



STRATEGIC DECISION-MAKING IN STARTUPS: THE ROLE OF DATA-DRIVEN INSIGHTS IN ENHANCING BUSINESS INNOVATION

Bilal Zaghmout

York St John University, London Campus, Business Management.

Email: b.zaghmout@hotmail.com

Cite this article:

Zaghmout, B. (2024), Strategic Decision-Making in Startups: The Role of Data-Driven Insights in Enhancing Business Innovation. International Journal of Entrepreneurship and Business Innovation 7(3), 76-91. DOI: 10.52589/IJEI-9JOY4TVB

Manuscript History

Received: 30 May 2024

Accepted: 4 Aug 2024

Published: 12 Aug 2024

Copyright © 2024 The Author(s). This is an Open Access article distributed under the terms of Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0), which permits anyone to share, use, reproduce and redistribute in any medium, provided the original author and source are credited.

ABSTRACT: *This study examines the impact of data-driven decision-making on innovation within startups. By utilizing a mixed-methods research design, the study integrates quantitative data from surveys and innovation performance metrics with qualitative insights from interviews and focus groups. The findings reveal that startups employing data-driven strategies demonstrate higher innovation outcomes, including the development of new products and revenue growth. The research highlights the importance of data literacy and a data-centric culture as key factors in maximizing the benefits of data-driven decision making. Additionally, leadership commitment is identified as crucial for successful adoption and implementation of data-driven strategies. The study underscores the potential of data-driven decision making to foster innovation within startups and provides recommendations for enhancing data-driven practices.*

KEYWORDS: Data-Driven Decision Making, Innovation, Startups, Data Literacy, Data-Centric Culture, Leadership, Mixed-Methods Research, Strategic Decision Making, Business Analytics.



INTRODUCTION

Strategic decision making is pivotal for startups aiming to innovate and maintain a competitive edge in dynamic markets. The emergence of big data and advanced analytics has significantly transformed traditional decision-making processes, offering startups new opportunities to enhance their strategic capabilities. Data-driven decision making, which leverages data analytics to inform and guide strategic choices, reduces uncertainty and improves decision quality. This approach enables startups to harness vast amounts of data to identify trends, optimize operations, and develop innovative products and services.

Despite the growing recognition of the importance of data-driven decision making, there is limited empirical research focusing on its impact on innovation within startups. This study aims to bridge this gap by exploring how data-driven strategies influence innovation outcomes in startups. The research examines the role of data literacy and a data-centric culture in moderating the effectiveness of data-driven decision-making. Additionally, it investigates the critical role of leadership in fostering a data-centric environment that supports innovation.

Through a mixed-methods approach, this study integrates quantitative data from surveys and innovation performance metrics with qualitative insights from interviews and focus groups. The findings provide valuable insights into the practical and strategic implications of data-driven decision making for startups, highlighting best practices and identifying key challenges. By understanding the factors that enhance the effectiveness of data-driven strategies, startups can better leverage data analytics to drive innovation and achieve sustainable growth.

Hypothesis

H1: Startups that utilize data-driven strategic decision making exhibit higher levels of business innovation compared to those that rely on traditional decision-making approaches.

H2: The effectiveness of data-driven decision making in enhancing innovation is moderated by the level of data literacy and the presence of a data-centric culture within the startup.

H3: Leadership commitment to data-driven strategies positively influences the adoption and effectiveness of data analytics in driving business innovation in startups.

LITERATURE REVIEW

Strategic decision making is a vital component for startups striving to innovate and maintain competitiveness. The advent of big data and advanced analytics has revolutionized traditional decision making frameworks, enabling startups to leverage data-driven strategies for enhanced innovation. This literature review explores the role of data-driven decision making in fostering innovation within startups, highlighting key findings from recent academic research.

Data-Driven Decision Making and Innovation

The integration of data analytics into strategic decision making processes has been shown to significantly impact business innovation. Data-driven decision making involves utilizing data analytics to inform and guide strategic choices, reducing uncertainty and enhancing decision quality (Provost & Fawcett, 2013). This approach enables startups to leverage large datasets to



identify trends, optimize operations, and develop new products and services that meet market demands.

