BOOST MACHINE LEARNING DEVELOPMENT OPERATIONS VALUE WITH INNOVATION MANAGEMENT INTEGRATION

Pham Le Minh Hoang*, Le Thi Kim Oanh

The University of Danang - University of Science and Technology, Viet Nam

*Corresponding author: plmhoang@dut.udn.vn

(Received: April 25, 2025; Revised: June 05, 2025; Accepted: June 18, 2025)

DOI: 10.31130/ud-jst.2025.23(9D).554E

Abstract - Despite the increasing adoption of machine learning across various sectors, many organizations, especially Small and Medium Enterprises (SMEs), struggle to scale machine learning initiatives into production. This paper proposes integrating Innovation Management into Machine Learning Operations (MLOps) to enhance organizations' ability to capture the true business value of machine learning. MLOps, a discipline comprising tools and practices, addresses the challenges of deploying machine learning products in real-world scenarios. Using a qualitative methodology, we analyze interviews, academic sources, and books to construct a best practice matrix aligned with both MLOps principles and innovation management. Findings reveal that innovation-oriented practices significantly enhance the value extraction, adaptability, and performance of machine learning deployments.

Key words - Artificial Intelligence; machine learning operations; innovation management; best practices; business value.

1. Introduction

Machine Learning is a method of data analysis that automates analytical model building by using algorithms that improve automatically using data. While Artificial Intelligence (AI) is the broad science of mimicking human abilities, machine learning is a specific subset of AI that trains a machine how to learn. Machine learning itself is not a brand-new science, but the ability to apply complex mathematical calculations rapidly and automatically to big data is a recent development. As such, machine learning is not a new science, but one that has gained fresh momentum [1]. Integrating machine learning into business is a multi-faceted process encompassing requirements, data, model development, deployment, monitoring, and updates, alongside user interfaces and infrastructure. Success is hindered by challenges across the system, including managerial concerns and technical issues like Data Leakage and Concept/Model Drift. Furthermore, diverse stakeholders, such as data scientists or DevOps engineers, often have conflicting requirements, complicating the smooth transition of machine learning systems into production.

Machine Learning Operations (MLOps) was developed and evolved in recent years by machine learning technology vendors to address the difficulties and operationalize a machine learning system effectively [2]. MLOps is a set of tools and best practices for deploying machine learning in real-world scenarios. The core components of MLOps are taken from DevOps and applied to machine learning. Due to the distinctions between conventional software and machine learning models, MLOps also contain additional capabilities like continuous monitoring and training, as well as tracking and versioning the experiments carried out to develop a model. Companies may manage their models with flexibility and change them quickly and easily by implementing MLOps. The advantages of MLOps can considerably shorten the time it takes to construct a model while also improving the quality of its development. Its purpose is to ensure that all components and technical stakeholders can work together to accomplish the requirements.

However, despite the advancement of Machine Learning and MLOps process, many companies, especially Small and Medium Enterprises (SMEs) are still struggling to deploy them into production. The process of model deployment is a difficult part of the machine learning project's life cycle [3]. In this research, we investigate the issues to utilize MLOps successfully for companies. Furthermore, we also propose a strategy for organizations to capture the business value by leveraging Innovation Management into MLOps process. Therefore, this research is guided by the following key questions:

- What are the primary managerial and technological challenges leading to the failure of machine learning projects?

- How can the integration of Innovation Management practices into the MLOps process enhance and extend the business value of machine learning products and deployments?"

2. Literature review

2.1. Machine Learning Operations

MLOps has emerged as a crucial discipline for scaling machine learning applications from experimental prototypes to production-ready systems. Drawing inspiration from DevOps principles, MLOps integrates continuous integration, deployment, and monitoring specifically for machine learning workflows [4]. It addresses the end-to-end machine learning lifecycle, including data preparation, model development, validation, deployment, governance, and retraining. Recent studies have highlighted MLOps as a key enabler of reliability, reproducibility, and scalability in machine learning systems [5]. In literature, many research studies have contributed to the changing environment of MLOps through in-depth reviews and analysis, focusing on practical applications [6].

Despite its potential, MLOps is not without challenges. Technical obstacles include model versioning, reproducibility across environments, and the need for realtime monitoring due to model drift or data anomalies [7]. Furthermore, MLOps implementation requires a high degree of cross-functional collaboration among data scientists, software engineers, and business units. Organizationally, this often results in friction due to differing priorities and metrics for success. Several frameworks have been proposed to streamline MLOps adoption, but empirical research on its real-world deployment, especially in SMEs, remains limited.

