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# To Gain Sustainable Competitive Advantages (SCA) Using Artificial Intelligence (AI) Over Competitors

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**Abstract**
The motivation behind this examination is to explore the relationship between AI, DC, and SCA in the telecom business in Pakistan. The paper embraced a quantitative exploration plan and utilized a survey method to collect data from 235 telecom sector employees and managers of three distinct hierarchical levels. The paper applied SEM to examine the hypotheses and analyse the data. The paper found that artificial intelligence affected digital capacity (DC), DC meaningfully affected SCA, and DC intervened in the impact of AI on SCA. The study adds to the works on the link between AI, DC, and SCA in the telecom business. It gives experimental proof to help the hypotheses that artificial intelligence influences DC, DC influences SCA, and DC explains the impact of AI on SCA. The paper gives helpful experiences to telecom sector employees and policymakers. It suggests that telecom companies should make investments in AI technologies and applications to improve their DC, which can help them gain a competitive advantage. Also, it recommends that policymakers work with and support the telecom business to execute DC and AI because these advancements can help financial development, effectiveness, and innovation. The research aims to identify the association between AI, DC, and SCA in the telecom industry in Pakistan. It offers an original viewpoint on how artificial intelligence can improve DC and how DC can prompt SCA in the telecom business.
**Keywords:** Artificial intelligence, Digital capacity, Sustainable competitive advantage, Telecom sector, Pakistan

## 1. Introduction

Sustainable competitive advantage (SCA) is broadly recognised as quite difficult for firms across different sectors in the 21st century. The importance of cultivating SCA or maintaining a competitive advantage has increased with global competition (Mahdi & Nassar, 2021). The essential concern is strength in a questionable inside and outer climate, affecting worldwide efficiency and competitive potential (Hsieh et al., 2020). Due to rising global competition, environmental challenges, and the knowledge economy, SCA is a hot issue in modern-day inquiry into business strategy management (Yu et al., 2017). SCA refers to achieving market objectives, which enable a company to increase profit margins or market share within the same customer group (Ranjith, 2016). The critical recommendation for achieving SCA includes securing and monitoring firms (Barney & Clark, 2007). Knowledge resources are critical in guaranteeing a competitive edge, as they are trying to copy and frame the establishment for manageable separation (Wiklund & Shepherd, 2003). SCA is a developing technique whose key components incorporate subjects, media, goals, and ceaseless change. It tends to existing business sector requests without risking the organisation's capacity to adapt to forthcoming difficulties (Mahdi, Nassar, & Almsafir, 2019).
The present research investigated the association between artificial intelligence (AI) and creating a competitive advantage concerning information technology (IT) skills. The findings revealed an extensive and favourable influence, highlighting the important part that IT capabilities have in forming this relationship (Awamleh & Bustami, 2022). Furthermore, AI governance's influence on competitive advantage was explored, proposing a comprehensive framework that integrates technical, organisational, and institutional dimensions. Another perspective examined AI-based systems as catalysts for competitive advantage, introducing a conceptual model that elucidates how these systems generate and sustain advantages through the lens of dynamic capabilities (Kordon, 2020). The literature also highlights AI's constructive influence on diverse business value streams, including efficiency, effectiveness, innovation, profitability, customer satisfaction, and social impact. Nevertheless, it acknowledges that AI introduces various challenges and risks for organizations, spanning ethical, legal, social, technical, and managerial issues (Perifanis & Kitsios, 2023).
There exists a demand for further advancement in theory and concepts, integrating artificial intelligence (AI) with established frameworks in business strategy, sustainability, and competitive advantage (Kemp, 2023; Kitsios & Kamariotou, 2021). Additionally, there is a necessity for innovative methodologies and technologies to tackle challenges like data quality, explainability, robustness, and scalability within AI (Zhao & Gómez Fariñas, 2023). A call is made for interdisciplinary and cross-cultural research to delve into the diverse perspectives and implications of AI for various stakeholders and societies (Zhao & Gómez Fariñas, 2023). Furthermore, ethical and responsible AI development is crucial, ensuring alignment with human values, rights, and norms (Van Wynsberghe, 2021).
SCA is a main idea in the area of strategic management, which means comprehending how organizations can accomplish and support sustainable competitive advantage (Day, 1994).SCA is crucial for managers and practitioners who must make strategic decisions and actions that can boost their businesses' competitiveness and profitability (De Wit & Meyer, 1999). SCA is likewise applicable to society and the climate, as it can impact the social and natural effects of firms' activities. SCA has the potential to inspire businesses to adopt practices that are more environmentally friendly and socially responsible, such as reducing waste, emissions, and resource consumption, enhancing human rights and working conditions, and contributing to social welfare and development (Tarnovskaya, 2023). SCA can also encourage social value creation, innovation, and economic growth (Barney, 1991).
The paper proposes that future direction ought to broaden the exploration model by including different factors that might influence the linking between AI and SCA, like organisational culture, leadership, innovation, and customer satisfaction (Awamleh & Bustami, 2022). In future exploration, this study would research different factors e.g., operational performance, sustainability performance and digital capacity (Nasiri et al., 2020). Fostering an exhaustive structure for estimating and assessing the effect of digital technologies on the long run time and competitiveness of the economy, considering the ecological, societal, and budgetary aspects (Nurova & Freze, 2021). For managers to maintain their relevance in an AI-based competitive landscape, AI adoption alters the basis of competitive edge (Krakowski, Luger, & Raisch, 2023). Recognizing intelligence and creativity as distinct disciplines, industries are urged to treat each differently when combined with AI to ensure a SCA in the