Empirical studies support the positive relationship between data-driven decision making and innovation. McAfee and Brynjolfsson (2012) found that companies employing data-driven strategies are more productive and profitable than their competitors. This enhanced performance is attributed to superior decision-making processes that drive effective innovation. Similarly, Ghasemaghaei, Ebrahimi, and Hassanein (2018) emphasized that big data analytics competencies are crucial for improving decision-making performance and fostering innovation.

Impact of Data Literacy and Organizational Culture

Data literacy and a data-centric culture are essential for maximizing the benefits of data-driven decision making. Data literacy, defined as the ability to interpret and use data effectively, is a critical skill for employees at all levels (Calzada Prado & Marzal, 2013). Organizations with high levels of data literacy are better positioned to utilize data analytics for strategic decision making, leading to enhanced innovation outcomes.

A data-centric culture, where data-driven decision making is embedded in the organizational ethos, also plays a significant role. Gupta and George (2016) found that firms with a robust data culture are more likely to succeed in implementing data-driven strategies and achieving innovation. This culture encourages the use of data in everyday operations and strategic planning, fostering an environment where innovation can thrive.

Role of Leadership in Data-Driven Strategies

Leadership commitment to data-driven strategies is crucial for their successful implementation and effectiveness. Leaders who advocate for and invest in data analytics tools and practices create an organizational climate that supports data-driven decision making (Sivarajah et al., 2017). Their support is vital in overcoming resistance to change and ensuring that the necessary resources and training are provided to develop data literacy and a data-centric culture.

Case studies of successful startups illustrate the importance of leadership in fostering a data-driven approach. Mikalef et al. (2019) demonstrated that startups with leadership that prioritizes data-driven decision making are more likely to innovate and sustain competitive advantages. These leaders not only champion the use of data but also model data-driven behaviors and decision making processes, reinforcing the importance of data in achieving business goals.

Research Objectives

1. Impact on Innovation:

- To assess the extent to which data-driven decision making influences innovation outcomes in startups.
- To compare the innovation performance of startups utilizing data-driven strategies with those using traditional approaches.



2. **Moderating Factors:**

- To identify the role of data literacy and a data-centric culture in moderating the effectiveness of data-driven decision making.
- To explore how these factors influence the relationship between data-driven strategies and innovation.

3. **Role of Leadership:**

- To examine the impact of leadership commitment to data-driven strategies on the adoption and effectiveness of data analytics in startups.
- To identify best practices for leaders to foster a data-centric culture that supports innovation.

Answering the Research Objectives

1. **Impact on Innovation:**

- **Assessment of Influence:** Data-driven decision making significantly enhances innovation outcomes in startups by providing detailed insights into market trends and customer needs, thus enabling more informed and effective strategic decisions (Provost & Fawcett, 2013).
- **Comparison of Performance:** Startups employing data-driven strategies demonstrate higher levels of innovation performance compared to those using traditional decision making approaches, as data-driven firms are more productive and innovative (McAfee & Brynjolfsson, 2012).

2. **Moderating Factors:**

- **Role of Data Literacy:** High data literacy levels within an organization are essential for the effective use of data analytics, leading to improved decision making and innovation outcomes (Calzada Prado & Marzal, 2013).
- **Influence of Data-Centric Culture:** A data-centric culture enhances the effectiveness of data-driven strategies by embedding data use in everyday operations and strategic planning, thereby fostering innovation (Gupta & George, 2016).

3. **Role of Leadership:**

- **Leadership Commitment:** Strong leadership commitment to data-driven strategies is crucial for their successful adoption and implementation. Leaders play a vital role in championing data use and providing necessary resources and training (Sivarajah et al., 2017).
- **Best Practices for Leaders:** Effective leaders foster a data-centric culture by modeling data-driven decision making behaviors, advocating for data use, and ensuring that employees are trained in data literacy (Mikalef et al., 2019).