2.2. Integrating with Innovation Management

Innovation management involves the structured oversight of innovation processes, from idea generation and evaluation to development and commercialization. It is widely recognized as a key driver of organizational competitiveness and adaptability [8]. Theories of innovation management emphasize cross-functional collaboration, customer feedback integration, and iterative cycles, principles that closely align with the needs of modern machine learning system development. In practice, innovation management offers methodologies like the Stage-Gate process, Design Thinking, and Agile Innovation, which guide teams through uncertainty and foster continuous improvement [9]. The relevance of these frameworks to technological innovation, including artificial intelligence and machine learning, has been increasingly noted [10].

Despite the established importance of both MLOps for scaling machine learning initiatives and innovation management for organizational competitiveness and adaptability, their synergistic integration remains largely underexplored, particularly in deriving practical frameworks for real-world deployment [11]. This paper addresses this gap by investigating the integration of Innovation Management practices into MLOps as a holistic solution, moving beyond theoretical discussions to construct a novel best practice matrix empirically derived from interviews and existing knowledge. This qualitative approach allows us to analyze how innovation-oriented practices can significantly enhance value extraction, adaptability, and performance of machine learning deployments, especially in constrained operational contexts like SMEs, offering a distinct contribution to the practical application of these combined disciplines. The novelty of this integration lies in its synergistic approach, combining the structured efficiency of MLOps with the strategic foresight of innovation management to create a more robust and adaptable framework for deployment. This framework provides a structured methodology for identifying, developing, deploying, and continuously improving machine learning solutions in alignment with business objectives.

3. Research Method

3.1. Theoretical frameworks for Best practice

Best practices refer to a set of guidelines, methods, or processes that have been proven to produce optimal results or outcomes in a particular field or industry. These practices are recognized and adopted as the most effective and efficient approaches to achieve specific objectives or address common challenges. Best practices are based on accumulated knowledge, experience, and research, and they serve as benchmarks for excellence, offering a standard of quality and performance. They are used to maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking [12]. The concept of best practices is prevalent in various domains. In each context, best practices represent a distillation of lessons learned and successful strategies that have been refined over time. They provide practitioners with valuable insights and informed decision-making tools, enabling them to avoid pitfalls and capitalize on proven methods. While they offer general guidelines, best practices can be tailored and modified to suit specific requirements. They serve as a foundation for continuous improvement and innovation, encouraging professionals to build upon existing knowledge and refine approaches as new insights emerge [11].

However, due to the ambiguity of the idea, determining the best practices to handle a certain policy challenge is a frequently used but poorly understood analytical method. Vagueness stems from the term "best" which is subjective. Thus, Eugene Bardach et al. [14] provides the following theoretical framework which is an eightfold path for best practices as follows: Define the problem, Assemble the evidence, Construct the alternatives, Select the criteria, Project the outcomes, Confront the trade-offs, Decide and Tell your story. Based on this framework, we fold the MLOps process to match the promising alternatives to conclude the best practices should be applied on each stage through our comprehensive application and execution of our analysis.

3.2. Data analysis

3.2.1. Preprocess data

In the data preprocessing phase, we gather raw input data from diverse sources, including video, audio, and document files obtained from interviews, research papers, and books. Interviews were a crucial source of primary data, complementing our analysis of academic papers and books. Our participant selection focused on product managers within companies that are actively involved in providing AI solutions to their customers. This targeted approach ensured that insights were directly relevant to the challenges of deploying machine learning in production within constrained operational contexts. The participants, as listed in Table 1, represent diverse roles and companies within the AI solutions sector, along with an academic head of AI product innovation. While not exhaustive in demographic detail, this selection provided perspectives on real-world challenges and innovation integration.

Our semi-structured interview protocol was designed to elicit detailed responses concerning:

- Challenges faced in deploying machine learning products into production.

- Existing MLOps practices and their perceived effectiveness.

- Experiences with innovation management within their organizations.

- Perceived gaps between technical machine learning deployment and strategic business value capture.

- Suggestions for integrating innovation principles into workflows.

