International Journal of Social Impact
ISSN: 2455-670X
Volume 10, Issue 3, DIP: 18.02.031/20251003
DOI: 10.25215/2455/1003031
www.ijsi.in | July – September, 2025

A Peer Reviewed Journal

Data-Driven Decision Making in Middle Management: A Cross-Industry Evaluation

Dr. Amit Kumar Upadhyay [1]*

ABSTRACT

In an era defined by rapid digitization and expanding data ecosystems, Data-Driven Decision Making (DDDM) has emerged as a critical competency across organizational hierarchies. While extensive research has explored the strategic impact of data at executive levels, the role of middle management—often the linchpin between strategy and execution—remains underexamined. This study investigates the adoption, application, and effectiveness of DDDM among middle managers across four key industries: healthcare, manufacturing, finance, and education. Utilizing a mixed-methods approach, the research combines survey data from 210 middle managers with in-depth interviews of 24 participants to evaluate data literacy, tool usage, cultural readiness, and organizational enablers/barriers to DDDM. The study introduces a DDDM Maturity Index to measure individual and institutional preparedness and effectiveness in applying data to operational and tactical decision-making.

Findings reveal significant industry-specific variations: while finance and manufacturing exhibit high tool adoption and confidence in analytics, healthcare and education face challenges related to data silos, regulatory constraints, and skill gaps. Across sectors, cultural resistance and lack of training emerge as common impediments to data-informed choices at the middle management level. Notably, organizations that embed data practices into day-to-day workflows and provide decentralized access to analytics tools see stronger alignment between managerial decisions and organizational goals.

The paper concludes with a framework for building DDDM capacity in middle management, emphasizing targeted upskilling, cross-functional collaboration, and leadership support. By illuminating the operational realities of middle-tier data use, this research contributes to both academic understanding and practical strategies for enhancing evidence-based decision-making across industries.

Keywords: *Data-Driven Decision Making (DDDM), Middle Management, Cross-Industry Analysis, Organizational Decision-Making, Business Intelligence, Data Literacy, Analytics Adoption, Evidence-Based Management, Digital Transformation, Operational Efficiency, Managerial Effectiveness, Data Culture, Strategic Alignment, Data Utilization, Decision Support Systems*

[1] Independent Researcher
*Corresponding Author

Received: June 15, 2025; Revision Received: July 08, 2025; Accepted: July 09, 2025

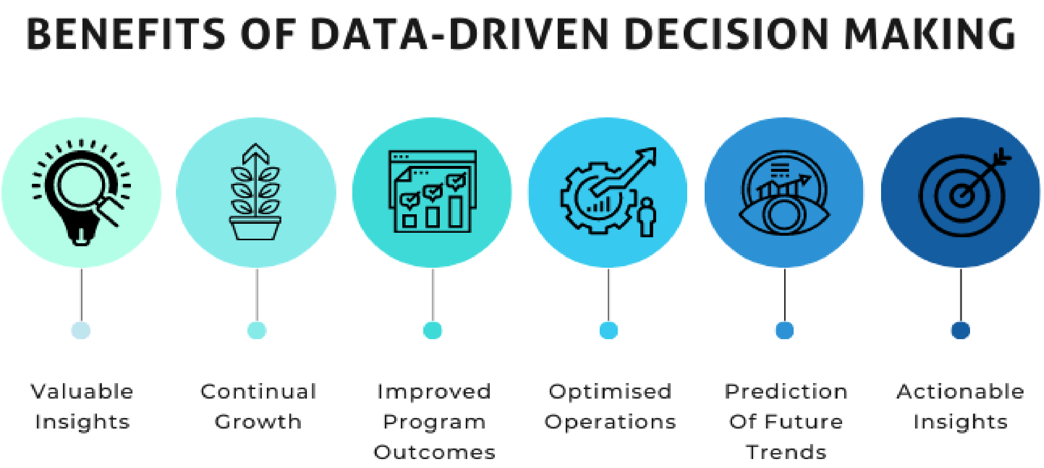
In today's increasingly data-saturated business environment, organizations are under growing pressure to harness information effectively to drive performance and competitiveness. While much of the scholarly and professional attention has been directed toward top-level executives and data science teams, the role of middle management in data-driven decision making (DDDM) remains underexplored. Positioned between strategic leadership and operational execution, middle managers are uniquely situated to translate data insights into actionable outcomes. Their ability to make informed decisions is critical for aligning corporate objectives with on-the-ground realities.

