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Utilization of Artificial Intelligence in Demand Forecasting: A Qualitative Study of Business Actors

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Abstract

Market uncertainty in the era of volatility, uncertainty, complexity, and ambiguity (VUCA) demands that businesses possess high predictive acumen. This study explores the use of Artificial Intelligence (AI) in demand forecasting through a descriptive qualitative approach. The study focuses on a deeper understanding of how the integration of AI technology transforms managerial decision-making processes and the dynamics of its adaptation within the digital business ecosystem in Indonesia. In-depth interviews were conducted with ten informants holding managerial and operational analyst positions in the e-commerce and technology retail sectors in Indonesia. The results show that the application of AI, particularly based on Machine Learning and Deep Learning, is able to reduce subjective human bias and capture non-linear data patterns that conventional statistical methods fail to identify. This implementation significantly improves inventory estimation accuracy, minimizes holding costs, and prevents loss of sales momentum (stockouts). However, the transition to an AI-based forecasting system faces significant structural challenges, including data quality issues (data silos), limited local talent with multidisciplinary competencies, and cultural resistance within the organization. From the perspective of managerial decision-making theory, AI acts as a cognitive amplification tool, shifting the paradigm from pure intuition to data-driven decision-making. This study concludes that the success of AI implementation is determined not only by the sophistication of the algorithm, but also by the readiness of data governance and the alignment of inclusive organizational strategies.

Keywords: Artificial Intelligence, Demand forecasting, Digital Business, Managerial Decision-Making, Qualitative Study

INTRODUCTION

Contemporary global market dynamics are moving at an unprecedented pace. The wave of digitalization is not only changing how consumers interact with products but is also completely overhauling the structure of global supply chains. In this highly competitive landscape, a business organization's ability to anticipate future market needs is a key determinant in maintaining competitive advantage (Benzidia et al., 2021).

Inaccurate consumer demand forecasts can have devastating financial consequences, ranging from inflated operational costs due to inventory buildup to lost revenue opportunities due to market shortages. Traditionally, demand forecasting *relies* heavily on the extrapolation of historical data using linear statistical models such as the Autoregressive Integrated Moving Average (ARIMA) or exponential *smoothing*. While these methods have served the industry for decades, their inherent limitations are beginning to be exposed when faced with the large volume, high velocity, and highly heterogeneous nature of modern data (Kahneman, 2021)

Classical statistical models assume linear relationships between variables and require relatively stable or stationary data patterns. However, today's market reality is characterized by extreme fluctuations, increasingly shortened product life cycles, and the intervention of complex external variables such as social media trends, weather anomalies, and macroeconomic disruptions.

Amidst this methodological impasse, the emergence of *Artificial Intelligence* (AI) offers a revolutionary new paradigm. Through sub-fields such as *Machine Learning* (ML) and *Deep Learning* (DL), AI has the computational capacity to process billions of rows of *non-linear data* from various external sources in real time (Benzidia et al., 2021). AI not only reads past sales figures but is also capable of integrating consumer behavior variables on digital platforms, competitor price movements, and public sentiment on social media to produce demand projections with a much higher level of precision. In Indonesia, the relevance of AI adoption is becoming increasingly crucial along with the exponential growth of the digital business sector. As one of the largest digital economic powers in Southeast Asia, Indonesia has a unique and challenging market landscape: high internet penetration, a dynamic young population, but also faces the highly complex logistical challenges of an archipelagic geography (Ivanov et al., 2021).

For digital businesses in Indonesia, accurate demand forecasting is not just a matter of internal efficiency, but a crucial operational strategy to ensure equitable distribution of goods across the archipelago. However, adopting AI into demand forecasting functions is not simply a matter of purchasing off-the-shelf software or hiring a few data scientists. This transformation touches fundamental aspects of organizational governance and managerial decision-making theory (Chopra & Meindl, 2016).. Managers are often faced with the dilemma of trusting their proven business intuition over years or leaving decisions entirely to AI algorithms, often considered *black boxes* due to their mathematical complexity and difficult to intuitively grasp (Davenport & Mittal, 2020).

There is a significant literature gap on how business actors, particularly in emerging market contexts like Indonesia, conceptualize, adopt, and negotiate the practical challenges of integrating AI into their daily operations.