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future (Timotheou et al., 2023). Through addressing identified theoretical gaps, this study seeks to respond to the subsequent examination inquiries:
*RQ1*. Are AI and DC related?
*RQ2*. Are DC and SCA related?
*RQ3*. Does DC mediate the relationship between AI and SCA?
The purpose of this inquiry is to explore the association between AI and SCA, as well as the DC used as a mediator between AI and SCA.

## 2. Theory and Hypotheses

### 2.1. Resource-Based View (RBV) Theory

The RBV theory investigates procedures included by organizations to achieve and support a competitive advantage by definitively using specific features. These characteristics, which are referred to as "valuable, rare, unique, and non-substitutable resources (VRIN)", "fall into three categories: physical capital, human capital, and organizational capital" (Barney, 1991). An insightful structure is purposefully created to examine the link between products and resources, revealing insight into suggestions for broadening and section obstructions. Organizations might have the option to acquire a competitive advantage by having resources that are esteemed for their uniqueness and oppose substitution or duplication, as indicated by the RBV idea (Wernerfelt, 1984). RBV explains fundamental concepts like resource heterogeneity and immobility by incorporating insights from industrial organization economics (Peteraf, 1993).
Innovation, entrepreneurship, internationalization, corporate governance, and sustainability are just a few of the areas of strategic management research where RBV can be applied (Barney & Arikan, 2001). In the domain of data frameworks, RBV offers a point of view on how firms use information technology (IT) resources for a competitive (Wade & Hulland, 2004). RBV develops through the knowledge-based angle on the organization, underlining knowledge as a vital advantage (Grant, 1996) and the dynamic capabilities view, featuring a company's capacity to immediately jump all over chances in dynamic environments (Teece, Pisano, & Shuen, 1997). In human resource management (HRM), RBV gives a structure to look at how human resources add to a company's performance and competitive advantage (Wright, McMahan, & McWilliams, 1994). The RBV theory fills in as a powerful reason for the proposed hypothetical design in this review, making it the most authentic source.