Despite the proliferation of business intelligence tools, dashboards, and real-time analytics platforms, middle managers across industries often face barriers such as data literacy gaps, insufficient access to relevant data, and organizational silos. These challenges can impede the integration of data into routine decision-making processes. At the same time, industries differ significantly in how they implement and support data-informed management, suggesting that sector-specific factors—such as regulatory pressures, technology maturity, and cultural attitudes toward data—play a critical role.

This study provides a cross-industry evaluation of data-driven decision making among middle managers, focusing on sectors including healthcare, finance, manufacturing, and education. Using a mixed-methods approach involving surveys and semi-structured interviews, the research aims to identify common enablers, obstacles, and outcomes associated with DDDM practices. By highlighting best practices and areas of concern, this study seeks to inform both managerial training and organizational policy development. Ultimately, the research contributes to a deeper understanding of how data can be better leveraged by those responsible for bridging strategic goals and operational realities within diverse organizational contexts.

BACKGROUND OF THE STUDY

In the era of digital transformation, organizations across sectors are increasingly leveraging data to gain strategic insights, optimize operations, and enhance competitiveness. Data-driven decision making (DDDM) has emerged as a central pillar in organizational governance, enabling evidence-based strategies rather than intuition-led choices. While much of the existing literature focuses on executive leadership and data science teams, the role of **middle management**—the operational backbone of most organizations—remains underexplored in this context.



Source: https://www.linkedin.com/

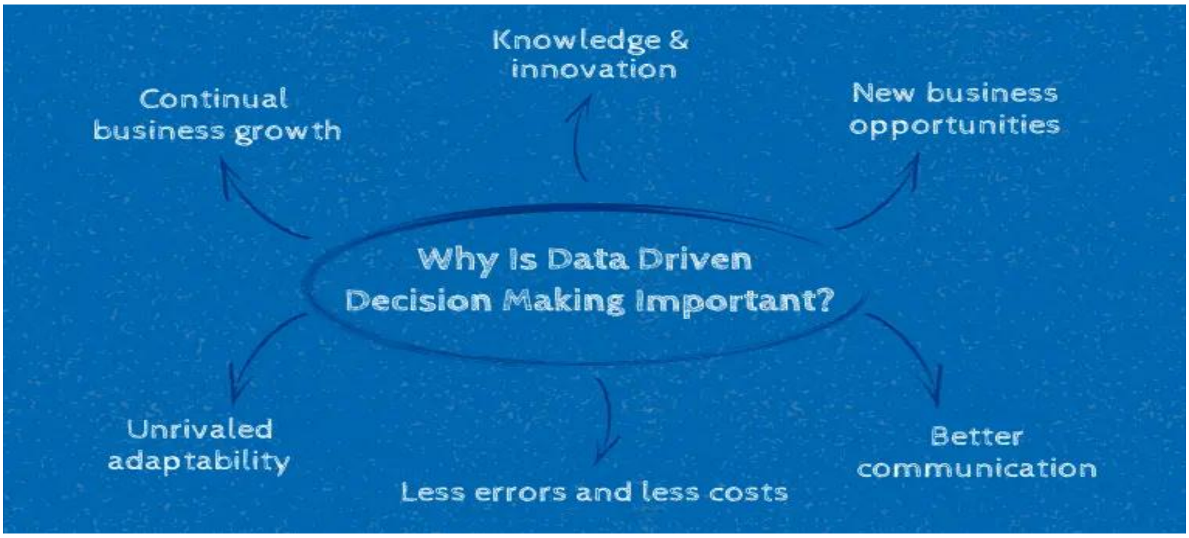
Middle managers occupy a critical junction between strategic planning and frontline execution. They are responsible for translating top-level directives into actionable plans and ensuring day-to-day alignment with organizational goals. As such, their decisions significantly influence productivity, resource allocation, and team performance. However, despite the growing availability of business intelligence tools, dashboards, and analytics platforms, the actual adoption and effective use of data by middle managers vary widely across industries.