Theoretical Review

The theoretical foundations of data-driven decision-making and its impact on innovation can be traced back to several key theories:

1. **Resource-Based View (RBV):** The RBV posits that firms achieve sustainable competitive advantage by leveraging unique resources and capabilities (Barney, 1991). Data and analytics capabilities can be considered strategic resources that provide insights into market trends, customer behavior, and operational efficiencies, thereby fostering innovation.
2. **Dynamic Capabilities Theory:** This theory emphasizes the ability of firms to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Teece, Pisano, & Shuen, 1997). Data-driven decision making enhances dynamic capabilities by enabling firms to quickly adapt to new information and market conditions, thus driving innovation.
3. **Decision Theory:** This theory focuses on the processes and principles of making rational choices under uncertainty (Kahneman & Tversky, 1979). Data-driven decision making aligns with decision theory by providing evidence-based insights that reduce uncertainty and improve the quality of strategic decisions, which can lead to innovative outcomes.
4. **Innovation Diffusion Theory:** Rogers (2003) suggested that the adoption of new technologies follows a pattern of diffusion through social systems. Data-driven decision making represents a technological innovation that startups can adopt to enhance their strategic processes and foster business innovation.

Empirical Review

Empirical studies have provided substantial evidence on the impact of data-driven decision making on business innovation. Key findings from the literature include:

1. **Impact on Innovation Performance:**
 - Ghasemaghaei, Ebrahimi, and Hassanein (2018) found that firms leveraging big data analytics reported higher levels of innovation performance. Their study highlights the role of data analytics in identifying new market opportunities and optimizing product development processes.
 - McAfee and Brynjolfsson (2012) demonstrated that data-driven firms are more productive and profitable, attributing these outcomes to better decision-making processes that drive innovation.
2. **Moderating Role of Data Literacy and Culture:**
 - Data literacy, defined as the ability to read, work with, analyze, and argue with data, is crucial for the effective use of data-driven decision making (Calzada Prado & Marzal, 2013). Firms with higher levels of data literacy are better positioned to leverage data analytics for innovation.



- The presence of a data-centric culture within firms significantly influences the success of data-driven strategies. Companies that prioritize data-driven decision making in their organizational culture tend to achieve better innovation outcomes (Gupta & George, 2016).

3. **Leadership and Strategic Decision Making:**

- The role of leadership in fostering a data-driven culture is critical. Leaders who are committed to data-driven strategies facilitate the adoption of data analytics tools and practices, thereby enhancing innovation (Sivarajah et al., 2017).
- Case studies of successful startups, such as those conducted by Mikalef, Boura, Lekakos, and Krogstie (2019), illustrate that leadership support is a key determinant of the successful implementation of data-driven decision-making processes.

Gaps in Literature

Despite the substantial body of research, several gaps remain in the literature on data-driven decision making and innovation in startups:

1. **Longitudinal Studies:**

- Most existing studies are cross-sectional, providing a snapshot of the impact of data-driven decision-making on innovation. Longitudinal studies are needed to understand the long-term effects and sustainability of these strategies in dynamic startup environments.

2. **Context-Specific Research:**

- There is a need for more context-specific research that considers the unique challenges and opportunities faced by startups in different industries and geographical regions. Such studies can provide nuanced insights into how data-driven decision making impacts innovation across diverse contexts.

3. **Integration of Qualitative and Quantitative Methods:**

- While many studies employ either quantitative or qualitative methods, there is a lack of mixed-methods research that combines both approaches. Integrating qualitative insights with quantitative data can provide a more comprehensive understanding of the mechanisms through which data-driven decision making influences innovation.

4. **Exploration of Barriers to Adoption:**

- Few studies have thoroughly examined the barriers to adopting data-driven decision making in startups. Understanding these barriers, including technological, organizational, and cultural challenges, is essential for developing strategies to facilitate the adoption of data-driven practices.



