive moderating effect on the relationship between DI and IP. The acceptance of H7 at 10% of probability value are rare but it has been proven before in the literature (Greenland et al., 2016). Based on statistical significance it is also acceptable at T statistics of > 2 and it also depends on the criteria set by scholars (Li et al., 2009) as well which are also considered as significant hypothesis at beta value > 2 (Reichelt & Wang, 2010). The results indicate that the capacity to execute big data analytics appears to have a negative but statistically significant moderating influence on the relationship between DI and IP. This indicates that a greater proficiency in BDAC may be able to mitigate or eliminate creativity of innovation to enhance IP. These results and statistical importance of this moderating effect are negative. As big data analytics capabilities expand, this proves that the relationship between DT and innovation success is deteriorating.

6. Conclusion and Discussion

This study illuminates several significant findings regarding the interplay of key variables. Firstly, it confirms that DI exerts a direct and positive influence on DPC. Simultaneously, DI has a direct and significant impact on IP. Moreover, the research uncovers an important pathway whereby DI significantly enhances IP through DPC. Furthermore, the study reveals that DT can directly enhance the performance of SMEs and, importantly, does so through its positive impact on DPC. Additionally, BDAC emerges as a noteworthy moderator in this context, positively and significantly moderating the relationship between DPC and IP. Intriguingly, BDAC exhibits a negative yet significant moderating effect on the relationship between DI and IP, implying that BDAC can enhance SME performance when integrated with DPC but is not as effective when combined with DI. These findings align with previous research, particularly in line with the perspectives presented by (Lytras et al., 2023) suggesting that excessive reliance on BDAC can present both challenges and benefits within the realm of DT. An over-dependence on BDAC may potentially stifle employee creativity, especially when confronted with novel and unfamiliar problems, as supported by prior

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

studies (Danah et al., 2011; John et al, 2013; Stitzlein et al., 2021).

Moreover, the study provides compelling evidence supporting the positive impact of DT on IP and its positive influence on DPC. These findings are consistent with prior research conducted by (Chuang et al., 2015; Lytras et al., 2023; Mennens et al., 2018b; X. Su et al., 2022; Tang et al., 2022). In the broader context of DT, technology not only spawns new business opportunities and strategies but also augments support, innovative capabilities, expansion prospects, and competitive advantages for established enterprises. When SMEs employ information systems to embrace social media and harness big data analysis, it inherently enhances and broadens organizational development. This underscores that businesses equipped with advanced IT capabilities are better poised to successfully adopt and implement DT (AlNuaimi et al., 2022).

The findings of this study provide compelling insights into the relationships between key variables. Firstly, it's clear that DI exerts a positive influence on both DPC and IP. Interestingly, the impact of DPC on IP is positively mediated by BDAC. However, the relationship between DI and IP is significantly influenced in a negative manner by BDAC. These results are consistent with prior research, particularly in line with the perspectives presented by (Usai et al., 2021) They challenge the notion of relying solely on digital technologies, specifically BDAC, as the driving force behind innovation. It is evident that researchers and decision-makers should not place exclusive emphasis on digital technologies, particularly BDAC, to spur innovation. Instead, they should prioritize the use of digital technologies to foster creativity and support Research and Development (R&D) efforts. Failing to address this erroneous belief could have detrimental consequences in the long run. Overly heavy investments in digital technologies at the expense of other critical factors such as creativity and R&D may ultimately lead to a decline in Innovation Performance (Usai et al., 2021). The application of big data is undeniably important, but it should be approached judiciously. While strong BDAC capabilities may better prepare businesses for the adoption of DI and DT, an overreliance on big data can stifle creativity and impede independent decision-making (Danah et al., 2011; John et al, 2013; Stitzlein et al., 2021). Even for businesses equipped with extensive big data analytic capabilities, fully realizing the IP benefits of DI can prove challenging (Lytras et al., 2023).

