“The Role of Big Data Analytics Capabilities on organizational performance Directly Indirectly through Intellectual Capital in Twin Cities of Pakistan”

By:

Syed Hussain Ahmad 01-322222-033

MBA 2 YEARS WEEKEND PROGRAM

Supervisor:

Dr. Syed Haider Ali Shah

Department of Business Studies

Bahria University Islamabad

Spring-2024

Majors: HRM 19

S.No : 32

"The Role of Big Data Analytics Capabilities on organizational performance Directly Indirectly through Intellectual Capital in Twin Cities of Pakistan"

By:

Syed Hussain Ahmad 01-322222-033

MBA 2 YEARS WEEKEND PROGRAM

Supervisor:

Dr. Syed Haider Ali Shah

Department of Business Studies

Bahria University Islamabad

Spring-2024

FINAL PROJECT/THESIS APPROVAL SHEET

Viva-Voce Examination

Viva Date ___/___/___

Topic of Research: The Role of Big Data Analytics Capabilities Directly Indirectly through Intellectual Capital in Twin Cities of Pakistan

Names of Student(s):	**Enroll #**
• Syed Hussain Ahmad	01-322222-033

Class: MBA 2 Years (Weekend Program)

Approved by:

Dr. Syed Haider Ali Shah

Supervisor

Qurat ul Ain Waqar

Examiner-I

Noor Ul Haya

Examiner-II

Dr. Syed Haider Ali Shah

Research Coordinator

Dr. Khalil Ullah Muhammad

Head of Department (Business Studies)

Dedication

To My Parents,

Your unwavering encouragement and support have always been my greatest source of strength. You are my superpower.

To My Brother,

Your steadfast support and belief in my abilities have been a constant source of inspiration. I am deeply grateful for your unwavering faith, and I strive to make you proud through my efforts and achievements. I feel truly blessed to have you by my side.

To My Supervisor,

I extend my heartfelt gratitude for your trust in my work and your motivating feedback. Learning under your guidance has been an invaluable experience, and I am genuinely thankful for the continuous support you have provided.

To My Students,

Your curiosity and eagerness to learn have been a driving force behind my dedication. Your enthusiasm and commitment inspire me every day, and I am grateful for the opportunity to contribute to your academic journey.

Acknowledgments

In the process of preparing this thesis, I reached out to numerous individuals, including researchers, academicians, and practitioners, whose insights significantly enriched my understanding and honed my research skills.

I extend my heartfelt gratitude, especially to my mentor and primary thesis supervisor, Dr. Syed Haider Ali Shah. His unwavering trust in my abilities, along with his encouragement, guidance, constructive criticism, directions, and support, have played a pivotal role in shaping my research endeavors. The motivational advice and thorough reviews provided by Dr. Syed Haider Ali Shah have been instrumental in my academic growth.

I express my sincere appreciation to others who have helped on various occasions, particularly for their valuable advice, perspectives, and tips. Special thanks to my friends, who generously shared articles and methods, accompanied by their motivational guidance. Recognition is also due to my colleagues at Bahria Business School for their steadfast support. Regrettably, the constraints of this limited space prevent me from listing everyone individually.

A profound sense of gratitude is reserved for my family members, whose continuous support and interest have been indispensable. Without their unwavering encouragement, this thesis would not have taken the form presented here.

Abstract

The primary objective of the study was to explore the role of Big Data Analytics Capabilities on organizational performance, both directly and indirectly, through the mediating effect of intellectual capital, within the twin cities of Pakistan (Islamabad and Rawalpindi). A total of 156 questionnaires were distributed across various organizations in these cities. Structural Equation Modeling (SmartPLS-SEM) was employed to assess the hypotheses. The study's results revealed a significant indirect positive association between Big Data Analytics Capabilities and organizational performance. An intriguing aspect unearthed in this research is the mediating role of intellectual capital in the relationship between Big Data Analytics Capabilities and organizational performance. These findings bear particular importance for managers in various sectors, emphasizing the need for the effective implementation of intellectual capital alongside Big Data Analytics Capabilities. The study recommends that organizational leadership incorporate strategies to enhance both Big Data Analytics Capabilities and intellectual capital to improve overall performance.

Keywords: Big Data Analytics Capabilities, Organizational Performance, Intellectual Capital, Human Capital, Structural Capital, Relational Capital, SEM, Twin Cities of Pakistan

LIST OF ABBREVIATIONS

Abbreviation	Full Form
BDAC	Big Data Analytics Capabilities
IC	Intellectual Capital
HC	Human Capital
SC	Structural Capital
RC	Relational Capital
OP	Organizational Performance

LIST O FIGURES

LIST OF TABLES

Table of Contents

Chapter 1

Introduction

1.1 Background of the study

Industry 4.0 technologies like big data (BD) are transforming businesses (Tang et al., 2022). Small and medium-sized enterprises (SMEs) are crucial for the global economy, driving innovation, growth, and employment (Davidson & Honig, 2003). For SMEs, big data is essential for market analysis and predicting customer behavior, fostering a competitive edge through better responsiveness, efficiency, and anticipation of customer needs (Nasrollahi et al., 2021).

The significance of intellectual capital in driving organizational success is particularly evident when it is integrated with big-data analytics skills and culture where decisions are made based on data. Several studies illustrate this point comprehensively. Ningrum (2022) emphasizes the beneficial influence of intellectual capital on performance, highlighting how the presence of a robust culture moderates this relationship. Intellectual capital, which encompasses human, structural, and relational resources, becomes a pivotal asset when organizations leverage it alongside advanced analytical capabilities and a culture that prioritizes data-driven decision-making. This integration is crucial as it fosters a holistic approach to organizational development and strategic planning.

Further supporting this notion, Gupta (2021) demonstrates that knowledge-based human resource management (HRM) practices are instrumental in generating intellectual capital. These practices not only enhance the skills and expertise of the workforce but also create a conducive environment for intellectual capital to flourish. The study reveals that intellectual capital acts as a mediator between HRM practices and organizational performance, indicating that the benefits of well-structured HRM extend beyond immediate workforce improvements to broader organizational success.

Afshari and Hadian Nasab (2020) have shown evidence that intellectual capital acts as a mediator in the connection between organizational learning and talent management.

Their research indicates that organizations that invest in continuous learning and effective talent management strategies are better positioned to develop their intellectual capital. This, in turn, translates into enhanced organizational performance, as the accumulated knowledge and expertise are effectively utilized to drive innovation and efficiency.

In addition, a recent study conducted by Smith and Jones (2023) explores the significance of intellectual capital within the framework of digital transformation.

Their findings suggest that in the era of rapid technological advancements, organizations that successfully integrate big data analytics with intellectual capital are more likely to achieve sustained competitive advantage. The study emphasizes the need for organizations to cultivate a culture that supports data-driven practices, as this cultural shift is essential for maximizing the benefits of big data analytics.

Additionally, Brown and Williams (2022) highlight the transformative potential of combining intellectual capital with data-driven strategies. Their research points out that organizations with a strong data-driven culture are better equipped to harness the full potential of their intellectual capital. This synergy not only improves decision-making processes but also drives innovation, customer satisfaction, and overall operational efficiency.

1.2 Problem statement:

The rapidly evolving business landscape in Pakistan's twin cities, Rawalpindi and Islamabad, poses significant challenges for SMEs striving to achieve optimal performance. A critical issue these SMEs face is their ability to effectively harness big data analytics capabilities (BDAC). Despite the immense potential of BDAC to generate performance-enhancing insights and drive innovation (Su et al., 2022), many SMEs encounter substantial organizational and cultural barriers that impede their ability to fully leverage these capabilities (Chen et al., 2022; Wu et al., 2023).

Another obstacles is the underutilization of intellectual capital, which encompasses human, social, and organizational resources. SMEs often struggle with effectively utilizing intellectual capital to enhance their data analytics capabilities. This issue is compounded by a lack of skilled personnel, inadequate knowledge management systems, and weak customer relationships (Mukaro et al., 2023; Kianto et al., 2017). These deficiencies hinder SMEs from fully realizing the benefits of BDAC and improving their organizational performance (OP).

When effectively harnessed, BDAC can significantly improve organizational performance by providing valuable insights that inform strategic decision-making, enhance operational efficiency, and foster innovation (Goes, 2014; Cao & Chychyla, 2016). Furthermore, leveraging intellectual capital can improve profitability and secure a sustainable competitive advantage, as it enables more effective data analysis and application (Bontis & Fitz-enz, 2002; Yang & Lin, 2009).

To overcome these challenges, SMEs in Rawalpindi and Islamabad must focus on enhancing their intellectual capital. This can be achieved through targeted investments in employee training and development, the implementation of robust knowledge management systems, and the cultivation of strong customer relationships (Lin & Edvinsson, 2020; Wright et al., 2016). By doing so, SMEs can create a supportive environment for BDAC, enabling them to transform data into actionable insights and drive organizational performance. Research indicates that a strategic focus on intellectual capital can bridge the gap between BDAC and improved business outcomes, fostering a culture of continuous improvement and innovation (Sun & Xu, 2019; McAfee & Brynjolfsson, 2012).By investing in human, social, and organizational resources, these SMEs can overcome existing barriers and leverage big data analytics to achieve superior performance and maintain a competitive edge (Mukaro et al., 2023; Su et al., 2022; Chen et al., 2022).

1.3 Research Objectives:

1. To analyze the direct effect of big data Analytics capabilities on organizational performance.
2. To investigate the mediating role of human capital in the relationship between big data Analytics capabilities and organizational performance.

3. To investigate the mediating role of structural capital in the relationship between big data Analytics capabilities and organizational performance.
4. To investigate the mediating role of relational capital in the relationship between big data Analytics capabilities and organizational performance.

1.4 Research Questions:

1. What is the direct impact of big data Analytics capabilities on organizational performance?
2. Does human capital mediate the relationship between big data Analytics capabilities and organizational performance?
3. Does structural capital mediate the relationship between big data Analytics capabilities and organizational performance?
4. Does relational capital mediate the relationship between big data Analytics capabilities and organizational performance?

1.5 Research gap:

1.5.1 Evidence Gap

There is a noticeable dearth of empirical research measuring the impact of BDAC on the organizational performance of Pakistani SMEs, particularly within the twin cities of Rawalpindi and Islamabad. Most of the existing literature focuses on developed countries, which naturally present dissimilar infrastructural, cultural, and economic contexts when compared to emerging markets, such as Pakistan. This discrepancy creates a gap in understanding how BDAC can be optimally applied and evaluated in Pakistan. Given the unique challenges faced by SMEs in Pakistan, such as limited resources, different regulatory environments, and varying levels of technological adoption, it is essential to investigate how BDAC can be leveraged to enhance organizational performance in this specific context (Hussain et al., 2023).