LITERATURE REVIEW

Understanding *Artificial Intelligence* (AI)

Epistemologically, *Artificial Intelligence* refers to the development of computer systems designed to mimic human cognitive capabilities, including learning, reasoning, problem-solving, perception, and natural language understanding (Anagnoste, 2018). AI is not a single entity, but rather an umbrella term encompassing various advanced computing architectures. The basic concept of AI rests on the creation of algorithms capable of exploring data search spaces, recognizing complex patterns, and adapting independently without the need for explicit programming for every possible scenario (Jurafsky & Martin, 2023).

In an operational context, the essence of AI lies in its ability to transform raw data into strategically valuable knowledge assets. Unlike conventional computer programs that operate rigidly based on " *if then* " instructions, AI-based systems have the flexibility to update their internal parameters as new data streams arrive. This adaptive characteristic makes AI superior in handling real-world phenomena fraught with uncertainty and statistical uncertainty (Bodie et al., 2021).

Types of *Artificial Intelligence* (AI) in a Business Context

In the commercial and operational management domains, AI manifestations can be classified into several complementary functional categories (Davenport & Ronanki, 2018). Understanding these types of AI is important because each architecture has a different suitability depending on the characteristics of the business problem at hand.

***Machine Learning* (Machine Learning)**

Machine Learning (ML) is the backbone of most commercial applications today. ML focuses on developing algorithms that enable computers to learn autonomously from historical data. In business, ML is generally divided into three main paradigms: *supervised learning,* used for predictions based on labeled data; *unsupervised learning* for market segmentation and anomaly detection; and reinforcement learning, which optimizes operational decisions through *reward* and *penalty mechanisms* (Creswell & Poth, 2018). Popular algorithms such as *Linear Regression, Random Forest, Support Vector Machines* (SVM), and *XGBoost* have become industry standards for predictive modeling.

***Deep Learning* (Deep Learning)**

As a subset of ML, *Deep Learning* utilizes *Artificial Neural Networks* (ANN) architecture with many *deep hidden layers* to mimic the workings of the human brain's neural network (Miles et al., 2022). DL is highly reliable in processing unstructured data such as images, sounds, and free text. In supply chains and forecasting, DL variations such as *Recurrent Neural Networks* (RNN) and *Long Short Term Memory* (LSTM) are very dominant due to their extraordinary capabilities in processing time series data *that* have complex long-term temporal dependencies (Simon, 2020).

Natural *Language Processing* (NLP)

Natural Language Processing enables computer systems to understand, interpret, and manipulate human language. In the context of digital business, NLP is used to analyze consumer sentiment on social media, product reviews on *e-commerce platforms,* and transcripts of *customer service interactions* ((APJII), 2024)

This qualitative data that has been quantified through NLP is then entered as additional predictor variables in the demand forecasting model to capture shifts in consumer preferences instantly.

***Robotic Process Automation* (RPA).**

While traditional RPA is static and only executes repetitive, rule-based tasks, the integration of AI gives birth to "Intelligent RPA" (*Intelligent Automation)*.

This system is capable of automating data collection from various fragmented ERP (*Enterprise Resource Planning) systems, performing automatic data cleansing, and running forecasting models without manual intervention from analyst staff (Anagnoste, 2018).*

Demand *Forecasting* Concept

Demand forecasting is the process of quantitative or qualitative estimation of the volume of products or services that will be purchased by consumers in the future within a certain time period (Davenport & Mittal, 2020).

The forecasting function occupies a central position in supply chain management because it is the driving force behind all other operational decisions, from raw material procurement planning and production scheduling to warehouse capacity management, to pricing and marketing strategies. Taxonomically, demand forecasting is grouped into two broad approaches:

1. Qualitative Approach: Relies on subjective judgment, intuition, accumulated experience, and expert consensus (e.g. Delphi Method or market surveys). This approach is typically used when historical data is not available, such as at the launch of a new product or penetration into a completely unfamiliar market.
2. Quantitative Approach: Uses mathematical and statistical models based on historical numerical data. This approach assumes that past patterns have a certain degree of continuity and are likely to repeat themselves in the future.