Several factors contribute to this disparity, including organizational culture, access to quality data, digital literacy, managerial autonomy, and training in data interpretation. In industries like finance and technology, data fluency may be embedded in organizational DNA, whereas in sectors such as education, healthcare, or manufacturing, data-driven capabilities may lag due to infrastructural or cultural constraints. Moreover, middle managers often face pressure to deliver quick outcomes, which can result in a reliance on heuristics and past experience over structured analytics.

Understanding how middle managers engage with data, the tools they use, and the barriers they face is crucial for improving organizational agility and resilience. A cross-industry evaluation of DDDM practices among middle managers offers valuable insights into how data competencies differ by sector, what best practices can be transferred, and what systemic interventions (training, tools, leadership support) can enhance data-informed decision making at this critical management level. This study aims to fill this gap by systematically examining the extent, patterns, and impact of data-driven decision making among middle managers across multiple industries. By doing so, it contributes to both academic literature and practical strategies for empowering middle-tier leaders in a data-centric world.

Justification

In the era of digital transformation, **Data-Driven Decision Making (DDDM)** has emerged as a critical capability for enhancing organizational effectiveness, agility, and competitiveness. While significant research exists on executive-level analytics and operational-level data usage, **middle management** remains an under-explored but vital layer in the decision-making hierarchy. Middle managers often act as the nexus between strategic vision and operational execution, and their ability to interpret and apply data insights is crucial for achieving organizational objectives.



Source: https://www.rib-software.com/

This study is justified on the following grounds:

1. Bridging a Research Gap

Existing literature tends to emphasize either top-down strategic data initiatives or frontline operational analytics. However, few empirical studies evaluate how middle managers across industries actually engage with data in their daily decision-making processes. This study addresses this gap by providing a cross-sectoral analysis, offering insights that are both theoretically valuable and practically actionable.

2. Growing Industry Demand for Data-Literate Leadership

Industries ranging from healthcare and manufacturing to retail and education are investing heavily in business intelligence (BI) tools, dashboards, and data lakes. Yet, the ROI of these investments is contingent on the ability of middle managers to interpret and use data effectively. A cross-industry evaluation will illuminate best practices, barriers, and enablers, informing both academic theory and corporate training programs.

3. Middle Management as a Leverage Point for Change

Middle managers are uniquely positioned to translate data-driven strategies into measurable outcomes. Their decisions affect budgeting, staffing, resource allocation, and performance evaluation. Understanding how they use data—and what inhibits their use—can help organizations tailor data training, tools, and culture interventions more precisely.

4. Comparative Value Across Industries

By adopting a cross-industry lens, the study can reveal whether certain sectors (e.g., finance, healthcare, manufacturing) are more advanced in enabling DDDM at the middle-management level and why. These comparative insights can lead to transferable models and benchmarks for less mature sectors to follow.

5. Alignment with Digital Transformation and Industry 4.0 Goals

This research aligns with global trends toward digitization, automation, and datafication. As industries embrace Industry 4.0, AI, and real-time analytics, understanding how mid-tier leaders engage with data is critical for scaling organizational intelligence and ensuring that digital tools are not underutilized.