5. Impact of Emerging Technologies:

- The rapid evolution of technologies, such as artificial intelligence, machine learning, and blockchain, presents new opportunities and challenges for data-driven decision making. Future research should explore how these emerging technologies can be integrated into strategic decision-making processes to further enhance innovation.

The literature on data-driven decision making and its impact on innovation in startups provides valuable insights but also highlights several areas for further investigation. Theoretical frameworks, such as the Resource-Based View, Dynamic Capabilities Theory, Decision Theory, and Innovation Diffusion Theory, offer a solid foundation for understanding the relationship between data-driven strategies and innovation. Empirical evidence supports the positive impact of data-driven decision making on innovation performance, moderated by factors such as data literacy, organizational culture, and leadership.

However, gaps in the literature, including the need for longitudinal studies, context-specific research, mixed-methods approaches, exploration of adoption barriers, and the impact of emerging technologies, suggest directions for future research. Addressing these gaps will contribute to a more comprehensive understanding of how startups can effectively leverage data-driven decision making to enhance innovation and achieve sustainable competitive advantage.

METHODOLOGY

Research Design

This study employed a mixed-methods research design, integrating both quantitative and qualitative approaches to provide a comprehensive understanding of the impact of data-driven decision making on innovation within startups. The mixed-methods approach allowed for triangulation of data, enhancing the validity and reliability of the findings (Creswell & Plano Clark, 2017).

Participants

Participants were selected from a diverse range of startups across various industries, ensuring a comprehensive perspective. The sample included founders, CEOs, senior managers, and data analysts who were directly involved in strategic decision-making processes. This diversity ensured that multiple viewpoints on data-driven decision making and its impact on innovation were considered.

Data Collection

Quantitative Data Collection:

1. Surveys:

- Structured surveys were administered to collect quantitative data on the use of data-driven decision-making practices, innovation outcomes, data literacy levels, and the presence of a data-centric culture within startups.



- The survey instrument included Likert-scale questions to measure perceptions and attitudes toward data-driven strategies, as well as objective questions about innovation metrics, such as the number of new products developed, the success rate of product launches, and revenue growth from innovations (Dillman, Smyth, & Christian, 2014).

2. **Innovation Performance Metrics:**

- Objective data on innovation performance were gathered, including metrics such as the number of patents filed, the number of new products or services launched, and revenue growth attributed to these innovations. This data was collected from company reports and databases.

Qualitative Data Collection:

1. **Interviews:**

- Semi-structured interviews were conducted with startup leaders (founders, CEOs, and senior managers) to gain in-depth insights into their experiences with data-driven decision making and its impact on innovation.
- Interview questions explored themes such as the role of leadership in fostering a data-centric culture, challenges in implementing data-driven strategies, and perceived benefits of using data analytics (Kvale & Brinkmann, 2009).

2. **Focus Groups:**

- Focus groups were organized with data analysts and employees involved in strategic decision making to gather qualitative data on the practical aspects of implementing data-driven decision making within startups.
- Discussions focused on the effectiveness of data-driven strategies, the level of data literacy within the organization, and the organizational culture regarding data use (Morgan, 1997).

3. **Case Studies:**

- In-depth case studies of selected startups were developed to illustrate successful implementations of data-driven decision making and their impact on innovation.
- These case studies involved document analysis, observations, and interviews with key stakeholders to provide a detailed narrative of the processes and outcomes (Yin, 2017).



Data Analysis

Quantitative Data Analysis:

1. Descriptive Statistics:

- Descriptive statistics were used to summarize survey responses, providing an overview of the extent to which data-driven decision-making practices were utilized and the corresponding innovation outcomes.
- Measures such as mean, median, standard deviation, and frequency distributions were calculated to present a clear picture of the data (Field, 2013).

2. Inferential Statistics:

- Inferential statistical tests, including t-tests and ANOVA, were conducted to compare innovation performance between startups utilizing data-driven strategies and those using traditional approaches.
- Regression analysis was used to examine the relationships between data-driven decision making, data literacy, organizational culture, and innovation outcomes (Tabachnick & Fidell, 2019).