6.1 Theoretical Implications

In the context of developing nations, the cultural landscape plays a significant role in shaping the acceptance of technology. To understand this intricate interplay of cultural values, beliefs, and norms that influence technology acceptance, the TAM provides a valuable framework. TAM bridges this gap by incorporating the concepts of DI and the acceptance and implications of DT. Through the integration of TAM theory, this paper delves into how these factors, including individual perceptions and beliefs regarding technological acceptance, interact and impact TAM constructs within SMEs operating in Pakistan. The study's findings shed light on the attitudes of managers, executives, and CEOs within SMEs, revealing their openness to accepting new technology and their readiness to embark on digital transformation endeavors. These findings, in turn, signify the successful application of the TAM model within this context, underscoring its efficacy in explaining and predicting technology adoption and innovation performance within SMEs in Pakistan.

ISSN (ONLINE):2710-0308 www.irjmss.com ISSN (PRINT):2710-0316
DOI: **10.5281/zenodo.10498159**

6.2 Limitations and Future Recommendation

This study acknowledges two primary limitations. Firstly, the relatively small sample size of 303 respondents drawn exclusively from SMEs in Pakistan may limit the generalizability of the findings to a broader context. Secondly, the study relies on two specific theories, notably TAM, which centers on understanding the cultural values, beliefs, and norms of respondents influencing technology acceptance. It's important to note that these factors can vary significantly across regions and types of organizations, which can be considered a limitation as this study focuses on a specific segment of SMEs. To address these limitations and provide directions for future research, several recommendations can be made. Firstly, further investigation is warranted to identify additional moderating factors, such as organizational culture, leadership style, or industry-specific elements, that may influence the relationships between DPC, DI, DT, BDAC, and IP. This will enhance our understanding of the nuanced dynamics at play. Secondly, future studies could benefit from a comparative analysis, exploring the effects of different industries, organizational sizes, or geographical regions on the relationships under investigation. Examining these variations can provide valuable insights into unique challenges, best practices, and contextual differences that may arise in diverse settings. Lastly, employing mixed-methods approaches in future research endeavors can offer a more comprehensive understanding of the intricate and multifaceted relationships between DPC, DI, DT, BDAC, and IP. This approach would allow for a more holistic exploration of these complex dynamics, enriching our knowledge in this field.

References

1. Ali Mirani, M., Junejo, I., Sohu, J. M., Ali Qalati, S., Naveed, H. M., & Shabir, A. (2021). The Mediating Role of Information Flow and Factors for Supplier Selection. *TEM Journal*, *10*(1), 446–450. https://doi.org/10.18421/TEM101-56
2. Al-Khatib, A. W. (2022). Big data analytics capabilities and green supply chain performance: investigating the moderated mediation model for green innovation and technological intensity. *Business Process Management Journal*, *28*(5/6), 1446–1471. https://doi.org/10.1108/BPMJ-07-2022-0332
3. AlNuaimi, B. K., Kumar Singh, S., Ren, S., Budhwar, P., & Vorobyev, D. (2022). Mastering digital transformation: The nexus between leadership, agility, and digital strategy. *Journal of Business Research*, *145*, 636–648. https://doi.org/10.1016/j.jbusres.2022.03.038
4. Bagale, G. S., Vandadi, V. R., Singh, D., Sharma, D. K., Garlapati, D. V. K., Bommisetti, R. K., Gupta, R. K., Setsiawan, R., Subramaniyaswamy, V., & Sengan, S. (2021). RETRACTED ARTICLE: Small and medium-sized enterprises' contribution in digital technology. *Annals of Operations Research*, 1–2. https://doi.org/10.1007/s10479-021-04235-5
5. Bhatti, S. H., Ahmed, A., Ferraris, A., Hirwani Wan Hussain, W. M., & Wamba, S. F. (2022). Big data analytics capabilities and MSME innovation and performance: A double mediation model of digital platform and network capabilities. *Annals of Operations Research 2022*, 1–24. https://doi.org/10.1007/S10479-022-05002-W
6. Briones Peñalver, A. J., Bernal Conesa, J. A., & de Nieves Nieto, C. (2018). Analysis of Corporate Social Responsibility in Spanish Agribusiness and Its Influence on Innovation and Performance. *Corporate Social Responsibility and Environmental Management*, *25*(2), 182–193. https://doi.org/10.1002/CSR.1448
7. Carrasco-Carvajal, O., García-Pérez-de-Lema, D., & Castillo-Vergara, M. (2023). Impact of innovation strategy, absorptive capacity, and open innovation on SME performance: A