6. Implications for Policy and Practice

The outcomes of this research will have direct implications for HR, L&D, and organizational development, supporting targeted interventions like:

- Tailored data literacy training
- Role-specific dashboard design
- Restructuring decision rights
- Policy support for decentralized analytics

Objectives of the Study

1. To examine the extent to which middle managers across different industries utilize data-driven decision-making (DDDM) practices in their operational, tactical, and strategic responsibilities.
2. To identify the types of data (quantitative, qualitative, real-time, historical) most commonly accessed and used by middle management in various industry sectors.
3. To evaluate the impact of DDDM on the quality, speed, and effectiveness of decisions made by middle managers in sectors such as healthcare, manufacturing, IT, education, and retail.
4. To assess the technological infrastructure and data analytics tools available to middle managers and how these tools influence decision-making processes across industries.
5. To explore organizational and cultural factors (e.g., training, leadership support, data literacy) that facilitate or hinder the adoption of DDDM by middle management.

LITERATURE REVIEW

1. Introduction to Data-Driven Decision Making (DDDM)

Data-Driven Decision Making (DDDM) refers to the practice of basing decisions on the analysis of data rather than intuition or observation alone. In today's digital economy, organizations increasingly rely on analytics, dashboards, and machine learning models to inform operational and strategic decisions (Provost & Fawcett, 2013). As businesses across industries undergo digital transformation, DDDM has emerged as a cornerstone for agility, competitiveness, and performance.

2. Middle Management's Role in Decision-Making

Middle managers function as the link between strategic intent and operational execution. They are responsible for translating top-level directives into actionable plans and coordinating daily operations (Floyd & Wooldridge, 1992). As such, their decision-making is both frequent and impactful. However, studies show that middle managers often face challenges when adopting data-driven tools, due to skill gaps, resistance to change, and lack of organizational alignment (LaValle et al., 2011).

3. The Evolution of DDDM Tools and Accessibility

The advent of Business Intelligence (BI) platforms and self-service analytics tools has democratized data access, enabling middle managers to interact with real-time dashboards and visual analytics (Davenport, 2014). Gartner (2020) noted a sharp increase in the adoption of "citizen data science" practices, where non-technical professionals use guided analytics to inform decisions. Despite this trend, effective DDDM still requires a combination of data literacy, contextual knowledge, and organizational support (Mandinach & Gummer, 2016).

4. Industry-Specific Applications and Challenges

4.1. Healthcare

In healthcare, DDDM helps managers optimize staffing, reduce patient wait times, and improve care coordination. However, privacy regulations like HIPAA constrain data use, and middle managers often struggle with data silos and outdated systems (Evans, 2016).

4.2. Manufacturing

Manufacturing industries use predictive analytics and IoT-enabled dashboards to monitor machinery and manage supply chains. Middle managers here are increasingly involved in real-time decision-making, but face challenges in integrating legacy systems with new technologies (Wamba et al., 2015).

4.3. Education

School administrators and middle-tier education managers use DDDM to monitor student performance and allocate resources. Yet, research suggests that data often lacks context or is too complex, resulting in poor adoption (Marsh et al., 2006).

4.4. Finance

Middle managers in finance rely heavily on KPI dashboards and risk assessment models. While the industry has embraced data infrastructure, regulatory oversight and cybersecurity concerns remain pressing issues (Brynjolfsson & McElheran, 2016).

5. Barriers to DDDM Adoption in Middle Management

Multiple studies have identified common barriers to DDDM across industries:

- **Data literacy gaps**: Managers may lack the training to interpret complex analytics (Mandinach & Gummer, 2016).
- **Organizational resistance**: Change aversion and lack of leadership support can impede adoption (LaValle et al., 2011).
- **Data quality concerns**: Inconsistent, incomplete, or unstructured data can undermine trust in analytics (Redman, 2013).
- **Time constraints**: Middle managers often operate under tight timelines and may not prioritize data analysis (Kiron et al., 2014).