### 2.2. Artificial Intelligence (AI) and Digital Capacity (DC)

Generating profit from digital capabilities, such as artificial intelligence, poses a challenge not primarily rooted in technology but in the adept harnessing of knowledge to continually optimize organizational understanding for deriving value from digital technology (Çark, 2022). The research illustrates how organizations can employ AI tools in their processes, flaking light on the tools that create value (Enholm et al., 2022). The blend of AI, big data analytics (BDA), and "machine learning (ML)", with digital twinning, a technology creating fundamental replicas of physical assets or processes, is explored (Rathore et al., 2021). The study explores how digital capacity affects innovation performance, and how absorptive capacity productions a focal part in the progress of digital transformation. The study also offers important policy suggestions for improving different aspects of the business ecosystem related to innovation, to deal with the challenges of digital transformation effectively (Kastelli et al., 2022). Addressing AI techniques for preventing cyber-attacks, the research emphasizes the challenges and limitations (Wafa & Hussain, 2021). Moreover, it investigates the job of AI and profound learning in expanding advanced limits, especially in areas with broad and high-layered information, like text, picture, video, discourse, and sound (Janiesch, Zschech, & Heinrich, 2021). Digital technology, encompassing hardware and software facilitating digital communication and computation, is discussed alongside digital capability, defined as an organization's ability to utilize digital technology for value creation. Moreover, digital innovation is distinct as the construction of innovative digital products, services, or processes (Khin & Ho, 2018). The formulation of the first hypothesis involves a comprehensive consideration of all potential relationships encompassing dimensions of artificial intelligence and digital capacity.
**H1:** A significant and positive connection between AI and DC.

### 2.3. Digital Capacity (DC) and Sustainable Competitive Advantage (SCA)

In the dominion of organizational improvement, big data capability is recognized as a pivotal factor in shaping sustainable competitive advantage. This influence is exerted through three distinct modes of innovation strategies: exploitative, explorative, and ambidextrous. The positive effect of big data capability on SCA is interceded by the joined element of an ambidextrous innovation strategy (Satar, 2024). Moving into the domain of SMEs, the correlation between competitive advantage and dynamic capability is scrutinized. The study identifies five key classes of variables encompassing methodological procedures, organizational environment, organizational performance, resources/profile, and organizational research (Fabrizio et al., 2022). Exploring the nexus between digital transformation and sustainable competitive advantage by (Rezaei, Hosseini, & Sana, 2022), analyzed 41 articles, unveiling four overarching themes. These themes include digital transformation drivers, outcomes, challenges, and enablers. The culmination of this study clues to the formation of another proposition.
**H2:** A significant and positive link between DC and SCA.

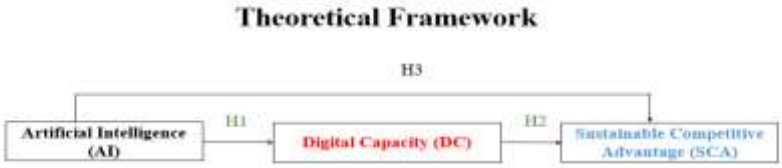


**Figure 1**

### 2.4. Mediating Role of Digital Capacity (DC)

Explores AI's role in business strategy, DC, SCA, and business model innovation (Reddy et al., 2022). Investigate digitalisation's impact on value creation, proposition, and capture in media and automotive industries. Examines how firms navigate challenges posed by increased digitalization (Rachinger et al., 2018). Emphasizes the interconnectedness of digital literacy and AI, advocating for a collaborative, multidisciplinary approach. Stresses the importance of developing digital literacy skills relevant to AI opportunities and risks (Ning & Yao, 2023). Focuses on AI as a strategic resource, examining sources, mechanisms, and

outcomes. Identifies key themes: AI and value creation, appropriation, protection, and sustainability (Kitsios & Kamariotou, 2021). Consequently, the ensuing hypotheses are formulated:
**H3:** DC mediate the relationship between AI and SCA.