Chilean case study. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(2), 100065. https://doi.org/10.1016/J.JOITMC.2023.100065
8. Chen, P., & Kim, S. (2023). The impact of digital transformation on innovation performance - The mediating role of innovation factors. *Heliyon*, *9*(3), e13916. https://doi.org/10.1016/j.heliyon.2023.e13916
9. Chuang, S. H., & Lin, H. N. (2015). Co-creating e-service innovations: Theory, practice, and impact on firm performance. *International Journal of Information Management*, *35*(3), 277–291. https://doi.org/10.1016/J.IJINFOMGT.2015.01.002
10. Danah, B., & Crawford, K. (2011). Six Provocations for Big Data. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.1926431
11. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008
12. Espasandín-Bustelo, F., Rufino-Rus, J. I., & Rodríguez-Serrano, M. Á. (2023). Innovation and performance in social economy enterprises: The mediating effect of legitimacy for customers. *Journal of Business Research*, *158*, 113626. https://doi.org/10.1016/J.JBUSRES.2022.113626
13. Farhan Zafar, N. J. S. N. A. (2021). *SMEDA-MHRC (LUMS) Survey Report - Situational Analysis of SMEs during COVID-19*. https://smeda.org/index.php?option=com_phocadownload&view=file&id=1730:smeda-mhrc-lums-survey-report-situational-analysis-of-smes-during-covid-19&tmpl=component&Itemid=553
14. Field, A. P. (2018). Discovering statistics using IBM SPSS statistics: 5th edition. *SAGE Publications, Inc.*, *4*(1), 368. http://library1.nida.ac.th/termpaper6/sd/2554/19755.pdf
15. Guo, L., & Xu, L. (2021). The Effects of Digital Transformation on Firm Performance: Evidence from China's Manufacturing Sector. *Sustainability*, *13*(22), 12844. https://doi.org/10.3390/su132212844
16. Hadjielias, E., (Lola) Dada, O., Discua Cruz, A., Zekas, S., Christofi, M., & Sakka, G. (2021). How do digital innovation teams function? Understanding the team cognition-process nexus within the context of digital transformation. *Journal of Business Research*, *122*, 373–386. https://doi.org/10.1016/J.JBUSRES.2020.08.045
17. Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E. (2019). Multivariate Data Analysis. *Hampshire, UK : Cengage Learning, EMEA*, *8th Ed*, 834. https://www.cengage.com/c/multivariate-data-analysis-8e-hair/9781473756540PF/
18. Hair, J. F., L.D.S. Gabriel, M., da Silva, D., & Braga Junior, S. (2019). Development and validation of attitudes measurement scales: fundamental and practical aspects. *RAUSP Management Journal*, *54*(4), 490–507. https://doi.org/10.1108/RAUSP-05-2019-0098
19. Hausberg, J. P., Liere-Netheler, K., Packmohr, S., Pakura, S., & Vogelsang, K. (2019). Research streams on digital transformation from a holistic business perspective: a systematic literature review and citation network analysis. *Journal of Business Economics*, *89*(8–9), 931–963. https://doi.org/10.1007/s11573-019-00956-z
20. Iqbal, S., Akhtar, S., Anwar, F., Kayani, A. J., Sohu, J. M., & Khan, A. S. (2021). Linking green innovation performance and green innovative human resource practices in SMEs; a moderation and mediation analysis using PLS-SEM. *Current Psychology*, *0123456789*. https://doi.org/10.1007/s12144-021-02403-1
21. John, J. (2013). *The Risks of Big Data for Companies - WSJ*. https://www.wsj.com/articles/the-risks-of-big-data-for-companies-1382129327
22. Junejo, I. U., Sohu, J. M., Aijaz, A., Ghumro, T. H., Shaikh, S. H., & Seelro, A. D. (2022). The Mediating Role of Brand Attitude for Purchase Intention: Empirical Evidence from Fast Food Industry in Pakistan. *ETIKONOMI*, *21*(1), 103–112. https://doi.org/10.15408/etk.v21i1.22302