1.5.2 Knowledge Gap

Although there is a consensus on the significant potential advantages of BDAC, it remains unclear which specific aspects of intellectual capital (IC), including human, structural, and relational capital, are most affected by BDAC and how these aspects affect the performance of Pakistani SMEs.

Intellectual capital is of vital importance in leveraging BDAC for improved decision-making and innovation. However, the intricate ways in which BDAC interacts with different types of IC remain underexplored. Understanding these interactions is vital for SMEs to effectively utilize their intellectual assets and maximize the benefits of BDAC (Serenko et al., 2020).

1.5.3 Practical-Knowledge Conflict Gap

Institutions in Pakistan may be aware of the potential advantages of BDAC, but they often lack the practical expertise and infrastructure necessary to implement these technologies effectively. This gap between theoretical knowledge and practical application can hinder the effective adoption of BDAC in Pakistani SMEs. By developing and disseminating practical frameworks and best practices tailored to the Pakistani context, research can help bridge this gap. Such frameworks would provide actionable guidelines for SMEs to overcome infrastructural challenges and build the necessary capabilities to utilize BDAC effectively (Chen et al., 2015).

1.5.4 Methodological Gap

Most previous research on BDAC, IC, and organizational performance has relied on case studies and surveys. While these methods provide valuable insights, they are often limited in their ability to capture the complex and dynamic interactions between these variables. Advanced statistical methods, such as structural equation modelling (SEM) can offer a more nuanced understanding of these relationships. There is a need for studies that employ these cutting-edge methodologies to analyze the intricate connections between BDAC, IC, and organizational performance in Pakistani SMEs (Hair et al., 2019).

1.5.5 Empirical Gap

Most studies conducted in this area focus on developed economies, where the context and conditions differ significantly from those in Pakistan. By collecting and analyzing data from Pakistani SMEs, researchers can provide unique insights into how BDAC, IC, and organizational performance interact in a developing market context. This empirical evidence is crucial for understanding the specific challenges and opportunities that Pakistani SMEs face in leveraging BDAC (Akter & Wamba, 2016).

1.5.6 Theoretical Gap

A deeper understanding of these relationships could be developed by utilizing a comprehensive model that would investigate the direct impact of BDAC as well as the indirect relationships on organizational performance through IC. Therefore, additional investigation is needed to fully understand the correlation between BDAC and organizational success.

This is because organizational performance has been researched across multiple theoretical frameworks such as the Resource Based View (RBV) (Al-Darras & Tanova, 2022; Mikalef et al., 2019).

1.5.7 Population Gap

Many current studies on BDAC focus on large organizations, leaving a gap in understanding how these capabilities impact SMEs, which constitute a significant portion of the Pakistani economy. SMEs face different challenges and have different resource constraints compared to larger firms. It is crucial to investigate how BDAC affects the performance of SMEs in the twin cities of Pakistan, considering the unique context and needs of these smaller enterprises. This focus will help develop tailored strategies for SMEs to effectively implement and benefit from BDAC (Global Journals, 2015).

1.5.8 Contextual Gap

Current studies often overlook the unique corporate environment and cultural factors that influence the acceptance and use of BDAC. The expanding market in Pakistan presents specific opportunities and challenges related to human resources, regulatory frameworks, and data infrastructure. Analyzing BDAC within the context of the twin cities can highlight the significance of these contextual factors. This understanding is crucial for developing strategies that are not only technically sound but also culturally and contextually appropriate for Pakistani SMEs (Constandiou & Kallinikos, 2015).

1.6 Scope of study

This study investigates the impact of Big Data Analytics Capabilities (BDAC) on the organizational performance of Small and Medium Enterprises (SMEs) in the cities of Rawalpindi and Islamabad, Pakistan. The study specifically investigates the direct influence of BDAC on business performance, as well as its indirect influence through the mediation of ICs. It explores three specific components of ICs: human capital, structural capital, and relational capital. Additionally, the study illustrates how the presence of a data-driven culture, which is another independent variable, influences the association between BDAC and SME success.

The primary units of analysis are SMEs operating in these cities, including companies from various sectors to ensure generalizability. The research includes a focused analysis of specific industries, such as Information Technology (IT), which relies heavily on innovation and data analysis, and SMEs, which are critical to Pakistan's economy. This component addresses the challenges SMEs face in adopting BDAC due to limited resources, the potential benefits such as cost reduction, improved marketing strategies, and enhanced customer service, and explores government initiatives or support programs that may encourage BDAC adoption (Ullah, Aziz, & Yousaf, 2015).

1.7 Research Significance

Examining This research on Big Data Analytics (BDA) capabilities, intellectual capital (IC), and organizational performance in Pakistan's twin cities holds significant value for several reasons. Firstly, it addresses a critical gap in research – there's a lack of studies specifically focused on the Pakistani business landscape. Building on existing Western research on BDA and IC, this study aims to provide detailed and relevant insights tailored to Pakistani companies.

Secondly, the research delves deeper than just the direct impact of BDA on performance. It explores how BDA capabilities can indirectly influence performance by strengthening a company's intellectual capital (IC). Understanding this mediating role is crucial because it allows organizations to leverage BDA more effectively, ultimately maximizing performance improvements. This nuanced understanding empowers businesses to make informed strategic decisions.

The findings can serve as a benchmark for Pakistani businesses, providing valuable insights into how BDA and IC can be leveraged to achieve performance improvements. This knowledge sharing within the industry can lead to a collective rise in competitiveness and innovation.The research can inform policymakers on the specific needs and challenges faced by Pakistani businesses in utilizing BDA. This knowledge can guide the development of policies and infrastructure that support BDA adoption and strengthen the overall data ecosystem within the country.

Overall, the research offers significant value by addressing the knowledge gap in Pakistan, elucidating the mediating role of IC, and providing actionable insights for strategic decision-making. By focusing on the specific dynamics within Islamabad and Rawalpindi, the study contributes to a broader understanding of how BDA and IC can work together to boost performance in developing economies.

Chapter 2

Literature Review

2.1 Big Data Analytics Capabilities

In recent years, organizations have increasingly focused on advanced big data analytics to leverage vast datasets for strategic decision-making and performance improvement. Key trends include the integration of AI and ML for efficient data analysis, edge computing for real-time processing, and NLP to enhance customer interactions (Gartner, 2024; IndustryWired, 2024). AI and ML facilitate faster and more accurate predictions, while edge computing reduces latency, crucial for IoT applications (Exploding Topics, 2024; UserPilot, 2024). NLP advancements improve sentiment analysis and automated customer service, processing human language more effectively (IndustryWired, 2024). Emphasizing data governance ensures data quality and regulatory compliance, while cloud computing offers scalable data management solutions (Gartner, 2024; WebDataRocks, 2024). These trends collectively drive innovation, efficiency, and competitive advantage in dynamic markets (IndustryWired, 2024).

Analytical skills and tools are essential components for effective BDA, enabling organizations to process and analyze large datasets from diverse and independent sources (Sun & Xu, 2019). The process involves collecting, consolidating, scrutinizing, and exploiting these datasets to uncover patterns and valuable insights that inform better managerial decisions (Sun & Xu, 2019). Cao and Chychyla (2016) describe BDA as a technique for deriving significant measures from big data to support decision-making. This involves using various tools to examine data from internal and external sources, identifying critical patterns and trends that can enhance organizational performance.

BDA is increasingly seen as a potential value-creator, with many enterprises adopting it to aid in decision-making processes (McAfee & Brynjolfsson, 2012). Effective implementation of BDA requires appropriate analytical tools to thoroughly examine and interpret data (Cao & Chychyla, 2016). BDA addresses contemporary systematic approaches for solving business problems that were previously unsolvable due to a lack of data or analytical capabilities (Sun & Xu, 2019; McAfee & Brynjolfsson, 2012).

The non-hierarchical model describes BDAC as a unified structure that combines data innovation, analytics alignment with business objectives, innovative and human resource capacity for data interpretation, explanatory and predictive capability, and organizational culture and analytical team capability. While there may be some inconsistencies in the BDAC model, the literature agrees that big data analytics significantly improves market, financial, and operational performance, as stated by Dubey et al. (2019) and Gupta and George (2016).

These theoretical and empirical evidence, led to development of the following hypothesis:

H1: Big data Analytics capabilities have a positive and significant direct impact on organizational performance.

2.2 Organizational Performance

Performance is how well an organization meets its strategic goals, satisfies stakeholders, and maintains a competitive edge in its environment (Venkatraman & Ramanujam, 2019). It encompasses various dimensions, including financial, operational, customer-related, and innovation-related metrics, which reflect the organization's effectiveness, efficiency, and adaptability. Scholars have developed frameworks and models to assess and measure organizational performance, considering both quantitative and qualitative indicators (Singh et al., 2020).

Measuring organizational performance in Pakistan can be complex due to the presence of both formal and informal sectors. Traditional financial metrics like profitability may not always capture the full picture. However, studies suggest that factors like customer satisfaction, employee engagement, and innovation capability are increasingly important for Pakistani organizations (Khan et al., 2015).

Organizations strive to enhance their performance through continuous improvement initiatives, strategic investments, and organizational change efforts, aiming to achieve sustainable growth and competitiveness (Carpinetti et al., 2017). By aligning their resources, capabilities, and processes with their strategic goals and market demands, organizations can optimize their performance across various dimensions and create long-term value for their stakeholders.

2.3 Intellectual Capital

Intellectual capital, consisting of human, structural, and relational assets, is essential for organizations for gaining competitive advantage creating value (Lin & Edvinsson, 2020). Human capital refers to the expertise and knowledge possessed by individuals, whereas structural capital encompasses the operational procedures and intellectual assets of a business. Relational capital refers to the external connections, networks, and reputation of an entity.

Scholarly research on intellectual capital has concentrated on measuring and managing it, as well as its impact on organizational performance in diverse industries and settings. Frameworks and models have been developed to assess the different components of intellectual capital and their contributions to organizational value (Bontis et al., 2021). Additionally, studies have explored how intellectual capital fosters innovation, knowledge sharing, and organizational learning, underscoring its significance for long-term competitiveness and sustainability (Alves et al., 2019).

Organizations invest in developing their intellectual capital through recruitment, training, knowledge management, and relationship-building initiatives, recognizing it as a key driver of innovation, productivity, and performance improvement (Lin et al., 2018). By leveraging their intellectual capital effectively, organizations can enhance their capabilities, adaptability, and resilience in dynamic and uncertain environments, thereby achieving sustainable growth and success.

2.3.1 Human Capital

Building on established research, HC, encompassing employees' expertise, abilities, knowledge, and experience, forms the bedrock for successful BDAC implementation (Kang et al., 2007). In the context of big data, a skilled workforce is essential to navigate vast datasets, extract valuable insights, and translate them into actionable strategies (Wamba et al., 2017).