## 3. Methodology

The investigation builds on existing theories and literature to establish hypothetical connections among variables of interest. These theoretical links undergo testing using data gathered from participants. Consequently, opting for a quantifiable positivist, deductive method aligns with the research goals (Saunders, 2016). Additionally, as the aim is to generalize findings, deduction proves to be a suitable technique in this context (Saunders, 2016). Choosing a quantifiable practice is also influenced by the main risk related to it possible non-return of survey questionnaires. In contrast, qualitative inquiries may struggle to extract meaningful insights from existing data (Cooper & Schindler, 2014).

### 3.1. Measures

Twelve question items of AI are adopted from Awamleh and Bustami (2022)Awamleh and Bustami (2022)Awamleh and Bustami (2022), "Using AI in your organization offerings". The alpha value of this item was 0.788. The most common Likert scale, ranges from 1 to 5, with 5 denoting strongly agree on the right-hand side and 1 denoting strongly disagree on the left-hand side. Awamleh and Bustami (2022), created these items with the help of previous studies. The survey used in prior research used a Likert scale with a score of five.

Four items of digital capacity were adopted (Bui & Le, 2023). All four question items belong to one construct. The Cronbach alpha value of the item "Our firm acquires skills in online payment and procurement procedures" was 0.68. Previously, the seven-point Likert scale was utilized in the review. One is utilized for strongly disagree and seven is utilized for strongly agree. The SCA is measured by four dimensions created by (Barney, 1991). In this examination, the 5-point Likert scale was made use of in the assessment. There are four dimensions "*valuable, rare, imperfectly Imitable, and non-substitutiveable"* and each dimension has one item. "key resources represent value for exploring and/or a reduction in spending". The "Cronbach's Alpha" value of SCA was 0.875.

### 3.2. Data Collection and Sampling Technique

The data collection of this study is from individuals within the telecommunications industry in Pakistan, spanning from entry-level to management positions, each with a minimum of one year of professional experience. The most recent data, provided by the Pakistan Telecommunication Authority (PTA), reveals that licenses have been granted to five cellular companies operating in the region. Approximately, more than 44,000 employees work in the telecom sector in Pakistan Amir (2023). According to PTA (2024), Jazz had 37% of the market share in cellular companies. Jazz is the market leader in Pakistan.

Using the adjusted sample size technique for measuring the sample size for a questionnaire that takes into account the fixed people and the sampling strategy (Levy & Lemeshow, 2013; Lohr, 2021). A 5% margin of biases and 95% confidence interval, proposed by (Fowler Jr, 2013). 600 Online self-administered questionnaires were distributed and received only 310 questionnaires. After receiving 285 questionnaires, some respondents partially respond to the questionnaire. The response rate of the questionnaire is 47.5% after getting the questionnaires. After the screening of the questionnaire, the remaining 235 questionnaires were appropriate for data analysis. 50 questionnaires were discarded because not fully completed. 45 questionnaires were received from top-level management (CEO, boss owner etc.) 100 questionnaires were received from middle-level management (manager's rank). 90 questionnaires were received from lower ranks. The surveys were provided to all employees, regardless of gender, and during regular business hours at various telecom sector branches in Pakistan.

In this study, the application of stratified sampling ensures the inclusiveness of the sample, reflecting the diverse hierarchical levels among telecom sector staff. This method involves selecting a random sample from distinct, homogenous sections or subgroups within the population. Each section is delineated based on shared demographic factors like job position, experience, or education, enhancing the sample's representativeness (Cohen et al., 2014). Table 1 provides respondents' demographic information.

**Table 1: Demographic Variables**

| Variables | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Female | 85 | 36.2% |
| | Male | 150 | 63.8% |
| Age | 25-35 | 70 | 29.8% |
| | 36-45 | 115 | 49.0% |
| | 46-55 | 50 | 21.2% |
| | Above the 55 | 45 | 19.2% |
| Current Position | Top Level | 35 | 15.0% |
| | Middle Level | 105 | 44.6% |
| | Lower Level | 95 | 40.4% |
| Experience | 1-4 Years | 50 | 21.2% |
| | 5-9 Years | 110 | 46.8% |
| | Above 10 Years | 75 | 32.0% |