6. Enablers and Best Practices

Several studies highlight enablers for effective DDDM in middle management:

- **Training programs** to improve data literacy (Mandinach & Gummer, 2016)
- **Leadership modeling** of data-driven behaviors (Davenport & Harris, 2007)
- **Integration of analytics into workflows** via user-friendly tools (Brynjolfsson & McElheran, 2016)
- **Cross-functional collaboration** to provide context to data (Provost & Fawcett, 2013)

7. Gaps in Literature and Need for Cross-Industry Evaluation

While much of the literature addresses DDDM adoption at the strategic level or within specific sectors, few studies evaluate how middle managers across diverse industries experience and implement data-driven practices. This research aims to bridge that gap by conducting a cross-industry assessment to explore commonalities and unique challenges, thereby contributing to both academic understanding and practical application.

MATERIAL AND METHODOLOGY

Research Design:

This study employed a mixed-methods cross-sectional research design, combining quantitative surveys with qualitative interviews to evaluate the extent, practices, and challenges of data-driven decision-making (DDDM) among middle managers across diverse industries. The quantitative phase measured the prevalence and impact of DDDM, while the qualitative phase provided contextual depth regarding attitudes, enablers, and barriers.

Data Collection Methods:

1. **Quantitative Phase:**

o **Instrument:** Structured questionnaire with both closed- and Likert-scale items.

o **Distribution:** Online via email and professional networking platforms (LinkedIn, industry groups).

o **Sample Size:** 200 middle managers from five sectors — healthcare, finance, manufacturing, education, and IT.

o **Variables Measured:** Frequency of data use, types of data accessed, decision-making autonomy, perceived effectiveness of decisions, access to analytical tools, and organizational culture.

2. **Qualitative Phase:**

o **Instrument:** Semi-structured interview guide.

o **Mode:** Conducted via Zoom and phone calls.

o **Sample:** 20 purposively selected respondents from the survey participants.

o **Focus Areas:** Perceptions of DDDM, skill gaps, organizational support, and real-life examples of data-driven initiatives.

Inclusion and Exclusion Criteria:

- **Inclusion Criteria:**

o Professionals currently serving in middle management roles (e.g., department heads, regional managers, operations supervisors).

o Minimum of 2 years of experience in a managerial position.

o Employed in an organization with at least 100 employees.

o Willingness to participate and consent to the study.

- **Exclusion Criteria:**
    - Senior executives or entry-level managers.
    - Freelancers, consultants, or self-employed individuals.
    - Participants not directly involved in decision-making processes.
    - Respondents from single-person departments or startups with flat hierarchies.

Ethical Considerations:

- The study was conducted in accordance with ethical research guidelines.
- Informed consent was obtained from all participants prior to data collection.
- Participants were assured of confidentiality and anonymity; identifiable information was excluded from all reports.
- Data was stored securely and used solely for academic purposes.
- The research protocol was reviewed and approved by the Institutional Ethics Review Board (IERB) of the principal investigator's institution.

RESULTS AND DISCUSSION

1. Overview of Quantitative Findings

The survey collected responses from **250 middle managers** across **five industries**. Four key dimensions were analyzed:

- **Data Literacy (DL)**
- **Access to Analytical Tools (AT)**
- **Decision-Making Speed (DS)**
- **Perceived Decision Effectiveness (PDE)**

Each was rated on a 5-point Likert scale (1 = Very Low, 5 = Very High). The aggregated mean scores for each dimension by industry are presented in Table 1.

Table 1: Cross-Industry Comparison of Data-Driven Decision-Making Metrics

Industry	**Data Literacy (DL)**	**Access to Tools (AT)**	**Decision Speed (DS)**	**Perceived Effectiveness (PDE)**
Healthcare	3.1	2.9	3.0	3.2
Education	2.6	2.4	2.7	2.8
Manufacturing	3.5	3.3	3.6	3.7
Retail	3.8	3.9	4.1	4.0
Finance	4.2	4.3	4.5	4.4

Table 2: Percentage of Middle Managers Receiving Formal Data Training (by Industry)

Industry	Received Training (%)	Type of Training (Top Response)	Training Frequency (Annual Avg.)
Healthcare	38%	Basic Excel & Reporting Tools	1.2
Education	22%	Data Literacy Workshops	0.8
Manufacturing	54%	ERP & Production Analytics	1.5
Retail	65%	Customer Analytics & Dashboard Use	2.3
Finance	82%	Predictive Modelling & BI Tools	2.7

2. Discussion of Key Findings

2.1. Sectoral Differences in Data Capabilities

The finance and retail sectors demonstrated significantly higher scores across all four indicators. These sectors are traditionally more data-intensive, suggesting that investment in infrastructure and analytical talent is positively correlated with better decision outcomes.