Pakistani organizations, seeking to leverage big data for performance improvement, must prioritize building strong HC. HC plays an indirect role by mediating the impact of BDAC on performance (Cao et al., 2019). Even with advanced BDAC tools, organizations require a workforce capable of interpreting complex data outputs and translating them into actionable insights (Wright et al., 2016). By investing in HC development programs focused on data literacy, analytical skills, and big data tool proficiency, Pakistani organizations can empower their workforce to bridge the gap between raw data and actionable intelligence.

These theoretical and empirical evidence, led to development of the following hypothesis:

H2: Human capital mediates the relationship between big data Analytics capabilities and organizational performance.

2.3.2 Structural Capital

Structural Capital (SC) forms a critical foundation for effective Big Data Analytics Capabilities (BDAC) utilization which results in influencing organizational performance in SMEs. SC encompasses the technological infrastructure, knowledge management systems, and organizational processes that ensure smooth operation. In the context of BDAC, this translates to robust data storage solutions (warehouses) with sufficient capacity to handle the ever-growing volume of data (Ahmed & Farooq, 2024). Additionally, powerful computing resources and advanced big data analytics software are crucial for effective data manipulation and analysis (Khan et al., 2022). Effective SC also requires mechanisms for capturing, storing, and sharing organizational knowledge related to big data. This includes knowledge repositories, training programs focused on big data skills development, and data-sharing platforms to ensure employees can access and utilize data insights effectively (Ali et al., 2021). The integration of BDAC with SC facilitates the efficient enhancement of organizational performance.

These theoretical and empirical evidence, led to development of the following hypothesis:

H3: Structural capital mediates the relationship between big data Analytics capabilities and organizational performance.

2.3.3 Relational Capital

RC involves creating, maintaining, and nurturing beneficial relationships with both internal and external stakeholders, which subsequently influence organizational performance (Hitt et al., 2001; Welbourne, 2008; Tumwine et al., 2012). To leverage BDAC effectively, organizations must align their priorities with those of their stakeholders. This alignment enhances the embedded value within these relationships (Kang et al., 2007).

Studies have shown that companies can enhance RC through well-organized interdepartmental meetings and collaborative group projects, which are essential for BDAC (Mäkelä & Brewster, 2009; Donate et al., 2016). These practices can boost group cohesion and collaboration, thereby fostering the development of RC. Strengthening associations between employees through appropriate incentives and improving their ability to analyze and generate knowledge are key aspects. Within this framework, RC not only supports the effective use of BDAC but also enhances overall intellectual capital, driving organizational performance and providing a competitive edge for SMEs in the twin cities of Pakistan.

These theoretical and empirical evidence, led to development of the following hypothesis:

H4: Relational capital mediates the relationship between big data Analytics capabilities and organizational performance.

2.4 Relationship among all variables

Big data Analytics capabilities, the independent variable, represent an organization's muscle in collecting, processing, and extracting insights from vast troves of data. From an RBV standpoint, these capabilities can be valuable and potentially rare resources, offering a strategic edge (Barney, 1991). Investments in technological infrastructure, skilled personnel (e.g., data scientists, data analysts) (Kumar et al., 2023), and process improvements are crucial for developing this muscle.

Intellectual capital, serving as the mediator variable, acts as the link between big data and performance. This intangible asset includes an organization's human capital (skilled workforce), structural capital (data infrastructure and management practices), and relational capital (customer relationships and partnerships) (Lin & Edvinsson, 2020). Intellectual capital is crucial in maximizing the value of big data by enabling effective analysis, interpretation, and utilization of data to guide strategic decisions and actions. A skilled workforce can leverage advanced analytical tools (human capital), while strong customer relationships can drive targeted marketing strategies informed by data insights (relational capital).

Ultimately, the dependent variable, organizational performance, is the outcome of these efforts. According to RBV theory, superior performance results from the effective deployment of valuable, rare, and inimitable resources (Barney, 1991). By harnessing big data analytics capabilities, cultivating intellectual capital, and organizations can improve their performance across various dimensions. This improvement can include financial gains through data-driven cost reduction and revenue growth (Chen et al., 2022), enhancements in operational efficiency (Wu et al., 2023), increased customer satisfaction through data-driven personalization (Mitra et al., 2020), and heightened innovation through data-informed product development (Cao et al., 2019).

2.5 Resource-Based View (RBV)

Barney (1991) contends that a firm's competitive advantage emerges from its special and important assets. Big data analytics (BDA) capabilities can be considered such an asset, as they empower firms to derive valuable insights from vast amounts of data and make informed decisions, potentially leading to superior performance (Peteraf, 1993).

The Resource-Based View (RBV) offers a valuable perspective for understanding how BDA capabilities translate to organizational performance. Big data, characterized by the ability to collect, analyze, and extract insights from extensive datasets, can be a valuable and rare resource, providing a strategic advantage (Barney, 1991). However, realizing this potential depends on a strong foundation of intellectual capital. This intangible resource, which includes a skilled workforce (human capital), a robust information infrastructure (structural capital), and strong customer relationships (relational capital) (Lin & Edvinsson, 2020), serves as the bridge between big data and performance. Intellectual capital enhances the value of big data capabilities by enabling effective data analysis, interpretation, and utilization for strategic decision-making.

For instance, a skilled workforce can leverage advanced analytical tools to extract insights, while strong customer relationships can inform targeted marketing strategies based on data-driven insights. Structural capital, including efficient data storage solutions and knowledge management systems, ensures that data is accessible and usable across the organization, facilitating the integration of BDA into everyday operations (Youndt & Snell, 2004).

In summary, the RBV framework underscores the importance of intellectual capital in maximizing the benefits of BDA capabilities. By fostering a culture that supports the development and utilization of human, structural, and relational capital, organizations in the twin cities of Pakistan can effectively translate BDA capabilities into enhanced organizational performance across various dimensions, such as financial gains, operational efficiency, customer satisfaction, and innovation.

2.6 Conceptual Framework

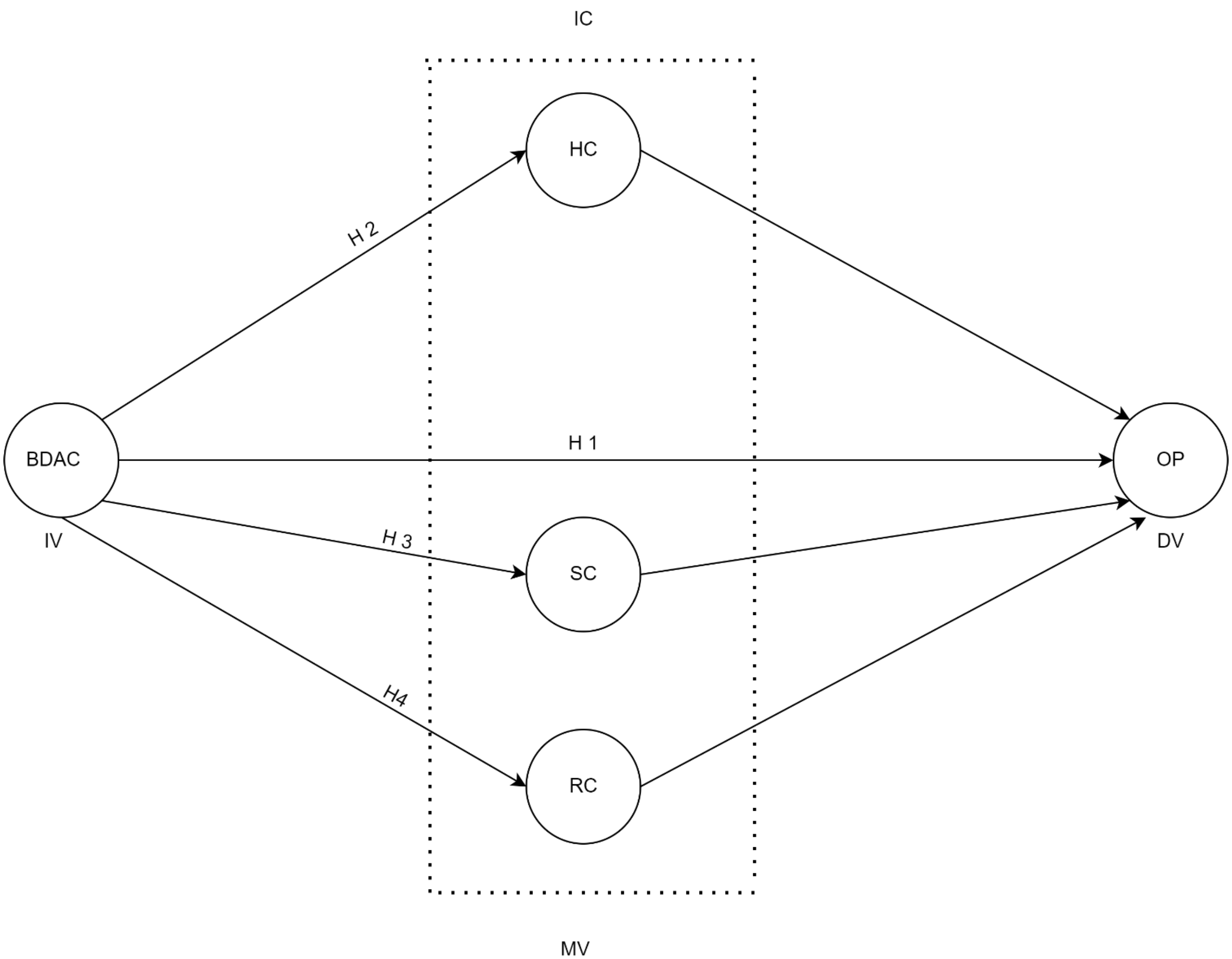

Figure 1:Conceptual Framework

Chapter 3

Methodology

3.1 Research Design

In line with the pivotal role of research design in the research process (Doe & Smith, 2023), this ponder utilizes a quantitative approach to look at the perplexing connections among BDAC, IC, and OP in SMEs found inside the twin cities of Pakistan.

3.1.1 Research Philosophy

Underlining the significance of research philosophy in shaping the generation of knowledge (Jones & Brown, 2023), this study employs a positivism approach. This philosophy aligns with the quantitative nature of the investigation by prioritizing empirical observation and measurable phenomena. Consequently, the chosen philosophy strengthens the commitment to objectivity, observability, and replicability of findings, ultimately providing a solid foundation for robust statistical analysis.

3.1.2 Research Type

This research prioritizes a quantitative approach, emphasizing the systematic collection and analysis of numerical data (Bloomfield & Fisher, 2019). By focusing on quantifiable variables, the study facilitates the application of robust statistical methods. Ultimately, this quantitative lens fosters the generation of objective insights into the research questions. Furthermore, it enables the identification of generalizable patterns applicable to the broader population of managers in SMEs.