### 3.3. Treatment of Missing Values

According to Little (1988) missing data is an undeniable issue in model examinations (p. 287). Research in the social sciences has confronted challenges in managing missing data (Rezaei et al., 2016). According to (Rezaei & Ghodsi, 2014) imputation has been primarily important for experts among different methods to determine the concern of missing values. According to (Schafer & Olsen, 1998) "Imputation methodology" (Rubin, 1987) is a reenactment strategy that exchanges each missing datum with a collection of complete data >1 possible value (p. 545). The review utilized nearly Little (1988) assumption augmentation calculation in SPSS for the "imputation" of missing values.

### 3.4. Common Method Variance (CMV)

This study found a way, a couple of ways to control the common method bias issues. Firstly, we guaranteed secrecy to the respondents and insignificance too. Secondly, we additionally randomize the question items in the survey and make it impossible for the respondent to guess the variables whether dependent and independent or other variables (Podsakoff et al., 2003). The review suggests that CMV could be surveyed with the full collinearity test about SEM. Using the VIF resulting from a full collinearity test, the current study dealt with common method bias using this real-time approach. (Kock, 2015). A VIF higher than 3.3 (Hair et al., 2017) demonstrates that the model might be disgusting by the CMV. Thus, accepting the potential gains of VIFs with a full collinearity test lower than 3.3, the model could be viewed as liberated from CMV. The flow research showed that the VIF value is under 3.3, which makes sense because there is no CMV in the information. As a result, the study found that CMV was not a problem in table 2.

According to Lewis, Hardy and Snaith (2013), The nonresponse bias is a real and noteworthy modification between respondents to a questionnaire and those who were not concerned with the features of the study's attention (pp. 240–241). The exploration used wave assessment to assess the nonresponse bias. Responses before for instance around the start of the information assortment process, were named the "early respondents" while the responses close to the completion of the data collection process were named the "late respondents". Through a free example t-test, we initiate no huge alterations between the "early respondents" and "late respondents" proclaiming the obstacle of nonresponse liking.

## 4. Results

### 4.1. Structural Equation Modelling (SEM)

The proposed model's parametric parts (measurement model) and hypotheses were analyzed using the PLS-SEM in this study. A two-stage technique for model assessment, estimated model assessment followed by structural model evaluation, was also proposed by (Chin, 2009). The exploration made sense of the PLS-SEM strategy considering different rationales; first, the PLS-SEM has flexibility to the extent that test size is essential and data normality. Second, smart-PLS was utilized for information investigation as it is considered a famous and high-level assessment method (Ali et al., 2018). Third, the PLS computation followed by the "bootstrapping method" was used to choose factor loadings, separate immense levels and, path coefficients. Last, PLS-SEM has been suggested as a higher inspection method for SEM (Nitzl, Roldan, & Cepeda, 2016). In the current investigation, digital capacity is a mediating factor between artificial intelligence and sustainable competitive advantage.

### 4.2. Measurement Model

Assessment properties of the proposed model like convergent validity (CV), internal reliability, and discriminant legitimacy (DV) and regularly analyzed before testing the essential relationship of factors. We assessed internal consistency using a composite reliability (CR) score as CR is tolerably an unrivalled extent of inward consistency when diverged from Cronbach's alpha (Hair et al., 2017). A score of 0.60 on CR is considered palatable for examinations of an exploratory nature (Avkiran, 2018). Artificial intelligence received a CR of 0.85, a digital capacity of 0.80 and a sustainable competitive advantage CR of 0.88, in this study. As a result, the study's internal consistency and reliability were all present.