Table 1. *Sources of Data*

No.	Documents	Type
1	Integrated AI and Innovation Management	Paper
2	Challenges in Deploying Machine Learning - A Survey of Case Studies	Paper
3	Managing AI in the Enterprise	Book
4	Artificial Intelligence Innovation in the Enterprise - Adobe	Interview
5	Doris Xin - CEO, Linear.AI	Interview
6	Julien Simon - Chief Evangelist, HuggingFace	Interview
7	Brian Ray - Managing Director, Maven Wave	Interview
8	Simon Stiebellehner - Amsterdam Gov.	Interview
9	Arvin Lat - CTO, NuWorks Interactive Labs. Inc	Interview
10	John Ross Nether - Head of the AI product innovation, Duke University	Interview

Finally, these data are then transformed into a unified text format, facilitating further analysis and enabling seamless integration for text-based data processing. Through this preprocessing step, we ensure that the information from different sources is standardized, making it easier to extract insights and derive valuable knowledge from the text data.

3.2.2. Summarize information

The primary objective in this step is to extract essential points from the contents of each transcript, facilitating further analytical tasks. This process involves identifying and capturing the most relevant and significant information present in the transcripts, which can then be used for in-depth analysis and exploration. By extracting key points, researchers can focus their efforts on meaningful insights and trends, optimizing their ability to draw accurate conclusions and make informed decisions based on the analyzed content. This step is crucial in streamlining the analytical workflow, ensuring that valuable information is effectively utilized in subsequent research tasks.

3.2.3. Extract MLOps key features (rows)

In the context of MLOps, the MLOps process is broken down into five main features: Model Development, Productionalization and Deployment, Monitoring, Iteration and Life Cycle, and Governance.

Main features	Key features
Model Development	Establishing Business Objectives
	Data Sources and Exploratory
	Data Analysis
	Training and Evaluation
	Reproducibility
	Responsible AI
Productionalization and Deployment	Model Deployment
Monitoring	Technical Concerns
	Business Concerns
Iteration and Life Cycle	Iteration
Governance	Data Governance
	Process Governance

Figure 1. *MLOps Key Features and their components: hierarchical breakdown of the MLOps process into main features and their respective key components used as rows in the best practice matrix*

Each main feature encompasses several key components as illustrated in Figure 1, providing a structured view of the product lifecycle. Through this method, relevant information pertaining to each category is extracted and organized, enabling a comprehensive understanding of the different components involved in the MLOps framework. This breakdown serves as the row structure for our best practice matrix, allowing for a detailed analysis of innovation integration at each stage.

3.2.4. Extract Best practices key features (columns)

In this task, the focus is on extracting and employing topic modeling techniques to identify and analyze pertinent content related to the key features of Best Practices, namely, Problem, Solution, Criteria, Outcome, and Trade-off. The objective is to effectively discover and categorize relevant information within the text, enabling a comprehensive understanding of the essential aspects of Best Practices. These features, depicted in Figure 2, form the columns of our analytical matrix, providing a structured approach to understand and address challenges within MLOps through an innovation lens.

By utilizing topic modeling, researchers can efficiently process large volumes of text data and extract meaningful insights, contributing to more informed decision-making and valuable knowledge extraction in the domain of Best Practices.

Problems	Alternatives	Criteria	Outcomes	Trade-off

Figure 2. *Best Practices Key Features: This figure presents the five core dimensions of best practices that serve as the columns in our analytical framework*

3.2.5. Iterate

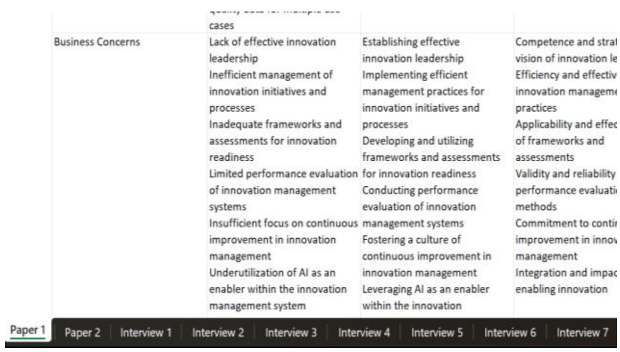

Figure 3. *Iterative Data Populating for the Best Practice Matrix: A snippet of the iterative process where raw data from each document is analyzed and mapped to specific cells within the developing best practice matrix, organizing insights by MLOps features and best practice dimensions*

In this analysis, we iterate through the 2nd, 3rd, and 4th steps for each transcript obtained, resulting in a matrix of size 11x5 for each transcript. This combination of data sources yields more than 500 cells of text data in total. With this extensive dataset, we aim to conduct a comprehensive examination of the content, enabling us to extract valuable insights and patterns from textual information. The matrices will serve as valuable resources for uncovering themes, trends, and relationships within the texts, contributing to a thorough and evidence-based analysis.