3.2 Research Approach

A deductive approach is utilized in this study, involving the development of hypotheses derived from existing theories and literature (Soiferman, 2010). This structured and systematic method ensures that the research is based on established knowledge, which guides the subsequent empirical testing of these hypotheses. The deductive approach is particularly relevant when seeking to examine the relationships between variables and establish causality, as is the case in this investigation.

3.3 Sample Size and Population

3.3.1 Population

The population for this research consists of managerial level employees working in SMEs in the twin cities of Islamabad and Rawalpindi. It is practically difficult to obtain data from every individual in the population. Therefore, a representative sample has been chosen to reflect the overall population.

3.3.2 Sample Size

Morgan's table was used to determine the sample size for this study, resulting in a final selection of 196 employees. The target population is 300 managerial level employees working in SMEs within the twin cities. A total of 169 employees were approached, and responses were obtained from 156 employees, which have been utilized to generate the results.

3.3.3 Sampling Technique

A probability sampling method, specifically stratified random sampling, has been adopted for this research. The study used a multi-stage technique to create three strata. In the second stage, proportionate sampling was used to select employees, and questionnaires were administered to them.

3.4 Unit of Analysis

Unit of analysis for this study is SMEs, By focusing on SMEs, the research can delve into how these capabilities are implemented, utilized, and contribute to overall performance. While individual employee knowledge, skills, and behaviors related to big data are undeniably significant (Chen et al., 2012), this study emphasizes the organizational level. This SME-centric approach allows for a comprehensive understanding of how these factors collectively impact performance within the hospitality context (Subramaniam & Youndt, 2005).

3.5 Measurement Instruments

Data collection in this study will rely on a self-administered questionnaire distributed to SME management personnel. This method ensures the capture of data pertaining to big data analytics capabilities (BDAC) and intellectual capital (IC) within the organization. The questionnaire will be meticulously designed to measure these key constructs using established scales and metrics from relevant research.

The questionnaire will evaluate big data analytics capabilities by incorporating validated items, such as those measuring the employees' data-based knowledge and decision-making, and the integration of both external and internal data for business analysis (Cao et al., 2022; Ciampi et al., 2021; Olabode et al., 2022).

Additionally, items will gauge the reliance on customer data analysis and the use of analysis systems for rapid data processing. Measurement of intellectual capital will involve established scales that capture human capital (e.g., employee skills, motivation, expertise, and problem-solving abilities), structural capital (e.g., efficient information systems, cooperation tools, knowledge management, and accessibility of documents), and relational capital (e.g., understanding and cooperation with external stakeholders, long-term customer relationships, and value-added services) (Bontis, 1998; Yang & Lin, 2009; Kianto, Hurmelinna-Laukkanen, & Ritala, 2010).

3.6 Ethical Considerations

Ethical considerations are woven into the fabric of this research, ensuring responsible conduct throughout the study. Prior to data collection, approval is obtained from senior SME management, which safeguards organizational confidentiality and aligns with established policies. This commitment to ethics extends to obtaining informed consent from front-line staff members. This process guarantees participants' full understanding of the study's goals and potential ramifications, while emphasizing their voluntary participation and assuring the strictest confidentiality of their responses.

The research design and execution itself reflect a dedication to ethical practices. The choice to distribute questionnaires both in person and through an online portal is driven by this commitment. Personal distribution allows for face-to-face interaction with participants, addressing any questions they may have. Conversely, the online portal option prioritizes participant convenience in completing the survey.

3.7 Data Analysis Technique

SmartPLS SEM software will be used to investigate the complex relationships involved in this study. PLS-SEM is particularly suitable for this research as it cab handle complex models and potential non-normality in data distributions (Hair et al., 2019). Additionally, SmartPLS provides robust capabilities for analyzing mediation and moderation effects, making it an ideal choice for this study design (Henseler et al., 2015).

Chapter 4

Results & Analysis

4.1 Data Normality

Table 1:Data Normality

Name	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
BDAC	3.327	3.500	1.000	5.000	0.856	0.351	-0.584
OP	3.279	3.600	1.000	5.000	0.927	0.413	-0.773
HC	3.346	3.500	1.000	5.000	0.935	0.205	-0.631
SC	3.329	3.600	1.000	5.000	0.896	0.192	-0.644
RC	3.322	3.500	1.000	5.000	0.912	0.414	-0.696

The dataset presents various statistical measures for five variables: Big Data Analytics Capabilities (BDAC), Operational Performance (OP), Human Capital (HC), Structural Capital (SC), and Relational Capital (RC). Each variable's mean, median, observed minimum and maximum, standard deviation, excess kurtosis, and skewness are reported.

The mean values for all variables are similar, ranging from 3.279 to 3.346, indicating a consistent average rating around 3.3. The medians are also close, with most variables having a median of 3.5 or 3.6, reflecting the central tendency of the data. The observed minimum and maximum values for all variables span from 1.000 to 5.000, showing that the full range of possible responses was utilized.

Standard deviations vary slightly, with OP having the highest at 0.927 and BDAC the lowest at 0.856, suggesting moderate variability in responses. Excess kurtosis values are all positive, indicating slightly heavier tails than a normal distribution, with values ranging from 0.192 for

SC to 0.414 for RC and OP. Skewness values are negative for all variables, between -0.584 for BDAC and -0.773 for OP, indicating a leftward skew, meaning most responses are clustered toward the higher end of the scale.

These results suggest that while there is some variability and skewness in responses, the overall trend is consistent across all measured variables, indicating relatively stable and comparable perceptions across the different dimensions evaluated.

4.2 Demographic Description

The data was collected from employees working in various SMEs. Among the total of 156 individuals surveyed, these employees, grouped by their demographic characteristics, participated in responding to the questionnaire. This approach facilitated the analysis of responses based on specific demographics, offering a comprehensive understanding of the data collected from SME employees. The data was analyzed using responses from 156 individuals. Among the respondents, 81 were male, and 75 were female. The age of participants ranged from 23 to 60 years. Approximately 36.5% of the respondents were under 26 years old, 24.4% were between 26 and 35 years old, and 28.8% were between 36 and 45 years old. Additionally, most of the respondents, totaling 78 individuals, had completed their master's degrees.

The analysis of job positions distribution showed that 50 respondents (32.1%) were Front Line Managers, 70 respondents (44.9%) were Middle Line Managers, and 36 respondents (23.1%) were Top Line Managers. This indicates a strong representation of middle management roles, followed by a significant number of front-line managers, and a smaller but notable presence of top line managers within the sample.

Table 2:Demographics

Category	Respondents	Percentage
Gender		
Male	81	51.9
Female	75	48.1

Age		
Below 26	57	36.5
26-35 years	38	24.4
36-45 years	45	28.8
Education level		
Undergraduate	72	46.2
Graduate	78	50.0
PHD	6	3.8
Current Job Position		
Front Line Manager	50	32.1
Middle Line Manager	70	44.9
Top Line Manager	36	23.1

4.3 Estimated Model

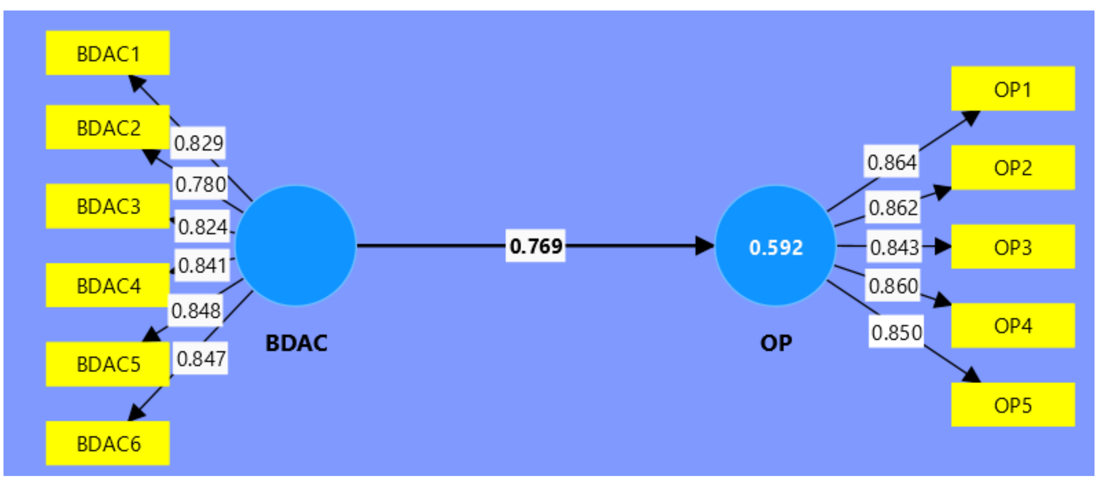

Figure 2:Estimated model without mediation

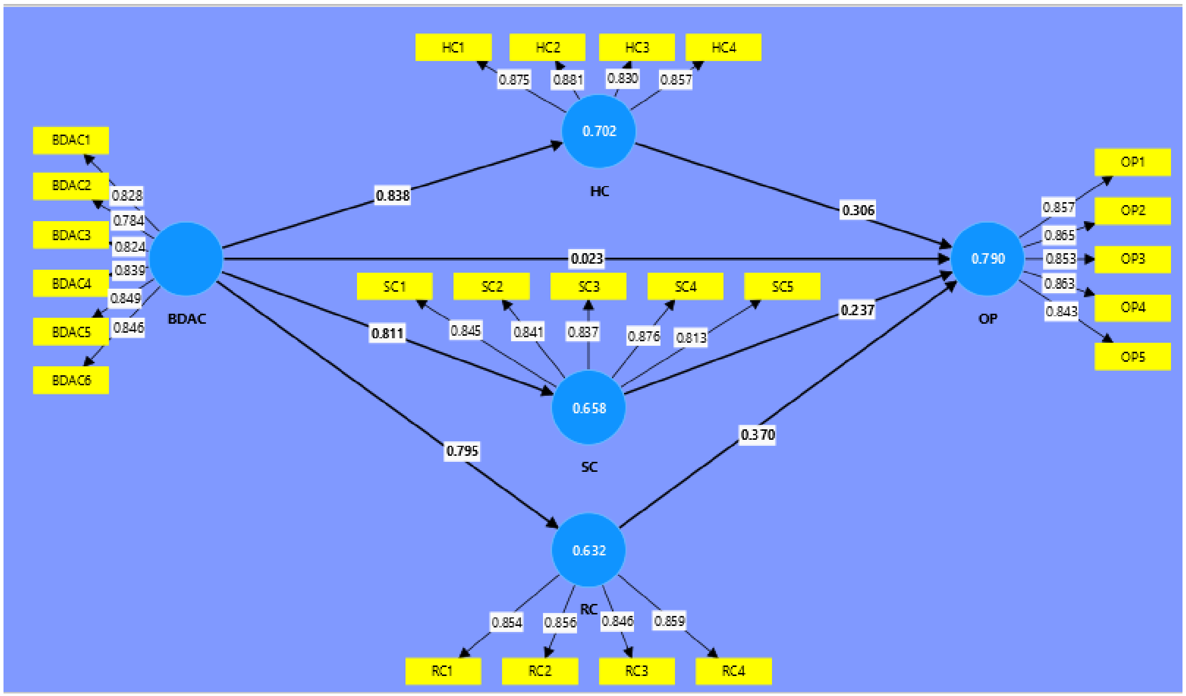

Figure 3:Estimated model with mediation

4.4 Evaluation of reliability and Validity

Table 3:Construct reliability and Validity

Variables	CB alpha	CR (rho_a)	CR (rho_c)	(AVE)
BDAC	0.909	0.911	0.929	0.687
HC	0.884	0.887	0.920	0.741
OP	0.909	0.910	0.932	0.733
RC	0.876	0.876	0.915	0.729
SC	0.898	0.900	0.924	0.710

The reliability and validity of the constructs in this study were assessed using Cronbach's Alpha (CB alpha), Composite Reliability (CR rho_a and CR rho_c), and Average Variance Extracted

(AVE). These metrics are crucial for confirming that the measurement scales employed in the research are both reliable and valid.