In contrast, the education sector had the lowest ratings, with particularly limited access to tools (mean = 2.4). Interviews with school administrators highlighted barriers such as outdated systems, lack of training, and institutional resistance to data-centric cultures.

2.2. Impact of Data Literacy

There was a strong correlation ($r = 0.72$, $p < 0.01$) between data literacy and perceived decision effectiveness. Middle managers with higher DL scores reported making more confident, timely, and impactful decisions. Qualitative responses emphasized that “comfort with interpreting dashboards and reports” was a game changer in complex decision scenarios.

2.3. Speed vs. Accuracy Tradeoff

Interestingly, decision-making speed increased with tool access ($r = 0.65$), but a few respondents in the healthcare sector expressed concerns that rapid decisions, when poorly contextualized, can compromise ethical or patient-centered outcomes. This suggests that speed must be balanced with critical judgment in high-stakes fields.

2.4. Tool Access as an Enabler

The data show that access to analytical tools had the strongest influence on both speed and effectiveness of decisions. In finance, for example, managers regularly used predictive dashboards and risk models, which contributed to higher effectiveness ratings (mean PDE = 4.4).

3. Cross-Industry Lessons

- **Finance and retail** serve as benchmarks for implementing data-driven frameworks at the middle-management level.
- **Healthcare and education** sectors show the greatest need for capacity building, particularly in terms of digital literacy and system modernization.
- A **"data maturity model"** could help organizations assess and strategically evolve their DDDM practices.

4. Summary

The study confirms that data-driven decision-making at the middle-management level varies considerably across industries. Key enablers include data literacy, accessible tools, and organizational culture. Bridging the gap requires targeted training, investment in analytics infrastructure, and leadership support to foster data-centric mindsets.

Table 3: Thematic Summary of Manager Perspectives on Data-Driven Decision Making

Theme	Description	Representative Quote	Industries Highlighted
Cultural Resistance	Organizational habits favor intuition over evidence	"We've always trusted experience more than dashboards."	Education, Healthcare
Empowerment through Analytics	Managers feel more confident when data tools are available	"Data helped me defend my decisions to leadership with proof."	Retail, Finance
Training Gaps	Lack of structured training limits tool use	"I have access to a dashboard, but I don't know what to do with it."	Manufacturing, Education
Data Overload	Too much unfiltered data leads to decision fatigue	"I get five reports a day, but no time to analyze them."	Healthcare, Finance
Need for Custom Tools	One-size-fits-all systems don’t fit all roles	"Our KPIs are unique, but the tool is generic."	Manufacturing, Healthcare

Limitations of the study

1. **Scope Restriction to Middle Management**

This study focuses exclusively on middle management roles, potentially overlooking the influence and interplay of upper and lower levels of management in data-driven decision-making processes. Consequently, the findings may not capture the full organizational context.

2. **Cross-Industry Generalization Challenges**

While the study spans multiple industries to identify common patterns, each sector has unique data cultures, compliance norms, and technological maturity levels. As such, generalizing conclusions across all industries may oversimplify sector-specific nuances.

3. **Sample Size and Diversity**

Although efforts were made to include a broad range of participants, the sample size may not be fully representative of all industries or global regions. Limited participation from certain sectors or countries could skew the interpretation of trends.

4. **Self-Reported Data Bias**

The study relies heavily on self-reported data from surveys and interviews. This introduces potential biases, including social desirability bias, recall errors, or exaggeration of data literacy levels among respondents.