3.2.6. Merge

In the subsequent phase of the analysis, we consolidate the information from each cell across all the documents that were examined in the previous step. This process involves merging the data points to create a final summary, which will be presented in the form of a matrix with dimensions 11 x 5. This matrix encapsulates the essential findings and patterns identified during the analysis. By merging the cells, we can distill the collective insights obtained from the individual documents, providing a comprehensive overview of the entire dataset.

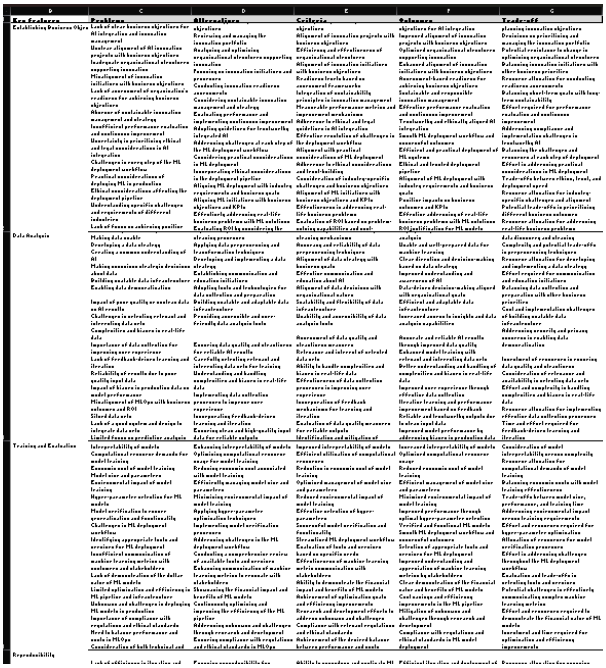

Figure 4. *Consolidated Best Practice Matrix: A section of the final 11x5 matrix, where insights from all analyzed documents have been merged into a comprehensive table, representing the synthesized findings of the qualitative analysis*

This final summary matrix will serve as a condensed and informative representation of the analyzed information, facilitating a clear and efficient understanding of the key aspects and trends discovered throughout the data analysis process. It will enable researchers and stakeholders to draw meaningful conclusions and make well-informed decisions based on the synthesized results from the diverse set of documents under scrutiny.

3.2.7. Gain insights

Following data preprocessing and summarization of key information from all sources, we employed a multi-stage thematic coding technique to systematically analyze the qualitative data. This involved:

1. Open Coding: We began by reading through the transcribed interviews, papers, and books to identify initial concepts, ideas, and recurring themes related to MLOps, innovation management, project failures, and business value. These initial codes were descriptive and kept close to the raw data.

2. Axial Coding: In the next stage, we grouped these initial codes into broader categories, identifying relationships between them. This process was guided by the theoretical framework of best practices and the identified MLOps key features and Best Practices key features.

3. Selective Coding (Matrix Construction): The final stage involved integrating these categories into our proposed best practice matrix. This involved iterating through each transcript and mapping relevant textual segments to the intersection of MLOps key features (rows) and Best Practices key features (columns). This structured approach allowed us to systematically populate the 11x5 matrix for each document, ensuring comprehensive coverage and facilitating cross-document comparisons.