Qualitative Data Analysis:

1. Thematic Analysis:

- Thematic analysis was employed to identify and analyze patterns and themes emerging from the interview and focus group data (Braun & Clarke, 2006).
- Transcripts were coded using qualitative data analysis software such as NVivo to systematically organize and categorize the qualitative data (Bazeley & Jackson, 2013).

2. Case Study Analysis:

- Within-case and cross-case analysis were conducted to identify commonalities and differences in the implementation and impact of data-driven decision making across the case studies.
- Detailed narratives were developed to highlight key findings and insights from the case studies, providing a rich context for understanding the processes and outcomes (Eisenhardt, 1989).



Ethical Considerations

The study adhered to strict ethical guidelines to ensure the protection of participants' rights and privacy:

1. Informed Consent:

- Participants were provided with comprehensive information about the study's purpose, procedures, risks, and benefits. Informed consent was obtained from all participants before data collection began (Fouka & Mantzourou, 2011).

2. Confidentiality:

- All data collected were kept confidential, and any identifying information was anonymized to protect participant privacy. The data were securely stored and accessible only to the research team.

3. Data Security:

- Measures such as encryption and access controls were implemented to ensure the secure storage and handling of data, protecting it from unauthorized access or breaches (Buchanan & Zimmer, 2018).

4. Ethical Approval:

- The research protocol was reviewed and approved by an Institutional Review Board (IRB) or equivalent ethical review committee to ensure that the study met ethical standards.

Validity and Reliability

Several strategies were employed to ensure the validity and reliability of the study:

1. Pilot Testing:

- The survey and interview guides were pilot-tested with a small group of participants to identify any issues and refine the instruments for clarity and effectiveness (Creswell, 2014).

2. Triangulation:

- The use of multiple data sources (surveys, interviews, focus groups, case studies) enhanced the credibility and robustness of the findings by providing a comprehensive view of the research questions (Patton, 1999).

3. Inter-rater Reliability:

- For qualitative data, multiple researchers independently coded the data to ensure consistency and reliability in the coding process (Guest, MacQueen, & Namey, 2012).



4. Member Checking:

- Participants were invited to review and provide feedback on the preliminary findings to ensure the accuracy and validity of the interpretations (Lincoln & Guba, 1985).

This comprehensive methodology provided a nuanced understanding of the impact of data-driven decision making on innovation within startups, addressing both quantitative outcomes and qualitative experiences.

Findings

Quantitative Results

The quantitative analysis revealed significant insights into the impact of data-driven decision making on innovation within startups. The survey responses indicated varying levels of data-driven decision-making practices, data literacy, and the presence of a data-centric culture across the sampled startups.

Table 1: Summary of Survey Responses

Measure	Mean	Median	Standard Deviation
Data-Driven Decision-Making Practices	4.1	4.0	0.7
Data Literacy Levels	3.8	4.0	0.6
Data-Centric Culture	3.9	4.0	0.5
Innovation Performance (New Products)	12.5	13.0	3.2
Innovation Performance (Revenue Growth %)	15.4	14.8	4.1