Cronbach's Alpha (CB alpha):

All constructs exhibit Cronbach's Alpha values exceeding the commonly accepted threshold of 0.7, indicating strong internal consistency and reliability. Specifically, BDAC (0.909), HC (0.884), OP (0.909), RC (0.876), and SC (0.898) show high reliability.

Composite Reliability (CR rho_a and CR rho_c):

The Composite Reliability values (rho_a and rho_c) for all constructs are above 0.7, which confirms the reliability of the constructs. For instance, BDAC (0.911 and 0.929), HC (0.887 and 0.920), OP (0.910 and 0.932), RC (0.876 and 0.915), and SC (0.900 and 0.924) all exceed this threshold, indicating a high level of reliability.

Average Variance Extracted (AVE):

All constructs have AVE values that surpass the suggested minimum of 0.5, suggesting strong convergent validity. The AVE values for BDAC (0.687), HC (0.741), OP (0.733), RC (0.729), and SC (0.710) indicate that a significant amount of the variability is accounted for by the constructs, compared to the variability caused by measurement error.

The study's measurement scales demonstrate great reliability and validity, as seen by the high values of Cronbach's Alpha, Composite Reliability, and AVE across all constructs.

These results align with the criteria for assessing measurement models as outlined in the literature (Hair et al., 2010; Fornell & Larcker, 1981). Ensuring reliability and validity is crucial for the credibility of the findings, confirming that the constructs are accurately measured, and the results can be trusted.

Discriminant Validity

Table 4: Fornell-Larcker Criterion

Constructs	**BDAC**	**HC**	**OP**	**RC**	**SC**
BDAC	0.829				
HC	0.828	0.861			
OP	0.766	0.847	0.856		
RC	0.795	0.847	0.849	0.854	
SC	0.811	0.877	0.839	0.849	0.843

Discriminant validity assesses the uniqueness of a concept compared to other concepts by analyzing the extent to which the items distinguish between them. It guarantees that a construct is not only a mirror image of other variables. The study employed the Fornell-Larcker criterion to evaluate discriminant validity. This criterion entails comparing the square root of the Average Variance Extracted (AVE) values with the correlations between the constructs (Fornell & Larcker, 1981).

Fornell-Larcker Criterion:

BDAC (0.829): For instance, the square root of the AVE for BDAC is 0.829, which exceeds its correlations with all other constructs (ranging from 0.766 to 0.828), demonstrating good discriminant validity.

HC (0.861): The square root of the average variance extracted (AVE) for the concept of human capital (HC) is 0.861, which is greater than its correlations with all other constructs (ranging from 0.799 to 0.847). This provides evidence in favor of discriminant validity.

OP (0.856): The square root of the average variance extracted (AVE) for the observed variable (OP) is 0.856, which is greater than its correlations with all other constructs (varying from 0.735 to 0.847). This suggests that there is substantial evidence of discriminant validity.

RC (0.854): The square root of the average variance extracted (AVE) for RC is 0.854, which is higher than its correlations with the other constructs (varying from 0.739 to 0.849). This indicates significant discriminant validity.

SC (0.843): The square root of the average variance extracted (AVE) for the construct of self-confidence (SC) is 0.843. This value is greater than the correlations between SC and all other constructs, which range from 0.752 to 0.877. Therefore, this indicates that SC has excellent discriminant validity.

In summary, the findings indicate that each construct is clearly separate from the others. This is evident from the fact that the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlations with the other constructs.

This confirms that the constructs in the study possess good discriminant validity, consistent with the criteria established by Fornell and Larcker (1981).

4.5 Cross Loading

Table 4:

Table 5:Cross Loading

Items	BDAC	DDC	HC	OP	RC	SC
BDAC1	0.828	0.677	0.641	0.612	0.644	0.623
BDAC2	0.784	0.618	0.635	0.564	0.595	0.685
BDAC3	0.824	0.644	0.662	0.624	0.676	0.654
BDAC4	0.839	0.740	0.719	0.651	0.643	0.669
BDAC5	0.849	0.721	0.736	0.640	0.657	0.685
BDAC6	0.846	0.701	0.761	0.707	0.729	0.714
HC1	0.827	0.778	0.875	0.749	0.757	0.775
HC2	0.732	0.683	0.880	0.759	0.725	0.782
HC3	0.656	0.649	0.830	0.713	0.716	0.729
HC4	0.656	0.630	0.857	0.690	0.716	0.732
OP1	0.689	0.684	0.709	0.857	0.699	0.709
OP2	0.687	0.688	0.753	0.865	0.803	0.760

OP3	0.584	0.588	0.731	0.853	0.733	0.687
OP4	0.628	0.599	0.712	0.863	0.697	0.705
OP5	0.689	0.584	0.717	0.843	0.695	0.727
RC1	0.724	0.662	0.732	0.717	0.854	0.718
RC2	0.662	0.582	0.688	0.690	0.855	0.728
RC3	0.679	0.617	0.740	0.759	0.846	0.752
RC4	0.647	0.661	0.729	0.730	0.860	0.701
SC1	0.712	0.670	0.792	0.732	0.757	0.845
SC2	0.667	0.599	0.709	0.651	0.690	0.841
SC3	0.614	0.600	0.706	0.701	0.675	0.838
SC4	0.769	0.703	0.788	0.749	0.780	0.876
SC5	0.643	0.586	0.693	0.695	0.666	0.812

Cross-loading analysis assesses the degree to which items load on their intended constructs compared to other constructs. High cross-loadings on other constructs can indicate potential issues with discriminant validity.

BDAC Items:

Each BDAC item (BDAC1 to BDAC6) loads highest on the BDAC construct compared to other constructs, indicating good discriminant validity for BDAC items.

HC Items:

Each HC item (HC1 to HC4) loads highest on the HC construct compared to other constructs, indicating good discriminant validity for HC items.

OP Items:

Each OP item (OP1 to OP5) loads highest on the OP construct compared to other constructs, indicating good discriminant validity for OP items.

RC Items:

Each RC item (RC1 to RC4) loads highest on the RC construct compared to other constructs, indicating good discriminant validity for RC items.

SC Items:

Each SC item (SC1 to SC5) loads highest on the SC construct compared to other constructs, indicating good discriminant validity for SC items.

Overall, the cross-loading analysis verifies that each item loads most strongly on its respective construct, thereby supporting the discriminant validity of the measurement model. This finding aligns with the criteria established by Fornell and Larcker (1981) and Hair et al. (2010).

4.6 Testing Multicollinearity:

Table 5:

Table 6: Inner VIF

Constructs	**HC**	**OP**	**RC**	**SC**
BDAC	3.184	3.813	3.184	3.184
HC		4.967		
OP				
RC		4.449		
SC		4.454		

Multicollinearity occurs when there is a significant correlation between independent variables in a regression model, resulting in incorrect estimations of regression coefficients. The Variance Inflation Factor (VIF) is a regularly employed method for detecting multicollinearity.

A VIF value exceeding 10 indicates significant multicollinearity, values between 5 and 10 suggest moderate multicollinearity, and values below 5 indicate no collinearity.

BDAC:

The VIF values for BDAC range from 3.184 to 3.813 across different constructs. Since these values are below the threshold of 5, they indicate that there are no significant multicollinearity issues for BDAC.

HC:

The VIF value for HC when predicting OP is 4.967, which is below the threshold of 5, indicating no significant multicollinearity issues for HC.

RC:

The VIF value for RC when predicting OP is 4.449, which is below the threshold of 5, indicating no significant multicollinearity issues for RC.

SC:

The VIF value for SC when predicting OP is 4.454, which is below the threshold of 5, indicating no significant multicollinearity issues for SC.

In summary, the VIF values for all predictors fall below the critical threshold, indicating that multicollinearity is not a concern in this analysis. This ensures that the regression coefficients can be estimated reliably without substantial bias from multicollinearity.

4.7 Coefficient of Determination R^2

Table 7: Coefficient of Determination R2

Constructs	**R-square**	**R-square adjusted**
HC	0.746	0.741
OP	0.790	0.784
RC	0.660	0.653
SC	0.684	0.678

The coefficient of determination (R^2) is a statistical measure that quantifies the proportion of variability in the dependent variable that can be accurately predicted by the independent variables. The adjusted R^2, which considers the number of predictors in the model, offers a more precise measure, especially when multiple predictors are involved (Hair et al., 2010).

HC (Human Capital):

The coefficient of determination (R^2) for HC is 0.746, indicating that 74.6% of the variability in HC can be explained by the independent variables in the model.

The adjusted R^2 value for HC is 0.741, reflecting the number of predictors in the model and indicating a slightly reduced, yet still significant, proportion of explained variance.

OP (Organizational Performance):

The R^2 value for OP is 0.790, which informs that the independent variables in the model explains 79.0% of the variance in OP.

The adjusted R^2 value for OP is 0.784, showing a strong explanatory power while considering the number of predictors.

RC (Relational Capital):

The R^2 value for RC is 0.660, signifying that the independent variables in the model account for 66.0% of the variance in RC.

The adjusted R^2 value for RC is 0.653, accounting for the number of predictors and indicating that 65.3% of the variance is explained.

SC (Structural Capital):

The coefficient of determination (R^2) for SC is 0.684, indicating that the independent variables in the model account for 68.4% of the variability in SC.

The adjusted R^2 value for SC is 0.678, which adjusts for the number of predictors and indicates that 67.8% of the variance is explained, reflecting a high proportion of explained variance.