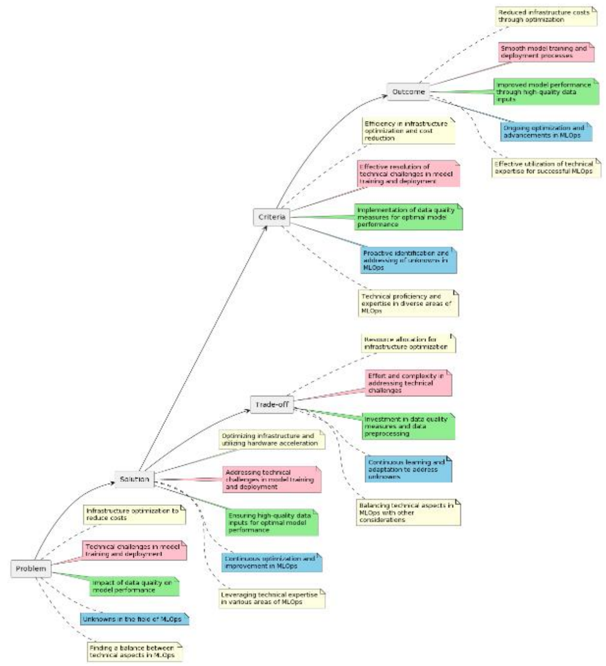

Figure 5. *Visualization of an MLOps Optimization Process*

To further illustrate the relationships within the analyzed data and to gain insights, we visualize the results as exemplified by the optimization process in MLOps. This diagram traces connections from identified problems to proposed solutions, criteria for evaluation, anticipated outcomes, and inherent trade-offs, making the complex interdependencies more apparent.

To support the data analysis process, several advanced tools were employed: OpenAI's GPT models through their API for text processing, topic modeling, and summarization tasks; Otter.ai for extraction and conversion textual information from various document formats, streamlining the preprocessing phase [15]; Kh-Coder for detailed topic modeling and semantic analysis. Together, these tools enabled a comprehensive, multi-stage qualitative analysis that ensured accuracy, reproducibility, and depth in interpreting the diverse data sources collected during the research. To ensure the reliability of AI-assisted outputs, a human-in-the-loop approach was consistently applied, involving manual review and iterative refinement of prompts to align with our analytical objectives and prevent issues like AI hallucinations.

3.3. Qualitative analysis results

Our ultimate achievement is: Instead of recommending a single best approach to address MLOps issues, the research provides a table with various solutions, their implementation methods, and the types of machine learning problems they solve.

To illustrate the clarity and actionability of our best practices matrix, we shall consider a common challenge faced by many companies in deploying machine learning models: "Lack of focus on achieving positive business outcomes and KPIs". This problem is often observed during the "Establishing Business Objectives" phase of Model Development.

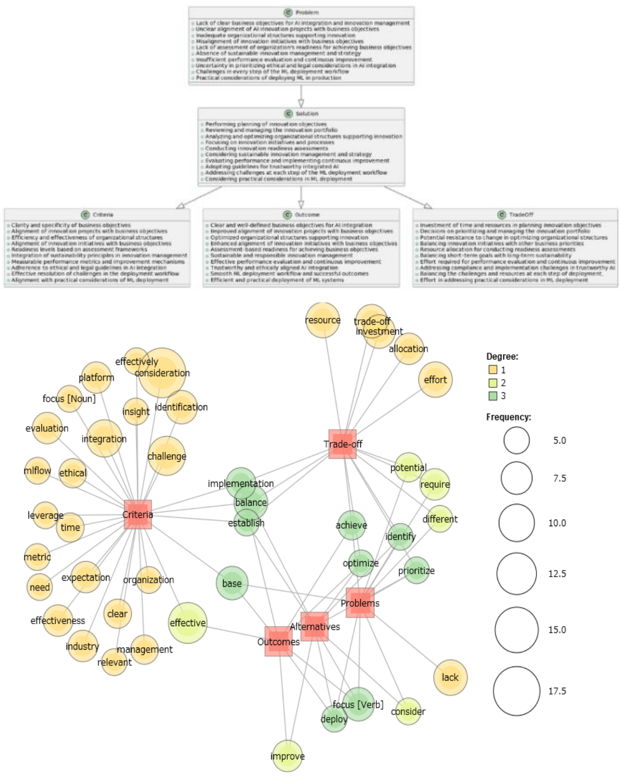

Figure 6. Co-occurrence Network and Recommendation Graph for Analyzed Results.