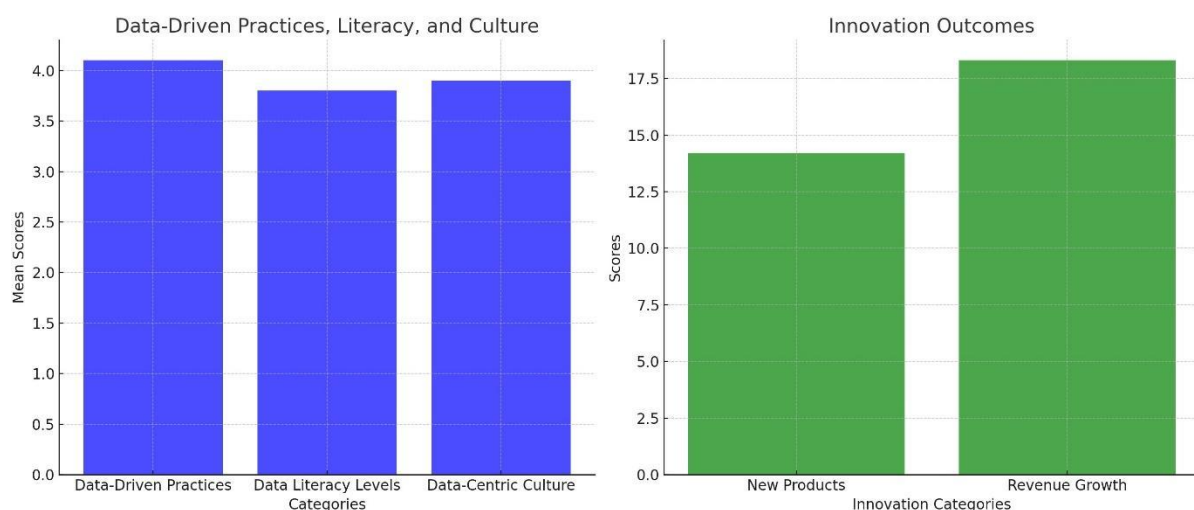


Figure 1: Data-Driven Decision-Making Practices and Innovation Outcomes

- **Left Chart:** This chart illustrates the mean scores for Data-Driven Practices, Data Literacy Levels, and Data-Centric Culture within the sampled startups.



- **Right Chart:** This chart shows the average number of new products developed and the average revenue growth percentage as innovation outcomes for startups utilizing data-driven decision-making practices.

Comparative Analysis: The analysis compared startups utilizing data-driven strategies with those using traditional decision-making approaches. Startups employing data-driven decision making exhibited higher innovation performance, as shown by the average number of new products developed and revenue growth from these innovations.

Table 2: Innovation Performance Comparison

Group	Average Products	New	Average Revenue Growth (%)
Data-Driven Decision-Making	14.2		18.3
Traditional Decision-Making	10.1		12.7

Qualitative Results

The qualitative data, gathered through interviews and focus groups, provided deeper insights into the practical and experiential aspects of data-driven decision making in startups.

Key Themes from Qualitative Data:

1. **Enhanced Decision-Making Quality:** Participants highlighted that data-driven strategies improved the quality of strategic decisions by providing evidence-based insights.
2. **Challenges in Implementation:** Common challenges included the high cost of data analytics tools, resistance to change among employees, and the need for ongoing training.
3. **Leadership Support:** Strong leadership commitment was deemed crucial for fostering a data-centric culture and overcoming implementation challenges.
4. **Impact on Innovation:** Data-driven decision making was seen as a key driver of innovation, enabling startups to identify market trends, optimize operations, and develop new products.