According to Hair et al. (2017)Hair et al. (2017)Hair et al. (2017)Hair et al. (2017)Hair et al. (2017)Hair et al. (2017) explained that CV is "the extent to which a measure correlates positively with alternative measures of the same construct", (p. 112). Seeing the external loading of every item of a certain variable and working out the AVE are the most proposed ways to deal with choosing a CV (Hair Jr et al., 2014). An external loading values the more noticeable representativeness of a question item for the connected variable (Memon et al., 2017). In existing research, the external factor loading went from 0.70 to 0.89 for artificial intelligence, 0.77 to 0.88 for digital capacity and 0.67 to 0.86 for sustainable competitive advantage. Likewise, all factors showed a decent AVE score: artificial intelligence (0.66), digital capacity (0.70) and sustainable competitive advantage (0.63) - accordingly affirming the united legitimacy.

**Table 2: Measurement Model**

| Variables & Constructs | Loading | VIF | α Value | AVE | CR |
|---|---|---|---|---|---|
| Artificial Intelligence (AI) | | | 0.84 | 0.65 | .87 |
| AI1 | 0.86 | 2.00 | | | |
| AI2 | 0.70 | 1.80 | | | |
| AI3 | 0.75 | 2.58 | | | |
| AI4 | 0.74 | 3.02 | | | |
| AI5 | 0.83 | 3.01 | | | |
| AI6 | 0.79 | 2.99 | | | |
| AI7 | 0.80 | 2.67 | | | |
| AI8 | 0.82 | 2.66 | | | |
| AI9 | 0.83 | 2.60 | | | |
| AI10 | 0.84 | 2.63 | | | |
| AI11 | 0.85 | 2.72 | | | |
| AI12 | 0.89 | 2.79 | | | |
| Digital Capacity (DC) | | | 0.86 | 0.69 | 0.89 |
| DC1 | 0.80 | 2.01 | | | |
| DC2 | 0.80 | 1.70 | | | |
| DC3 | 0.88 | 2.93 | | | |
| DC4 | 0.77 | 2.00 | | | |
| Sustainable Competitive Advantage (SCA) | | | 0.81 | 0.62 | 0.86 |
| SCA1 | 0.80 | 1.55 | | | |
| SCA2 | 0.82 | 1.76 | | | |
| SCA3 | 0.86 | 2.18 | | | |
| SCA4 | 0.67 | 1.62 | | | |

DV is "the extent to which a construct is truly distinct from other constructs by empirical standards" (Hair Jr et al., 2014, p. 104). The HTMT technique was utilized to assess DV (Henseler et al., 2015) and Fornell-Larker's system. There is a slight assortment in as far as possible values of HTMT. According to (Clark & Watson, 2016) it shouldn't cross the 0.85 threshold value; regardless, (Gold, Malhotra, & Segars, 2001) acknowledged that a 0.90 score for DV is similarly palatable. Results showed that DV for the examination build was undeniably settled at HTMT 0.85 level - in this way, approving that every variable in the model is assessing a remarkable thought. In addition, the DV was settled using Fornell-Larker's standard.

**Table 3: Discriminant Validity of variables**

| Construct & Items | AI | DC | SCA |
|---|---|---|---|
| HTMT Ratio Method | | | |
| AI | | | |
| DC | 0.17 | | |
| SCA | 0.777 | 0.81 | |
| Fornell-Larker's Method | | | |
| AI | 0.81 | | |
| DC | 0.38 | 0.83 | |
| SCA | 0.29 | 0.44 | 0.70 |

### 4.3. Structural Equation Modelling (SEM)

The examination applied a bootstrapping strategy with 5,000 resamples to study the significance of our proposed model (Hair et al., 2017). The hypotheses' outcomes are presented in Table 4, as shown in figure 2. H1 states that AI has positive and significant effects on DC. The b-value of 0.35 demonstrates that a one-unit expansion in artificial intelligence is related to a 0.35-unit expansion in DC. At a 0.05 significance level, the effect is statistically significant because the t-value of 3.00 is greater than the threshold of 1.96 for a two-tailed test. The R2 of 0.16 demonstrates that artificial intelligence makes sense for 16% of the variety in digital capacity. Therefore, H1 is supported by the data.