According to our matrix, a key alternative or solution for this problem is "Aligning machine learning initiatives with business objectives and KPIs". This involves actively engaging business stakeholders from the outset, clearly defining successful metrics that go beyond technical accuracy, and translating business needs into project requirements. The Criteria for evaluating the success of this alignment include "Clarity and specificity of business objectives" and "Effectiveness in addressing real-life business problems". This means assessing whether the objectives are well-defined and if the machine learning solution genuinely tackles the core business issue it was designed for. The expected Outcomes of implementing this solution are significant: "Positive impacts on business outcomes and KPIs" and "Effective addressing of real-life business problems with machine learning solutions". Ultimately, this leads to a better return on investment (ROI) for the models and optimized technical performance aligned with the business's strategic goals. However, there's a crucial Trade-off to consider: "Resource allocation for addressing real-life business problems". Prioritizing business outcomes may require more upfront time and resources for stakeholder engagement and problem definition, potentially extending the initial project timeline compared to a purely technical development approach. This highlights the need to balance short-term goals with long-term value.

This example demonstrates how the matrix provides a structured approach: identifying a problem, offering a solution rooted in innovation management, outlining how to measure success, detailing the benefits, and acknowledging the necessary compromises. This actionable insight empowers organizations to make informed decisions for capturing business value from their machine learning initiatives. By analyzing the data, we gain a lot of insights regarding the current state of the industry, MLOps practices, innovation and perform topic modeling to link with the best practice that can be done or improved. The qualitative analysis results are translated to the contents, which discussed about benefits, challenges of machine learning product operation, as well as the merits of integrating innovation management into the operation procedure and how it expands organizations values.

Compared to other research in MLOps field, we strongly focus on investigating the practical applications of incorporating innovation management to leverage the innovative values from machine learning products. In some of the sections of MLOps procedure, the essentials of innovation management frameworks are frequently discussed, especially the need to capture business values from the products through the framework.

4. Discussion

4.1. Capture business value through MLOps

Capturing business value refers to the process of identifying, extracting, and maximizing the tangible and intangible benefits that an organization can derive from its activities, strategies, and resources [16]. Through analyzed data, by understanding market trends, and fostering collaboration between domain experts and business stakeholders, organizations can ultimately state their machine learning product success and capture the full benefits from it. However, organizations must prioritize some key aspects, such as experimentation, iteration, and integration. Integration involves seamlessly incorporating its capabilities into existing workflows and systems, enabling the efficient deployment and utilization of insights.

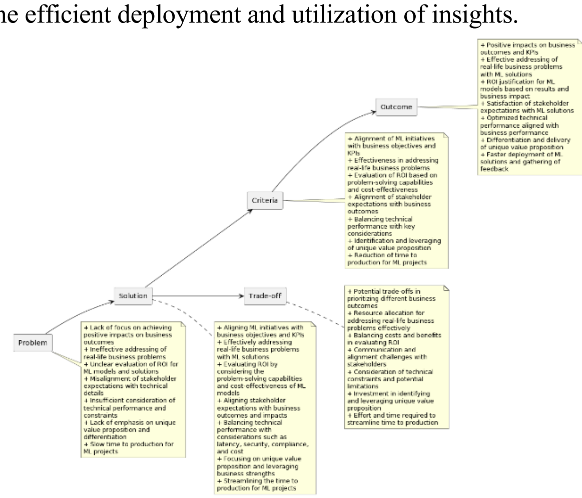

Figure 7. Business Concerns in applying MLOps taking from the analysis results

As suggested in Figure 7 derived from our analysis; to capture the value in the product market, organizations should continually monitor the performance of their initiatives and make data-driven decisions to optimize outcomes. Regular evaluation and iteration are critical to ensure that machine learning solutions are delivering the expected value and customer needs. By understanding and successfully capturing the business value from machine learning product, organizations can achieve increased operational efficiency, improved decision-making, enhanced customer experiences, and the development of new revenue streams. Ultimately, it enables organizations to stay ahead of competitors by fostering a culture of continuous learning and adaptation.

4.2. Limitations

Our qualitative analysis and the resulting best practices matrix offer a robust framework for integrating innovation management into MLOps. Through analyzing data from technical books, papers, and interviews with experts, we gained significant insights into the current state of the machine learning industry, MLOps practices, and innovation management, allowing us to link these to actionable best practices. This approach emphasizes investigating the practical applications of incorporating innovation management to leverage innovative values from machine learning products. The essentials of innovation management frameworks are frequently discussed within the MLOps procedure, especially the need to capture business values from the products through the framework.