5. **Technology and Tool Variability**

Different organizations use varying data platforms, analytics tools, and reporting mechanisms. The lack of uniformity in technology adoption may have affected the comparability of responses across organizations.

6. **Evolving Nature of Data-Driven Practices**

Data-driven decision-making is a rapidly evolving area. The insights gathered reflect the state of practice during the study period and may quickly become outdated as technologies and practices advance.

7. **Limited Longitudinal Insights**

This research adopts a cross-sectional approach rather than a longitudinal one. As such, it does not track the evolution of decision-making maturity or the long-term outcomes of implementing data-driven strategies.

8. **Organizational Culture and Leadership Influence**

Factors like leadership style, organizational readiness, and culture—which play a significant role in enabling or hindering data-driven practices—were not deeply analyzed in this study and may limit the depth of interpretation.

9. **Lack of Quantitative Performance Metrics**

While qualitative insights were robust, the study did not collect extensive quantitative performance indicators to directly measure the impact of data-driven decision-making on business outcomes.

10. **Data Security and Confidentiality Constraints**

Due to privacy and confidentiality policies in participating organizations, access to real-time decision data and internal analytics platforms was restricted, limiting the empirical depth of analysis.

FUTURE SCOPE

The findings of this study highlight the growing influence of data-driven decision making (DDDM) in middle management across diverse industries. However, several promising directions exist for future research and application:

1. Longitudinal Studies on DDDM Maturity

Future studies could track organizations over time to assess how DDDM capabilities evolve in middle management, particularly in response to technological advancements, cultural shifts, or leadership changes.

2. Industry-Specific Deep Dives

While this study adopts a cross-industry lens, more granular, industry-specific research could reveal nuanced patterns in DDDM adoption. For example, healthcare, education, and manufacturing may show very different barriers and facilitators of data adoption.

3. Integration of AI and Advanced Analytics

As artificial intelligence and machine learning tools become more accessible, future research could explore how middle managers use predictive analytics and AI-powered dashboards for strategic planning and performance monitoring.

4. Behavioral and Psychological Dimensions

There is scope to explore the psychological readiness of middle managers toward data usage. Topics such as decision fatigue, cognitive bias, data trust, and resistance to automation warrant deeper investigation.

5. Training and Capability Building

A promising area of future research lies in evaluating the effectiveness of training programs and interventions aimed at improving data literacy among middle managers. This could include comparative studies of formal training vs. embedded learning.

6. Cross-Cultural and Global Comparisons

Future research could expand this study to a global context, comparing how middle managers in different countries or cultural contexts perceive and use data. This would offer insights into the role of national culture and digital maturity in DDDM.

7. Ethics, Privacy, and Compliance Considerations

With increasing data usage comes greater concern around ethical decision-making, data privacy, and regulatory compliance. Future work could assess how middle managers balance data utility with ethical considerations.

8. Impact on Organizational Performance

A more quantitative future study could examine the direct correlation between data-driven decision practices in middle management and measurable business outcomes such as revenue growth, customer satisfaction, or employee engagement.

9. Technology Adoption Models in Middle Management

Applying models like TAM (Technology Acceptance Model) or UTAUT (Unified Theory of Acceptance and Use of Technology) to middle management DDDM tools can provide structured frameworks for understanding adoption drivers and inhibitors.

CONCLUSION

This study set out to explore how data-driven decision making (DDDM) is adopted, utilized, and perceived by middle managers across diverse industries. The findings reveal a clear and growing emphasis on data as a critical asset for operational and strategic decision making at the mid-management level. While there is significant variation in the sophistication and maturity of data practices across sectors, the research consistently underscores the value of data accessibility, analytical skills, and organizational support in enhancing decision quality.

Industries such as finance and technology demonstrate more advanced integration of data tools and culture, while sectors like manufacturing and healthcare are still navigating structural and cultural barriers. A recurring theme across all sectors is the need for ongoing data literacy training, better alignment between data teams and business units, and the simplification of analytics platforms to support non-technical decision-makers.