H2 states that DC directly influences SCA. A b-value of 0.41 indicates that an average 0.41-unit increase in SCA is correlated with an increase of one unit in DC. The impact is genuinely huge because the t-value of 4.10 is more prominent than the basic value of 1.96 for a two-tailed test at a 0.05 importance level. The R2 of 0.23 demonstrates that DC makes sense of 23% of the variety in SCA. Subsequently, H2 is supported by the data.

H3 states that AI in an indirect effect on SCA through DC. The indirect effect is positive, as evidenced by the b-value of 0.19, which indicates that the mediation of DC results in an average increase of 0.19 units in SCA for every one-unit increase in AIThe t-value of 2.50 is better than the critical value of 1.96 for a two-tailed test at a 0.05 critical level, it is quantifiably indispensable to suggest that the measurably huge. In this way, H3 is supported by the data. All the SEM Table 4, as shown in figure 2.

**Table 4: Path Analysis**

| Hypotheses | Path | β | t-value | R2 | Decision |
|---|---|---|---|---|---|
| H1 | AI → DC | 0.35 | 3.00* | 0.16 | Supported |
| H2 | DC → SCA | 0.41 | 4.10* | 0.23 | Supported |
| H3 | AI → DC → SCA | 0.19 | 2.50* | | Supported |

Note: AI, artificial intelligence; DC, digital capacity; SCA, sustainable competitive advantage, *p < 0.05

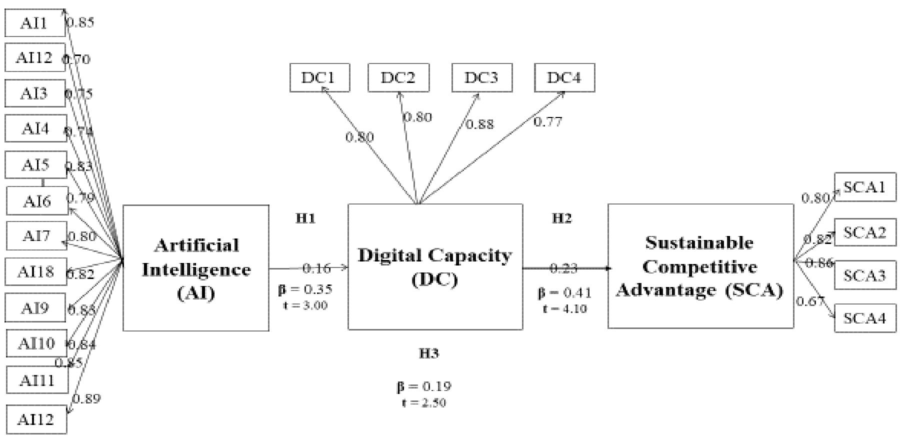


**Figure 2: Structural Model**

## 5. Discussion

The concept of competitive advantage is a broad area of strategic management. This study was planned to explore the outcomes of three hypotheses. The role of AI has positive and significant effects on DC in the telecom sector in Pakistan. The H1 hypotheses provide the literature support with previous studies (Çark, 2022; Rathore et al., 2022; Wafa & Hussain, 2021). The hypothesis was significant because the p-value < 0.05. The ability of telecom companies in Pakistan to use digital capacities and data to create value and boost performance can be improved with the help of AI. Artificial intelligence can be applied in

uncountable parts of the telecom area, for example, client administrations, network examination and generative artificial intelligence (Amar, 2022).
The role of DC has a positive and significant impact on SCA in the telecom industry in Pakistan. The result of the H2 hypothesis showed that accepted because of the significant p-value. The previous literature supports this hypothesis (Fabrizio et al., 2022; Rezaei, Hosseini, & Sana, 2022; Satar, 2024). The term "strategic supply chain" explains the steps of developing and putting into place networks that are both effective and efficient, thereby maximizing the flow of resources, data, and services between suppliers, customers, and other stakeholders. Telecom companies can improve their operational efficiency, customer satisfaction, innovation, and market valuation by investing in digital sustainability and strategic supply chains (Alquqa et al., 2024).
The DC was a mediated relationship between AI and the SCA of the telecom sector in Pakistan. The H3 hypotheses were supported by the previously existing work (Ning & Yao, 2023; Rachinger et al., 2018; Reddy et al., 2022). AI is the utilization of machines and calculations to execute activities that usually require human knowledge, like getting the hang of, thinking, and independent direction. DC is the capacity to utilize computerized advancements and information to make esteem and further develop execution in the telecom area. The ability to outperform rivals over time and achieve superior performance is known as SCA (Shehadeh et al., 2023).