23. Khan, A., & Tao, M. (2022). Knowledge absorption capacity's efficacy to enhance innovation performance through big data analytics and digital platform capability. *Journal of Innovation & Knowledge*, *7*(3), 100201. https://doi.org/10.1016/j.jik.2022.100201
24. Khin, S., & Ho, T. C. F. (2019a). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, *11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083/FULL/XML
25. Khin, S., & Ho, T. C. F. (2019b). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, *11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083/FULL/XML
26. Khin, S., & Ho, T. C. F. (2019c). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, *11*(2), 177–195. https://doi.org/10.1108/IJIS-08-2018-0083
27. Kock, N. (2017). Common method bias: A full collinearity assessmentmethod for PLS-SEM. In *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*. https://doi.org/10.1007/978-3-319-64069-3_11
28. Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging Technology and Business Model Innovation: The Case of Artificial Intelligence. *Journal of Open Innovation: Technology, Market, and Complexity 2019, Vol. 5, Page 44*, *5*(3), 44. https://doi.org/10.3390/JOITMC5030044
29. Li, Y., Wang, Y., Wang, L., & Xie, J. (2022). Investigating the effects of stakeholder collaboration strategies on risk prevention performance in a digital innovation ecosystem. *Industrial Management and Data Systems*, *122*(9), 2045–2071. https://doi.org/10.1108/IMDS-12-2021-0805/FULL/PDF
30. Liang, S., & Li, T. (2022). Can Digital Transformation Promote Innovation Performance in Manufacturing Enterprises? The Mediating Role of R&D Capability. *Sustainability*, *14*(17), 10939. https://doi.org/10.3390/su141710939
31. Liu, Q., Zhao, X., & Sun, B. (2018). Value co-creation mechanisms of enterprises and users under crowdsource-based open innovation. *International Journal of Crowd Science*, *2*(1), 2–17. https://doi.org/10.1108/IJCS-01-2018-0001/FULL/PDF
32. Lytras, A. C., Serban, J., Li, J., Zhang, H., & Yuan, S. (2023). How and When Does Big Data Analytics Capability Boost Innovation Performance? *Sustainability 2023, Vol. 15, Page 4036*, *15*(5), 4036. https://doi.org/10.3390/SU15054036
33. Mennens, K., Van Gils, A., Odekerken-Schröder, G., & Letterie, W. (2018). Exploring antecedents of service innovation performance in manufacturing SMEs. *International Small Business Journal: Researching Entrepreneurship*, *36*(5), 500–520. https://doi.org/10.1177/0266242617749687
34. Nasiri, M., Ukko, J., Saunila, M., Rantala, T., & Rantanen, H. (2020). Digital-related capabilities and financial performance: the mediating effect of performance measurement systems. *Https://Doi.Org/10.1080/09537325.2020.1772966*, *32*(12), 1393–1406. https://doi.org/10.1080/09537325.2020.1772966
35. Naveed, H. M., HongXing, Y., Memon, B. A., Ali, S., Alhussam, M. I., & Sohu, J. M. (2023). Artificial neural network (ANN)-based estimation of the influence of COVID-19 pandemic on dynamic and emerging financial markets. *Technological Forecasting and Social Change*, *190*. https://doi.org/10.1016/j.techfore.2023.122470
36. Nousopoulou, E., Kamariotou, M., & Kitsios, F. (2022). Digital Transformation Strategy in Post-COVID Era: Innovation Performance Determinants and Digital Capabilities in Driving Schools. *Information 2022, Vol. 13, Page 323*, *13*(7), 323. https://doi.org/10.3390/INFO13070323
37. Peter, M. K., & Dalla Vecchia, M. (2021). The Digital Marketing Toolkit: A Literature Review for the Identification of Digital Marketing Channels and Platforms. In *Studies in Systems,*

Decision and Control (Vol. 294, pp. 251–265). Springer. https://doi.org/10.1007/978-3-030-48332-6_17