However, a direct quantitative benchmarking of the proposed integration strategy against current industry standards or existing MLOps frameworks was beyond the scope of this qualitative study. Also, while this study mentions the struggles of many organizations, particularly SMEs, in scaling initiatives into production, and identifies challenges like differing stakeholder requirements and managerial concerns, a detailed segmentation analysis on how SME-specific resource constraints, team structures, or product lifecycles uniquely shape their MLOps readiness, compared to larger organizations was beyond the immediate scope of this qualitative investigation. Our aim was to construct a foundational matrix that synthesizes current knowledge and expert insights into a coherent, actionable blueprint.

5. Conclusion

In conclusion, the integration of innovation management processes in MLOps presents significant opportunities for enhancing the efficiency, effectiveness, and value creation potential of machine learning productions. By incorporating innovation management principles and practices, organizations can foster a culture of continuous improvement, creativity, and strategic thinking in their MLOps workflows. This can lead to the development of novel solutions, streamlined processes, and optimized resource allocation, ultimately resulting in improved performance, competitive advantage, and business growth. Furthermore, with a proper set of innovative strategies, organizations can capture their business value within their degree of control, ultimately expand their business goal and success.

Future developments can focus on exploring advanced techniques and methodologies for generating and evaluating innovative ideas. Building upon the qualitative framework established in this research, future work could include empirical validation and benchmarking of the proposed integrated MLOps and Innovation Management strategies. This could involve conducting dedicated studies to specifically analyze how resource constraints, team structures, and product lifecycles unique to SMEs influence their MLOps adoption and readiness. Also, we may develop metrics to assess the effectiveness of the proposed best practices against established MLOps maturity models or industry benchmarks, potentially through surveys or comparative analyses across different organizational contexts. The ethics and responsibility of AI governed by innovation management is also a possible topic that can provide new avenues for nurturing new ideas that aligned with social demands.

Acknowledgment: This paper is a part of the University-level research project granted by The University of Danang - University of Science and Technology with grant number T2024-02-12.

REFERENCE

[1] T. H. Gan, J. Kanfoud, H. Nedunuri, A. Amini, and G. Feng, "Industry 4.0: why machine learning matters?", *Advances in Condition Monitoring and Structural Health Monitoring: WCCM 2019*, Springer Singapore, 2021.

[2] N. Gift and A. Deza, *Practical MLOps: Operationalizing Machine Learning Models*. O'Reilly Media Inc., 2021.

[3] G. Noah and A. Deza, *Practical MLOps*. O'Reilly Media, Inc., 2021.

[4] C. Huyen, *Designing Machine Learning Systems: An Iterative Process for Production-Ready Applications*. O'Reilly Media Inc., 2022.

[5] K. Haller, *Managing AI in the Enterprise*. Apress Inc., 2022.

[6] T. Mboweni, T. Masombuka, and C. Dongmo, "A systematic review of machine learning DevOps", *International conference on electrical, computer and energy technologies*, 2022, pp.1-6.

[7] I. Bratsis, *The AI Product Manager's Handbook*. Packt Publishing Ltd., 2023.

[8] N. David, "Managing Innovation: Integrating technological, market and organizational change", *Journal of the Market Research Society,* vol. 41, no. 2, 1999.

[9] P. Trott, *Innovation Management and New Product Development*, 6th edition. Pearson, 2017.

[10] J. Birkinshaw and C. Gibson, "Building Ambidexterity Into an Organization", *MIT Sloan Management Review*, vol. 45, no. 4, pp.47-55, 2004.

[11] C. Amrit and K. N. Ashwini, "An analysis of the challenges in the adoption of MLOps.", *Journal of Innovation & Knowledge*, vol. 10, no. 1, 2025.

[12] C. E. Bogan and M. J. English, "*Bench marking for Best Practices: Winning Through Innovative Adaptation*", New York: McGraw-Hill, 1994.

[13] P. Crawford, "Best practice guidelines for the management of women with epilepsy", *Epilepsia*, vol. 46, pp.117-124, 2005.

[14] Eugene Bardach, *A Practical Guide for Policy Analysis: The Eightfold Path to More Effective Problem Solving*, 4th edition. CQ Press, 2011.

[15] J. Sterne and S. Mehak, "The acousmatic question and the will to Datafy: Otter. ai, low-resource languages, and the politics of machine listening", *Kalfou*, vol. 9, no. 2, pp. 288-306, 2022.

[16] F. Timo, *Managing Value Capture*, Gabler Verlag, 2011.