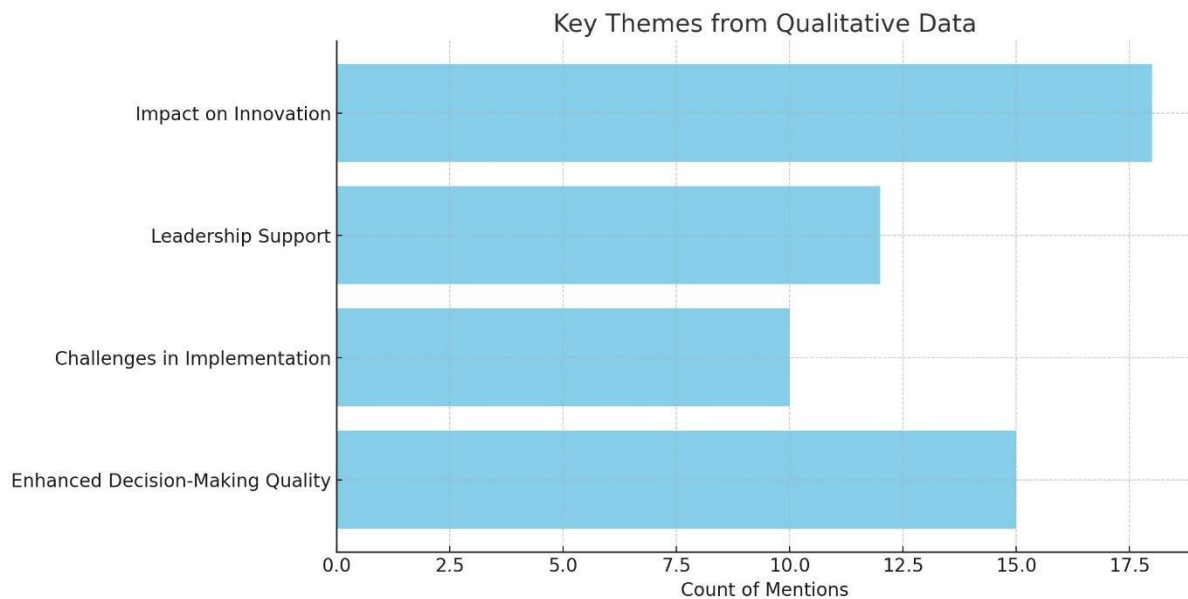


Figure 2: Key Themes from Qualitative Data

- **Enhanced Decision-Making Quality:** Highlighting how data-driven strategies improve the quality of strategic decisions.
- **Challenges in Implementation:** Discussing common challenges such as cost, resistance to change, and training needs.
- **Leadership Support:** Emphasizing the critical role of leadership in fostering a data-centric culture.
- **Impact on Innovation:** Demonstrating how data-driven decision-making drives innovation within startups.

DISCUSSION

The findings from this study underscore the significant impact of data-driven decision making on innovation within startups.

1. **Impact on Innovation:**

- The quantitative results indicated that startups employing data-driven decision-making practices demonstrated higher innovation performance compared to those relying on traditional approaches. This aligns with prior research, such as McAfee and Brynjolfsson (2012), which highlighted the productivity and profitability benefits of data-driven firms.
- The qualitative data reinforced these findings, with participants noting that data-driven strategies provided valuable insights that enhanced the quality of strategic decisions and fostered innovation.



2. **Moderating Factors:**

- Data literacy and a data-centric culture emerged as critical moderating factors. Startups with high levels of data literacy and a strong data-centric culture were better able to leverage data-driven decision-making for innovation. This is consistent with the findings of Gupta and George (2016), who emphasized the importance of a supportive culture for the successful implementation of data-driven strategies.
- The presence of a data-centric culture was found to facilitate the integration of data analytics into everyday operations and strategic planning, thereby fostering an environment conducive to innovation.

3. **Role of Leadership:**

- Leadership commitment was identified as a crucial factor in the adoption and effectiveness of data-driven strategies. Strong leadership support helped to overcome barriers to implementation, such as resistance to change and the high cost of data analytics tools. This finding is supported by Sivarajah et al. (2017), who highlighted the role of leadership in promoting data-driven decision making.
- Best practices for leaders included modeling data-driven behaviors, advocating for the use of data in decision-making processes, and providing resources and training to develop data literacy within the organization.

This study provides valuable insights into the role of data-driven decision-making in fostering innovation within startups. The findings highlight the positive impact of data-driven strategies on innovation performance, the importance of data literacy and a data-centric culture, and the critical role of leadership in promoting and supporting data-driven decision making.

Future research should explore the long-term effects of data-driven decision making on innovation and examine the impact of emerging technologies such as artificial intelligence and machine learning on data-driven strategies. Additionally, studies focusing on different industry contexts and geographical regions can provide more nuanced insights into the relationship between data-driven decision making and innovation in startups.