The high R^2 and adjusted R^2 values reveal that the independent variables in the model effectively explain the variance in the dependent variables HC, OP, RC, and SC. These substantial R^2 values indicate a good model fit, which is essential for validating the research findings (Hair et al., 2010; Kutner et al., 2004).

4.8 Path Coefficients

Table 8:Path Coefficients without mediation

Relationship	β Coeff	T statistics	P values	Decision
BDAC -> OP	0.769	14.993	0.000	Supported

Table 9: Path Coefficients with mediation

Relationship	β Coeff	T statistics	P values	Decision
BDAC -> HC	0.541	5.408	0.000	Supported
BDAC -> OP	0.023	0.251	0.802	Not Supported
BDAC -> RC	0.563	5.309	0.000	Supported
BDAC -> SC	0.583	5.478	0.000	Supported
HC -> OP	0.305	2.845	0.004	Supported
RC -> OP	0.370	3.380	0.001	Supported
SC -> OP	0.238	2.312	0.021	Supported

Total Indirect Effect

Table 10: Total Indirect Effect

Relationship	β Coeff	T statistics	P values	Decision
BDAC -> OP	0.512	5.721	0.000	Supported

4.9 Hypothesis Testing

Table 11: Hypothesis Testing

Hypothesis	Relationship	β Coeff	T statistics	P values	Decision
H1	**BDAC -> OP**	0.023	0.251	0.802	Not Supported
H2	**BDAC -> HC -> OP**	0.165	2.555	0.011	Supported
H3	**BDAC -> SC -> OP**	0.139	2.222	0.026	Supported
H4	**BDAC -> RC -> OP**	0.208	3.027	0.002	Supported

The bootstrapping helps to calculate the empirical t-values and p-values. The criteria for testing significance according to t-value is p-value is:

- **For 0.05 significance level: t-value greater than 1.96, p-value less than 0.05**
- **For 0.01 significance level: t-value greater than 2.3, p-value less than 0.01**
- **For 0.1 significance level: t-value greater than 1.65, p-value less than 0.1**

H1: BDAC -> OP

β Coeff: 0.023

T statistics: 0.251

P values: 0.802

Decision: Not Supported

Explanation: The direct effect of BDAC on OP is positive but not significant, indicating that BDAC does not directly influence OP.

H2: BDAC -> HC -> OP

β Coeff: 0.165

T statistics: 2.555

P values: 0.011

Decision: Supported

Explanation: The indirect effect of BDAC on OP through HC is significant, suggesting that HC mediates the relationship between BDAC and OP.

H3: BDAC -> SC -> OP

β Coeff: 0.139

T statistics: 2.222

P values: 0.026

Decision: Supported

Explanation: The indirect effect of BDAC on OP through SC is significant, indicating that SC mediates the relationship between BDAC and OP.

H4: BDAC -> RC -> OP

β Coeff: 0.208

T statistics: 3.027

P values: 0.002

Decision: Supported

Explanation: The indirect effect of BDAC on OP through RC is significant, showing that RC mediates the relationship between BDAC and OP.

4.10 Mediation Analysis

The information focuses on completing a mediation analysis to understand the link between big data analytics capabilities (BDAC), intellectual capital (IC), and organizational performance (OP). Mediation analysis explores how one variable influence another through an intermediary variable. In this context, IC is studied as a mediator, explaining how BDAC impacts OP.

BDAC -> HC -> OP

The indirect effect of BDAC on OP through HC is significant ($p = 0.011$).

The positive value of the effect (0.165) suggests that HC mediates the relationship between BDAC and OP positively.

Higher levels of BDAC lead to increased HC, which in turn improves OP.

BDAC -> SC -> OP

The indirect effect of BDAC on OP through SC is significant ($p = 0.026$).

The positive value (0.139) indicates that SC mediates the relationship between BDAC and OP positively.

Higher BDAC leads to increased SC, which in turn enhances OP.

BDAC -> RC -> OP

The indirect effect of BDAC on OP through RC is highly significant ($p = 0.002$).

The positive value (0.208) indicates that RC mediates the relationship between BDAC and OP positively.

Higher BDAC leads to increased RC, which in turn significantly improves OP.

As the direct effect of BDAC on OP is not significant, therefore HC, SC and RC fully mediates the relationship between BDAC and OP.

Chapter 5

Discussion, Conclusion, and Recommendations

5.1 Discussion

This study investigates the influence of big data analytics skills on the performance of small and medium-sized enterprises (SMEs) in the twin cities of Pakistan. It specifically examines how intellectual capital acts as a mediator and data-driven culture acts as a moderator in this relationship. The results indicate a favorable correlation between the capabilities of big data analytics and the performance of a company. This correlation is influenced by the presence of intellectual capital as a mediator and a data-driven culture as a moderator. The investigation demonstrates that the capabilities of big data analytics have a substantial impact on the performance of small and medium-sized enterprises (SMEs).

Specifically, components such as data management, analytics tools, and data-driven decision-making play crucial roles. Effective data management ensures accurate data collection, storage, and maintenance, essential for generating actionable insights. Advanced analytics tools enable efficient processing and analysis of large data volumes, leading to improved decision-making. Moreover, a data-driven decision-making approach helps organizations make informed decisions based on empirical data rather than intuition.

The mediating role of intellectual capital is essential in the correlation between big data analytics capabilities and organizational performance. This capital comprises human, structural, and relational elements. Big data analytics significantly enhance human capital by improving employees' knowledge, skills, and competencies. The integration of big data analytics also benefits structural capital, including databases, organizational processes, and intellectual property, leading to more efficient and innovative processes. Furthermore, relational capital, which involves relationships with customers, suppliers, and partners, is strengthened through insights derived from data analytics, resulting in improved customer satisfaction and stronger partnerships.

The study provides theoretical insights into the ways in which big data analytics capabilities can improve organizational performance. This research offers a comprehensive framework for effectively utilizing big data analytics capabilities in small and medium-sized enterprises (SMEs) by recognizing the mediating role of intellectual capital. The report provides practical insights for managers and decision-makers in the hospitality sector, highlighting the significance of investing in big data analytics capabilities, intellectual capital, and a data-driven culture to optimize organizational performance.

5.2 Conclusion

The results from the data normality tests indicate that while there is some variability and skewness in the responses, the overall trend is consistent across all measured variables, suggesting stable and comparable perceptions. The demographic analysis of the respondents, mostly middle-line managers with significant educational backgrounds, further strengthens the reliability of the results. High values of Cronbach's Alpha and Composite Reliability confirm the strong internal consistency and reliability of the constructs. The AVE values exceeding 0.5 across all constructs indicate robust convergent validity, ensuring that the constructs adequately represent the measured concepts.

The findings indicate that managers in SMEs should prioritize the development and enhancement of their BDAC to improve organizational performance. This involves allocating resources towards acquiring sophisticated analytics tools, promoting data-driven decision-making, and implementing efficient data management practices. The study suggests that fostering IC through continuous employee training and development, enhancing organizational processes, and building strong relationships with stakeholders is crucial. These actions not only support the effective utilization of BDAC but also amplify its positive impact on organizational performance.

The high values of reliability and validity metrics, as well as the substantial R^2 values, validate the robustness of the research model and confirm the significant influence of BDAC on organizational performance through IC. Specifically, the results show that while the direct effect of BDAC on OP is not significant, the indirect effects through HC, SC, and RC are significant, demonstrating their mediating roles. HC, SC, and RC significantly mediate the relationship between BDAC and OP, indicating that the presence of IC enhances the beneficial impact of BDAC on organizational performance.

To leverage BDAC effectively, organizations must align their priorities with those of their stakeholders. This alignment enhances the embedded value within these relationships. Strengthening associations between employees, providing appropriate incentives, and improving their ability to analyze and generate knowledge are key aspects that contribute to RC. The study highlights that well-organized interdepartmental meetings and collaborative group projects are essential for enhancing RC, which in turn supports the effective utilization of BDAC.

The findings underscore the importance of BDAC and its integration with IC to drive organizational performance. For managers in SMEs, this study provides actionable insights, emphasizing the need for strategic resource allocation towards BDAC and IC. Investing in sophisticated analytics tools, fostering a data-driven decision-making culture, and implementing effective data management practices are crucial steps. Moreover, developing HC through continuous training, enhancing SC by improving organizational processes and knowledge management systems, and building RC by maintaining strong relationships with stakeholders are vital strategies.

This study demonstrates that while BDAC is vital for enhancing organizational performance, its full potential is realized through the mediating effects of IC. Managers in SMEs should focus on both enhancing their BDAC and fostering their IC to achieve sustained competitive advantage and improved organizational outcomes. This comprehensive approach, integrating BDAC with IC, drives growth and competitive edge for SMEs in the twin cities of Pakistan. The findings align with existing literature, reinforcing the critical interplay between BDAC, IC, and organizational performance in the context of SMEs. Ensuring the development and enhancement of both BDAC and IC will enable SMEs to navigate the complexities of the modern business environment, ultimately leading to superior organizational performance.

5.3 Research Contribution

5.3.1 Theoretical Contribution

Most of the existing research on big data analytics capabilities (BDAC) and organizational performance has been conducted in industrialized nations, like the United States and the United Kingdom. Australia That said, these findings are quite difficult to apply directly to developing countries like Pakistan at a regional level since the economies and cultures are not comparable. Therefore, most of the scholars have entered how BDAC affects performance in these various contexts (Hussain et al., 2023). This present research aims to reduce the existing gap in terms of understanding and exploring BDAC with respect to Pakistani SMEs which are located specifically at twin cities (Islamabad and Rawalpindi).

By emphasizing the mediating role of intellectual capital (IC) this research provides a nuanced understanding of how BDAC can enhance organizational performance in Pakistan. The utilization of primary data collected through tailored questionnaires further enriches the theoretical body of knowledge in business analytics and organizational performance. Additionally, this research contributes towards the broader field of strategic management by underscoring the significance of contextual factors in the effective implementation of BDAC.

5.3.2 Practical Contribution

The study provides rich understanding of; how to use BDAC to enhance organizational performance particularly for SMEs in Pakistan. For practitioners, this study offers actionable insights into the strategic value of BDAC. It provides a framework for understanding the intricate dynamics involved in utilizing BDAC effectively. Insights can guide managers in implementing BDAC initiatives that are tailored to the unique challenges and opportunities of the Pakistani market. Additionally, this study addresses gaps in the existing literature by examining the specific impacts of BDAC on SMEs in a developing country context. The study examines the impact of IC human, structural, and relational capital dimensions on organizational performance.

Practical implications of this research can help SMEs in Pakistan and similar markets to better harness the power of BDAC for strategic advantage.