### 5.1. Theoretical and Practical Implication

The theoretical implication of this study is that it adds to the writing on the connection between AI, DC, and SCA in the telecom area. It gives exact proof to help the hypotheses that AI decidedly affects DC, DC affects SCA, and digital capacity intervenes in the impact of AI on SCA. It likewise expands the current theories on strategic management, digital transformation, and competitive advantage by applying them to the setting of the telecom business in Pakistan, which is a non-industrial nation with a quickly developing advanced economy.
The practical implication of this research is that it gives valuable experiences to telecom sector employees and policymakers. It suggests that telecom companies should make investments in artificial intelligence applications and technologies to increase their digital capacity, which can assist them in gaining a competitive edge. It likewise infers that telecom organizations ought to embrace digital sustainability and strategic supply chain practices to use their advanced limit and make an incentive for their clients and partners. In addition, it suggests that policymakers ought to encourage and make it easier for the telecom industry to implement digital capacity and artificial intelligence because these technologies have the potential to boost economic growth, efficiency, and innovation.

### 5.2. Limitations

First, relies on cross-sectional data, which may not capture the dynamic and causal relationships between AI, DC, and SCA in the telecom business. A longitudinal or experimental design would be more suitable to test the hypotheses and the inverting effect of DC (Sarstedt, Ringle, & Hair, 2021). Second, a one-country setting might restrict the generalizability of your discoveries to different districts or markets. We acknowledge this by stating that your results are specific to the telecom sector in Pakistan and that further research is required to investigate the applicability of the model in different contexts. A third limitation is that the telecom sector is a highly dynamic and competitive industry that may have specific characteristics and challenges that are not shared by other industries. Essentially, Pakistan is a non-industrial nation that might have different financial, social and cultural factors that influence the acceptance and application of AI and DC.

### 5.3. Future Direction

First, investigate how artificial intelligence and digital capacity can upgrade the client experience and faithfulness in the telecom area. The digital capacity can facilitate work with client after-sales services, feedback and commitment, through web-based entertainment, online surveys, and gamification (Leal Filho et al., 2023). Second, AI and DC can encourage development and joint effort in the telecom area. AI can empower new items and administrations, for example, savvy gadgets, distributed computing, and the Web of Things, that can make new incentives and markets (Luan et al., 2020). Third, artificial intelligence and digital capacity can add to the social and ecological supportability of the telecom area. Artificial intelligence can empower arrangements and practices that can diminish the ecological effect and asset utilization of telecom tasks, like energy proficiency, carbon impression and waste management (Jankovic & Curovic, 2023). Recognizing intelligence and creativity as distinct disciplines, industries are urged to treat each differently when combined with AI to ensure a SCA in the future (Timotheou et al., 2023). The paper proposes that future direction ought to broaden the exploration model by including different factors that might influence the connection between AI and competitive advantage, like organisational culture, leadership, innovation, and customer satisfaction (Awamleh & Bustami, 2022).

### 5.4. Conclusion

This paper analyzed the association between AI, DC, and SCA in the telecom business in Pakistan. It tried three hypotheses utilizing an overview of 235 telecom representatives on different managerial levels and used SEM analysis. The outcomes showed that AI affected DC, DC significantly affected SCA, and DC intervened in the impact of AI on SCA. The telecom industry's competitive advantage, digital transformation, and strategic management will all benefit from these findings, both theoretically and practically.

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