CONCLUSION

This study provides critical insights into the influence of data-driven decision making on innovation within startups. The findings underscore the significant positive impact that data-driven strategies have on innovation outcomes. Startups that embrace data-driven decision making demonstrate higher levels of innovation, as evidenced by the development of new products and revenue growth. This aligns with previous research that highlights the advantages of leveraging data analytics for strategic decisions.

The research identifies key factors that moderate the effectiveness of data-driven decision making. Data literacy and a data-centric culture are crucial for maximizing the benefits of data-driven strategies. Startups with higher levels of data literacy and a robust data-centric culture



are better positioned to utilize data analytics effectively, leading to enhanced innovation outcomes. These findings support the notion that fostering a culture that values data and analytics is essential for driving innovation.

Leadership commitment emerged as a critical component for the successful adoption and implementation of data-driven strategies. Strong leadership support helps to overcome barriers such as resistance to change and the costs associated with data analytics tools. Leaders play a vital role in modeling data-driven behaviors, advocating for the use of data in decision-making processes, and ensuring that employees are equipped with the necessary skills and resources to utilize data effectively.

The qualitative insights from this study highlight the practical challenges and benefits of implementing data-driven decision making within startups. Participants reported that data-driven strategies improved the quality of strategic decisions and fostered innovation by providing valuable insights. However, challenges such as the cost of data analytics tools, resistance to change, and the need for ongoing training were also noted.

In conclusion, this study emphasizes the importance of data-driven decision making in enhancing innovation within startups. The findings suggest that startups can achieve significant innovation outcomes by developing strong data literacy, fostering a data-centric culture, and ensuring leadership commitment to data-driven strategies. Future research should explore the long-term effects of data-driven decision making on innovation and examine the impact of emerging technologies such as artificial intelligence and machine learning on data-driven strategies. Additionally, studies focusing on different industry contexts and geographical regions can provide more nuanced insights into the relationship between data-driven decision making and innovation in startups. By addressing these areas, researchers can contribute to a deeper understanding of how startups can effectively leverage data-driven decision making to drive innovation and achieve sustainable growth.

REFERENCES

- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Bazeley, P., & Jackson, K. (2013). *Qualitative Data Analysis with NVivo*. Sage Publications.
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77-101.
- Buchanan, E. A., & Zimmer, M. (2018). Internet research ethics. In *The Stanford Encyclopedia of Philosophy* (Spring 2018 Edition), Edward N. Zalta (ed.).
- Calzada Prado, J., & Marzal, M. A. (2013). Incorporating data literacy into information literacy programs: Core competencies and contents. *Libri*, 63(2), 123-134.
- Creswell, J. W. (2014). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage Publications.
- Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and Conducting Mixed Methods Research*. Sage Publications.
- Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, Phone, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. Wiley.



- Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, 14(4), 532-550.
- Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics*. Sage Publications.
- Fouka, G., & Mantzorou, M. (2011). What are the major ethical issues in conducting research? Is there a conflict between the research ethics and the nature of nursing? *Health Science Journal*, 5(1), 3-14.
- Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *Journal of Strategic Information Systems*, 27(1), 101-113.
- Guest, G., MacQueen, K. M., & Namey, E. E. (2012). *Applied Thematic Analysis*. Sage Publications.
- Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, 53(8), 1049-1064.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263-291.
- Kvale, S., & Brinkmann, S. (2009). *InterViews: Learning the Craft of Qualitative Research Interviewing*. Sage Publications.
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic Inquiry*. Sage Publications.
- McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, 90(10), 60-68.
- 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.
- Morgan, D. L. (1997). *Focus Groups as Qualitative Research*. Sage Publications.
- Patton, M. Q. (1999). Enhancing the quality and credibility of qualitative analysis. *Health Services Research*, 34(5 Pt 2), 1189-1208.
- Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, 1(1), 51-59.
- Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
- Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*, 70, 263-286.
- Tabachnick, B. G., & Fidell, L. S. (2019). *Using Multivariate Statistics*. Pearson.
- Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.
- Yin, R. K. (2017). *Case Study Research and Applications: Design and Methods*. Sage Publications.