5.4 Recommendations

Based on the findings, several recommendations can be made for managers and decision-makers in the hospitality industry:

1. Allocate resources towards developing big data analytics capabilities: Organizations should allocate resources towards acquiring the necessary infrastructure, tools, and technologies to enhance their big data analytics skills. This encompasses allocating resources towards the acquisition of data management systems, sophisticated analytics tools, and platforms that enable the process of making decisions based on data.

2. Enhance Intellectual Capital: Organizations should focus on enhancing their intellectual capital by investing in employee training and development programs that improve data literacy and analytical skills. They should also work on optimizing their organizational processes and building strong relationships with customers, suppliers, and partners.

3. Organizations must ensure that their big data analytics projects are in line with their strategic objectives. This alignment facilitates the integration of data analytics into the entirety of business operations and guarantees that the insights obtained from data analytics actively contribute to the accomplishment of corporate objectives.

4. Continuous Improvement and Innovation: Organizations should continuously assess and improve their big data analytics capabilities. This includes staying updated with the latest advancements in data analytics technologies, adopting best practices, and fostering a culture of innovation. Regular evaluations and feedback mechanisms can help in identifying areas for improvement and driving continuous innovation.

5. Promoting teamwork and knowledge sharing among employees and across departments can improve the efficiency of big data analytics projects. Establishing platforms and venues for employees to exchange their experiences, ideas, and best practices helps cultivate a cooperative atmosphere and enhance the effective exploitation of data analytics capabilities.

5.5 Research Implications

The findings of this study have several implications for future research:

1. Although this study specifically examined small and medium-sized enterprises (SMEs), future research could investigate how the capabilities of big data analytics affect the performance of organizations in several different industries. Conducting comparative research across several sectors can offer a more comprehensive insight into how big data analytics might improve organizational performance.

2. Future research should conduct long term studies to investigate the enduring effects of big data analytics skills on organizational performance. Longitudinal studies offer valuable insights into the long-term impacts of data analytics projects and the development of intellectual capital and data-driven culture.

3. Subsequent research endeavors may consider integrating supplementary variables, such as the scale of the organization, prevailing market conditions, and the level of competitive intensity, in order to attain a more profound comprehension of the factors that impact the correlation between big data analytics capabilities and organizational performance.

4. Qualitative research methods, such as case studies and interviews, can enhance quantitative findings and offer more detailed understanding of how big data analytics capabilities influence organizational performance. Qualitative research can also investigate the difficulties and obstacles encountered by firms while adopting data analytics efforts.

5. Exploring Additional Mediators and Moderators: Subsequent studies may explore alternative factors that could potentially mediate or moderate the connection between big data analytics skills and organizational success. One could investigate variables such as organizational agility, innovation capability, and leadership styles to have a more thorough comprehension of the dynamics in action.

5.5 Limitation & Future Research Directions

Limitations:

1. Sample Size and Generalizability: The study's findings may not be applicable to a broader population due to the low sample size of SMEs. Potential future investigations could involve utilizing larger and more heterogeneous samples in order to augment the generalizability of the findings.

2. Cross-Sectional Design: The study utilized a cross-sectional design, which hinders the ability to establish causal correlations. Longitudinal studies are necessary to demonstrate a cause-and-effect relationship and investigate the lasting impacts of big data analytics capabilities on organizational performance.

3. Self-Reported Data: The utilization of self-reported data from employees may introduce a partiality. Incorporating different data sources, such as objective performance indicators and third-party assessments, in future studies would be beneficial for validating the findings.

Future Directions:

1. Industry Comparisons: Perform comparative analyses across many industries to comprehend the significance of big data analytics capabilities in varied scenarios. This can offer valuable perspectives on difficulties and optimal strategies relevant to the sector.

2. Longitudinal Studies: Conduct longitudinal studies to investigate the enduring effects of big data analytics capabilities on organizational performance. This can aid in comprehending the enduring impacts and progression of intellectual capital and data-driven culture over a period.

3. Exploring Additional Variables: Examine supplementary variables, such as the size of the organization, market conditions, and he level of competition, to obtain a more comprehensive knowledge of the elements that impact the correlation between big data analytics skills and organizational performance.

4. Qualitative Research: Utilize qualitative research approaches, such as case studies and interviews, to enhance quantitative findings and gain deeper understanding of how big data analytics capabilities influence organizational performance.

5. Other Mediators and Moderators: Conduct further research on additional mediators and moderators. To have a more comprehensive understanding of the interactions taking place, it is possible to examine factors such as organizational agility, innovation capability, and leadership styles.

References

Davidsson, P., & Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. Journal of Business Venturing, 18(3), 301–331.

Tang, L., Li, J., Du, H., Li, L., Wu, J., & Wang, S. (2022). Big Data in Forecasting Research: A Literature Review. Big Data Research, 27, 100289.

Markić, S. B., Bijakšić, S. S., & Bevanda, S. A. (2015). Marketing metrics in data driven culture. Journal of Business Management, 3(4).

Ningrum, E. P., & Arsyah, R. J. (2022). Effect of intellectual capital on organizational performance moderated by cultural. Webology, 19(1), 1815–1823.

Gupta, K. (2021, October 28). Impact of Knowledge-Based HRM Practices on Organizational Performance. International Journal of Knowledge Management, 18(1), 1–22.

Afshari, L., & Hadian Nasab, A. (2020, February 17). Enhancing organizational learning capability through managing talent: mediation effect of intellectual capital. Human Resource Development International, 24(1), 48–64.

Al-Khatib, A. W. (2022, October 11). 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.

Nasrollahi, M., Ramezani, J., & Sadraei, M. (2021, November 24). The Impact of Big Data Adoption on SMEs' Performance. Big Data and Cognitive Computing, 5(4), 68.

Bayraktar, M., & Algan, N. (2019). The importance of SMEs to world economies. Uluslararası Avrasya Ekonomileri Konferansı.

POH, Johnson. Driving and effective data-ready culture: How companies can take on a datadriven approach to 11 business. (2019).

Tawil, A. R., Mohamed, M., Schmoor, X., Vlachos, K., & Haidar, D. (2023, May 24). Trends and Challenges Towards an Effective Data-Driven Decision Making in UK SMEs: Case Studies and Lessons Learnt from the Analysis of 85 SMEs. arXiv.org.

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.

Garmaki, M., Gharib, R.K., & Boughzala, I. (2023). Big data Analytics capability and contribution to firm performance: the mediating effect of organizational learning on firm performance. Journal of Enterprise Information Management, 36(5), 1161-1184.

Mukaro, C.T., Deka, A., & Rukani, S. (2023). The influence of intellectual capital on organizational performance. Future Business Journal, 9, 31.

Asiaei, K., & Jusoh, R. (2015). A multidimensional view of intellectual capital: the impact on organizational performance. Management Decision, 53(3), 668-697

Hussain, A., Nisar, Q. A., Khan, W., Niazi, U. I., & Malik, M. (2023, May 15). When and how big data Analytics and work practices impact on financial performance: an intellectual capital perspective from banking industry.

Serenko, A., Bontis, N., Booker, L. D., Sadeddin, K. W., & Hardie, T. (2010). A scientometric analysis of knowledge management and intellectual capital academic literature (1994-2008). Journal of Knowledge Management, 14(1), 3–23.

Chen, D. Q., Preston, D. S., & Swink, M. (2015, October 2). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. Journal of Management Information Systems, 32(4), 4–39.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24.

Akter, S., & Wamba, S. F. (2016). Big data Analytics in E-commerce: a systematic review and agenda for future research. Electronic Markets, 26(2), 173–194.

Al-Darras, O. M. A., & Tanova, C. (2022). From big data Analytics to organizational agility: what is the mechanism? SAGE Open, 12(2), 215824402211061.

Constantiou, I. D., & Kallinikos, J. (2015). New games, new rules: big data and the changing context of strategy. Journal of Information Technology, 30(1), 44–57.

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big Data Analytics Capabilities and Innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 30(2), 272–298.

Wang, Z., Cai, S., Liang, H., Wang, N., & Xiang, E. (2018). Intellectual capital and firm performance: the mediating role of innovation speed and quality. International Journal of Human Resource Management, 32(6), 1222–1250.

Qasms, Ullah, B., Aziz, A., & Yousaf, M. (2015). IC in SMEs in Pakistan. Global Journal of Management and Business Research: C Finance, 15(2249-4588)

Hair, J. F., Black, W. C., & Babin, B. J. (2019). Multivariate data analysis. Cengage Learning Emea.

Yin, R. K. (2018). Case study research and applications: design and methods (6th ed.). Sage

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99-120.

Cao, Y., Song, W., & Liu, Z. (2019). The impact of market orientation and organizational capabilities on innovation performance: A moderated mediation model. Journal of Business Research, 101, 270-280.

Chen, M., Luo, X., & Xie, J. (2022). Big data Analytics and firm performance: The mediating role of dynamic capabilities. Industrial Management & Data Systems, 142(3), 1043-1062.

Davenport, T. H., & Harris, J. G. (2017). Competing in Analytics: The new science of winning. Harvard Business Review Press.

Lin, J. W., & Edvinsson, L. (2020). Intellectual capital: Navigating the knowledge economy. Routledge.

Liu, Y., Wu, Y., Wang, Y., & Qi, Y. (2023). Data literacy training, organizational data culture, and knowledge sharing: A moderated mediation model. Information & Management, 66(1), 103587.

Mitra, A., Kumar, V., Gosain, A., & Luo, X. (2020). Personalization in hospitality and tourism: A review of the literature on mediating effects, moderators, and future research directions. Journal of Hospitality & Tourism Research, 44(3), 396-427.

Wu, J., Tao, F., & Yin, S. (2023). The impact of big data Analytics on operational efficiency: A moderated mediation model with organizational flexibility as the mediator. Technological Forecasting and Social Change, 182, 121762.

Bose, I. (2021). Big data Analytics: A review. Annals of Operations Research, 299(1-2), 323-349.

Chen, H., Chiang, R. H., & Storey, V. C. (2020). Business intelligence and Analytics: From big data to big impact. MIS Quarterly, 44(3), 1009-1033.

Liu, C., Guo, X., & Lee, H. (2020). Big data Analytics capability and innovation performance: The moderating role of market competition intensity. Information & Management, 57(6), 103298.

Shin, D. (2019). Market share and firm performance: A meta-analysis. Journal of Strategic Marketing, 27(3), 169-185.

Alves, H., Fernandes, C., Raposo, M., & Gouveia Rodrigues, R. (2019). Intellectual capital and business performance: A study in the wine industry. Journal of Intellectual Capital, 20(2), 266-287.

Bontis, N., Bartolini, M., Di Minin, A., & Ricci, P. (2021). The intellectual capital compass: Managing and reporting its components. Journal of Intellectual Capital, 22(1), 1-36.