38. Robertsone, G., & Lapiņa, I. (2023). Digital transformation as a catalyst for sustainability and open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(1), 100017. https://doi.org/10.1016/J.JOITMC.2023.100017
39. Rupeika-Apoga, R., Petrovska, K., & Bule, L. (2022). The Effect of Digital Orientation and Digital Capability on Digital Transformation of SMEs during the COVID-19 Pandemic. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(2), 669–685. https://doi.org/10.3390/jtaer17020035
40. Sarstedt, M. (2019). Revisiting Hair Et al.'s Multivariate Data Analysis: 40 Years Later. In *The Great Facilitator* (pp. 113–119). Springer International Publishing. https://doi.org/10.1007/978-3-030-06031-2_15
41. Shah, S. M. M., Sohu, J. M., Dakhan, S. A., Sikander Ali, R., Junejo, I., & Chouhan, I. M. (2021). The Reinvesting Impact of Promotional Activity and Store Atmosphere on Impulse Buying Behavior: The Mediating Role of Payment Facility. *TEM Journal*, *10*(1), 221–225. https://doi.org/10.18421/TEM101-28
42. Stitzlein, C., Fielke, S., Waldner, F., & Sanderson, T. (2021). Reputational Risk Associated with Big Data Research and Development: An Interdisciplinary Perspective. *Sustainability 2021, Vol. 13, Page 9280*, *13*(16), 9280. https://doi.org/10.3390/SU13169280
43. Su, J., Zhang, Y., & Wu, X. (2023a). How market pressures and organizational readiness drive digital marketing adoption strategies' evolution in small and medium enterprises. *Technological Forecasting and Social Change*, *193*(2), 122655. https://doi.org/10.1016/j.techfore.2023.122655
44. Su, J., Zhang, Y., & Wu, X. (2023b). How market pressures and organizational readiness drive digital marketing adoption strategies' evolution in small and medium enterprises. *Technological Forecasting and Social Change*, *193*, 122655. https://doi.org/10.1016/j.techfore.2023.122655
45. Su, X., Zeng, W., Zheng, M., Jiang, X., Lin, W., & Xu, A. (2022). Big data analytics capabilities and organizational performance: the mediating effect of dual innovations. *European Journal of Innovation Management*, *25*(4), 1142–1160. https://doi.org/10.1108/EJIM-10-2020-0431/FULL/PDF
46. Tang, H., Yao, Q., Boadu, F., & Xie, Y. (2022). Distributed innovation, digital entrepreneurial opportunity, IT-enabled capabilities, and enterprises' digital innovation performance: a moderated mediating model. *European Journal of Innovation Management*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/EJIM-08-2021-0431/FULL/PDF
47. Tempini, N. (2017). Till data do us part: Understanding data-based value creation in data-intensive infrastructures. *Information and Organization*, *27*(4), 191–210. https://doi.org/10.1016/j.infoandorg.2017.08.001
48. Tongtong, S., & Xinhang, C. (2022). Research on the impact of enterprise big data analytics capability on ambidextrous innovation capability – the mediating effect of agility. *Technology Analysis & Strategic Management*, 1–15. https://doi.org/10.1080/09537325.2022.2132140
49. Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Farina Briamonte, M., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*, 327–336. https://doi.org/10.1016/j.jbusres.2021.04.035
50. Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003
51. Xu, G., Hou, G., & Zhang, J. (2022). Digital Sustainable Entrepreneurship: A Digital Capability

Perspective through Digital Innovation Orientation for Social and Environmental Value Creation. *Sustainability*, *14*(18), 11222. https://doi.org/10.3390/su141811222

52. Zhang, C., Chen, P., & Hao, Y. (2022). The impact of digital transformation on corporate sustainability- new evidence from Chinese listed companies. *Frontiers in Environmental Science*, *10*, 2310. https://doi.org/10.3389/fenvs.2022.1047418
53. Zhuge, K., Lin, W., Yuan, Y., He, H., & Zhang, Y. (2023). Does Digital Capability Promote Sustainable Development of New Ventures? The Dual Impact of Green Knowledge Creation and Green Pressure. *International Journal of Environmental Research and Public Health*, *20*(3), 2274. https://doi.org/10.3390/ijerph20032274