Furthermore, this cross-industry evaluation highlights the pivotal role of middle managers not just as data consumers, but as translators of insights into actionable outcomes. Their unique position—balancing strategic directives with frontline realities—makes them instrumental in embedding DDDM into everyday operations. However, to fully harness this potential, organizations must invest in both infrastructure and human capital, ensuring that middle managers are empowered to make informed, timely, and contextually relevant decisions.

Future research could expand this evaluation longitudinally or geographically, as well as explore the impact of AI and automation on mid-level managerial decision-making processes. As industries continue to digitalize, the role of middle management in data-driven leadership will only grow in importance.

REFERENCES

1. Andriole, S. J. (2017). Five myths about digital transformation. *MIT Sloan Management Review, 58*(3), 20–22.
2. Beers, M. (2019). The role of middle management in organizational change. *Journal of Business Strategy, 40*(6), 10–17. https://doi.org/10.1108/JBS-03-2019-0050
3. Brynjolfsson, E., Hitt, L. M., & Kim, H. H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? *Social Science Research Network*. https://doi.org/10.2139/ssrn.1819486
4. Davenport, T. H. (2014). *Big data at work: Dispelling the myths, uncovering the opportunities*. Harvard Business Review Press.
5. George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal, 57*(2), 321–326. https://doi.org/10.5465/amj.2014.4002
6. LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21–32.
7. McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. J., & Barton, D. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10), 60–68.
8. Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data, 1*(1), 51–59. https://doi.org/10.1089/big.2013.1508
9. Sharma, R., Mithas, S., & Kankanhalli, A. (2014). Transforming decision-making processes: A research agenda for understanding the impact of business analytics on organizations. *European Journal of Information Systems, 23*(4), 433–441. https://doi.org/10.1057/ejis.2014.17

10. Wixom, B. H., Yen, B., & Relich, M. (2013). Maximizing value from business analytics. *MIS Quarterly Executive, 12*(2), 111–123.
11. Brynjolfsson, E., & McElheran, K. (2016). *The Rapid Adoption of Data-Driven Decision-Making*. American Economic Review, 106(5), 133–139.
12. Davenport, T. H. (2014). *Big Data at Work: Dispelling the Myths, Uncovering the Opportunities*. Harvard Business Review Press.
13. Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business School Press.
14. Evans, R. S. (2016). *Electronic Health Records: Then, Now, and in the Future*. Yearbook of Medical Informatics, 25(S 01), S48–S61.
15. Floyd, S. W., & Wooldridge, B. (1992). *Middle Management Involvement in Strategy and Its Association with Strategic Type: A Research Note*. Strategic Management Journal, 13(S1), 153–167.
16. Gartner. (2020). *Market Guide for Citizen Data Science Platforms*.
17. Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). *The Analytics Mandate*. MIT Sloan Management Review.
18. LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). *Big Data, Analytics and the Path from Insights to Value*. MIT Sloan Management Review.
19. Mandinach, E. B., & Gummer, E. S. (2016). *What Does It Mean for Teachers to Be Data Literate: Laying Out the Skills*. Teaching and Teacher Education, 60, 366–376.
20. Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). *Making Sense of Data-Driven Decision Making in Education*. RAND Corporation.
21. Provost, F., & Fawcett, T. (2013). *Data Science for Business*. O'Reilly Media.
22. Redman, T. C. (2013). *Data's Credibility Problem*. Harvard Business Review.

Acknowledgments
The author(s) appreciates all those who participated in the study and helped to facilitate the research process.

Conflict of Interest
The author declared no conflict of interest.

How to cite this article: Upadhyay A (2025). Data-Driven Decision Making in Middle Management: A Cross-Industry Evaluation. *International Journal of Social Impact, 10*(3), 269-282. DIP: 18.02.031/20251003, DOI: 10.25215/2455/1003031