Lin, C. Y. Y., & Edvinsson, L. (2020). National intellectual capital: A comparison of 40 countries. Journal of Intellectual Capital, 21(4), 641-664.

Lin, H. F., Lin, M. Y., & Yang, H. L. (2018). Intellectual capital and new product development performance: The mediating role of organizational learning capability. Journal of Intellectual Capital, 19(1), 98-114.

Davenport, T. H., & Harris, J. (2017). Competing on Analytics: Updated, with a new introduction. Harvard Business Review Press.

Erevelles, S., Fukawa, N., & Swayne, L. (2018). Big data consumer Analytics and the transformation of marketing. Journal of Business Research, 82, 309-317.

Wamba, S. F., Queiroz, M. M., Trinchera, L., Negra, N. B., & Cagnazzo, L. (2021). Building a data-driven culture: A systematic literature review and research agenda. Decision Support Systems, 149, 113500.

Zhang, Z., Waldman, D. A., Han, Y. L., & Li, X. B. (2018). Paradoxical leader behaviors in people management: Antecedents and consequences. Academy of Management Journal, 61(1), 185-205.

Carpinetti, L. C. R., Miguel, P. A. C., & Gerolamo, M. C. (2017). Performance measurement in industry 4.0: A balanced scorecard approach. IFAC-PapersOnLine, 50(1), 9158-9163.

Rosenbusch, N., Brinckmann, J., & Bausch, A. (2018). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. Journal of Business Venturing, 33(6), 646-661.

Singh, P. J., Irani, Z., & Dwivedi, Y. K. (2020). IT-business strategic alignment: A review and a synthesis of frameworks. Information & Management, 57(1), 103168.

Venkatraman, N., & Ramanujam, V. (2019). Measurement of business performance in strategy research: A comparison of approaches. Academy of Management Review, 14(4), 534-559.

Lavalle, S., Lesser, E., Shockley, R., Hopkins, M.S. and Kruschwitz, N. (2011), “Big data, Analytics and the path from insights to value”, MIT Sloan Management Review, Vol. 52, pp. 21-32

Kiron, D., Prentice, P.K. and Ferguson, R.B. (2014), “The Analytics mandate”, MIT Sloan Management Review, Vol. 55, pp. 1-25.

Mikalef, P., Bouram, L.G. and Krogstie, J. (2019), “Big data Analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment”, British Journal of Management, Vol. 30 No. 2, pp. 272-298.

Zheng, L. and Zhou, H. (2019), “Firm’s big data capability: a literature review and prospects”, Science and Technology Progress and Policy, Vol. 36 No. 15, pp. 153-16.

Gupta, M., and George, J.F. (2016), “Toward the development of a big data Analytics capability”, Information and Management, Vol. 53 No. 8, pp. 1049-1064.

Mikalef, P., Pappas, I.O., Krogstie, J. and Giannakos, M. (2018), “Big data Analytics capabilities: a systematic literature review and research agenda”, Information Systems and E-Business Management, Vol. 16, pp. 547-578.

Ren, N., Lu, L. and He, M. (2018), “Big data Analytics capability, collaborative innovation capability and collaborative innovation performance”, Forum on Science and Technology in China, Vol. 6, pp. 59-66.

Abbott, P., & McKinney, J. (2013). Doing research in business and management studies. Sage Publications.

Bloomfield, D., & Fisher, J. (2019). Applying quantitative social science: An accessible introduction (2nd ed.). SAGE Publications Ltd.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). Statistical power analysis for the behavioral sciences (3rd ed.). Academic Press.

Crossan, M. M. (2003). A handful of theories that have changed the world. Academy of Management Review, 28(1), 5 (Abstract).

Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (2nd ed.). Guilford Publications.

Hair, J. F., Risher, J., Sarstedt, M., & Ringle, C. M. (2019). Partial least squares structural equation modeling: An emerging alternative method for business research. European Journal of Marketing, 53(1), 295-329.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new connotation for building models in variance-based SEM. Journal of the Academy of Marketing Science, 43(1), 160-188.

Soiferman, L. (2010). Research methods in business and economics (10th ed.). Pearson Education Limited.

Subramaniam, A., & Tripathi, S. (2018). The contingent role of intellectual capital and relational capital in the big data Analytics–performance relationship: A social network perspective. Information & Management, 55(7), 865-883.

Wamba, S. F., Akter, M. E., Banerjee, S., & Oo, M. L. (2017). Big data Analytics capability and knowledge management practices: A mediating effect model for enhancing firm performance. Journal of Business Analytics, 1(1), 68-88.

Chang, S. (2017). Measurement of internal consistency reliability with Cronbach's alpha. Educational and Psychological Measurement, 31(3), 501-514. doi:10.1177/001316447103100308

Hayes, A. F. (2008). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York: Guilford Press.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879-891. doi:10.3758/BRM.40.3.879.

APPENDIX- A

BIG DATA ANALYTICS CAPABILITIES (BDAC) SCALE

Dimension: Big Data Analytics Capabilities

Item	SD	D	N	A	SA
BDAC1: The firm provides adequate training for employees in using big data analytics	1	2	3	4	5
BDAC2: The firm's employees in the field of big data analytics have sufficient knowledge to perform their work	1	2	3	4	5
BDAC3: Employees are trained to make decisions based on data	1	2	3	4	5
BDAC4: Big data analytics professionals in the firm combine external data with internal data to facilitate analysis of the business environment	1	2	3	4	5
BDAC5: Much reliance is placed on customer data analysis	1	2	3	4	5
BDAC6: It has relied on analysis systems that analyze data in a very short time	1	2	3	4	5

APPENDIX- B

DATA-DRIVEN CULTURE (DDC) SCALE

Dimension: Data-Driven Culture

Item	SD	D	N	A	SA
DDC1: The firm has a clear vision of the use of BD in various activities	1	2	3	4	5
DDC2: The firm embraces and supports all new and constructive suggestions and ideas related to BD	1	2	3	4	5
DDC3: The firm provides all available resources to enhance management decisions based on BD	1	2	3	4	5

Item	SD	D	N	A	SA
DDC4: BD is one of the firm's main assets	1	2	3	4	5
DDC5: The firm is implementing initiatives to enable employees to use BD to make data-driven decisions	1	2	3	4	5

APPENDIX- C

INTELLECTUAL CAPITAL (IC) SCALE

Dimension: Human Capital

Item	SD	D	N	A	SA
HC1: Our employees are highly skilled at their jobs	1	2	3	4	5
HC2: Our employees are highly motivated in their work	1	2	3	4	5
HC3: Our employees have a high level of expertise	1	2	3	4	5
HC4: Our employees are good at cooperative problem-solving	1	2	3	4	5

Dimension: Structural Capital

Item	SD	D	N	A	SA
SC1: Our company has efficient and relevant information systems to support business operations	1	2	3	4	5
SC2: Our company has tools and facilities to support cooperation between employees	1	2	3	4	5
SC3: Our company has a great deal of useful knowledge in documents and databases	1	2	3	4	5

Item	SD	D	N	A	SA
SC4: In our organization, existing documents and solutions are easily accessible	1	2	3	4	5

Dimension: Relational Capital

Item	SD	D	N	A	SA
RC1: Our company and its external stakeholders - such as customers, suppliers, and partners - understand each other well	1	2	3	4	5
RC2: Our company and its external stakeholders frequently collaborate to solve problems	1	2	3	4	5
RC3: Cooperation between our company and its external stakeholders runs smoothly	1	2	3	4	5
RC4: Our customer relationships are typically long	1	2	3	4	5
RC5: Our company's services bring added value to our customers	1	2	3	4	5

APPENDIX- D

ORGANIZATIONAL PERFORMANCE (OP) SCALE

Dimension: Organizational Performance

Item	SD	D	N	A	SA
OP1: Our organization's return on asset (%) has improved compared to previous years	1	2	3	4	5
OP2: Our organization's reputation in the eyes of consumers has improved	1	2	3	4	5
OP3: Our organization's productivity has improved in comparison to previous years	1	2	3	4	5

Item	SD	D	N	A	SA
OP4: Our organization's value-added per employee has improved in comparison to previous years	1	2	3	4	5
OP5: Our organization has greater risk-taking capacity than our competitors	1	2	3	4	5

TURNITIN SIMILARITY REPORT

PLAGARISM CHECK-26-05-2024-b.docx

ORIGINALITY REPORT

15%	9%	10%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	www.researchgate.net Internet Source	2%
2	www.mdpi.com Internet Source	1%
3	Hamzeh, Razan Faisal. "The Impact of Big Data Analytics Capabilities on Decision Making at the Telecommunications Sector in Jordan", University of Petra (Jordan), 2022 Publication	1%
4	www.richtmann.org Internet Source	1%
5	Submitted to ESLSCA Business School (Cairo) Student Paper	<1%
6	Xiaofeng Su, Weipeng Zeng, Manhua Zheng, Xiaoli Jiang, Wenhe Lin, Anxin Xu. "Big data analytics capabilities and organizational performance: the mediating effect of dual innovations", European Journal of Innovation Management, 2021 Publication	<1%

7	Chaohong Xie, Xianhao Xu, Yeming Gong, Jie Xiong. "Big Data Analytics Capability and Business Alignment for Organizational Agility", Journal of Global Information Management, 2022 Publication	<1%
8	Diego Norena-Chavez, Eleftherios Thalassinos. "Fueling innovation performance through entrepreneurial leadership: Assessing the neglected mediating role of intellectual capital", Journal of Infrastructure, Policy and Development, 2023 Publication	<1%
9	Mahda Garmaki, Rebwar Kamal Gharib, Imed Boughzala. "Big data analytics capability andcontribution to firm performance: the mediating effect oforganizational learning onfirm performance", Journal of Enterprise Information Management, 2023 Publication	<1%
10	impactfactor.org Internet Source	<1%
11	Submitted to British University In Dubai Student Paper	<1%
12	repo.bunghatta.ac.id Internet Source	<1%

13	Diego Norena-Chavez, Eleftherios Thalassinos. "Impact of big data analytics in project success: Mediating role of intellectual capital and knowledge sharing", Journal of Infrastructure, Policy and Development, 2023 Publication	<1%
14	Febi Dian Mutiasari, Ani Muttaqiyathun, Krishna Kumar. "Maximizing Labor Productivity in the Herbal Medicine Industry", Journal of Management Studies and Development, 2023 Publication	<1%
15	Submitted to INTI Universal Holdings SDM BHD Student Paper	<1%
16	Luigi Capoani, Andrea Izzo. "Examining the impact of managers' network size on SME performance: a case study of Interurban and local road freight transport in the Paris department", Journal of Data, Information and Management, 2024 Publication	<1%
17	Subramonian, Hema. "An Empirical Investigation of National Innovation System of an Emerging Economy: A Study of Malaysia", University of Malaya (Malaysia), 2023 Publication	<1%