Forecasting accuracy is generally measured using standard error metrics such as *Mean Absolute Percentage Error* (MAPE), *Mean Absolute Error* (MAE), and *Root Mean Squared Error* (RMSE) (Hyndman & Athanasopoulos, 2018). The lower the value of these metrics, the more precise the forecasting model used, which directly correlates to the company's operational cost efficiency.

***Artificial Intelligence* in Demand Forecasting**

The integration of AI into the demand forecasting domain marks a paradigm shift from reactive statistical models to proactive predictive models. Conventional statistical models such as ARIMA or *Holt-Winters* have significant structural limitations: they are only capable of processing one-dimensional (univariate) data and assume constant variance over time (Hyndman & Athanasopoulos, 2018)

When faced with high volatility, aggressive sales promotions, or irregular seasonal effects, the performance of these classic models tends to decline drastically. AI overcomes these limitations through large-scale multivariate analysis capabilities.

AI models are capable of assimilating internal data (historical sales, discount rates, advertising circulation budgets) simultaneously with external macro data (economic indicators, competitor price indexes, daily weather trends, and even community mobility data) (Bodie et al., 2021).

For example, the LSTM (*Long Short-Term Memory)* architecture is capable of recognizing seasonal patterns that not only repeat annually, but also micro-patterns that occur on specific days of the week or even specific hours of the day. The non-linear flexibility of AI allows it to map highly complex relationships between variables without the need for up-front statistical assumptions, resulting in significantly lower MAPE values than traditional methods (Google et al., 2024).

Digital Business in Indonesia: Characteristics and Challenges

Indonesia's digital business landscape exhibits unique dynamics and has emerged as one of the most aggressive digital economy incubators in the Asia Pacific region (Bishop & Bishop, 2023). The key characteristics of the Indonesian market are shaped by several determining factors:

1. Massive Market Scale and *Geographic Fragmentation*: Indonesia has a population of over 270 million spread across tens of thousands of islands. This creates incredibly complex logistical challenges, with domestic logistics costs as a ratio of GDP among the highest in the region.
2. Highly Dynamic Consumer Behavior: Indonesian digital consumers are characterized by relatively low brand loyalty and high price sensitivity, which is exacerbated by a strong reliance on promotions, discounts, and double-date shopping campaigns (such as 11.11 or 12.12).
3. *Aggressive* Mobile Device Penetration: The majority of people access the internet *mobile first* or even *mobile only,* resulting in massive volumes of unstructured transaction data from mobile applications and digital wallets (APJII, 2024).

The combination of these factors creates a highly volatile operating environment for businesses. The inability to accurately predict regional demand can lead to a backlog of goods in Java's main warehouses while acute stock shortages occur outside Java, increasing emergency shipping costs and instantly damaging customer satisfaction.

Managerial Decision Making Theory

Theoretically, managerial decision-making is viewed through the lens *of Bounded Rationality,* pioneered by Herbert Simon. This theory states that the human capacity to process information and make rational decisions is limited by *cognitive limitations,* time constraints, and the availability of imperfect information (Goodfellow et al., 2016).

In complex business situations, managers are often forced to rely on heuristics (mental shortcuts) and intuition, which, although fast, are susceptible to various *cognitive biases* such as confirmation bias or *anchoring effect.*

The development of AI technology has had transformative implications for this theory. AI is triggering a shift from purely intuitive decision-making *to* data *-driven decision-making.* In contemporary management literature, this interaction is explored through the concept of *Augmented Intelligence,* where AI is not positioned to completely replace human managers but rather functions as a cognitive extension (Soust-Verdaguer et al., 2020).

AI handles heavy computational workloads, pattern processing, and large-scale probability calculations, while human managers concentrate on contextual interpretation, ethical considerations, strategic negotiations, and visionary leadership (Jararra et al., 2023).

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METHOD

Research Design

This research uses a descriptive qualitative approach with a multicenter (*multicase)* study strategy. The qualitative approach was chosen because the phenomenon of AI integration in business operations is not simply a matter of mathematical optimization, but rather a complex process involving technology adoption, organizational cultural adaptation, and managerial mindset restructuring that requires a deep and nuanced contextual understanding (Russell & Norvig, 2020).Through qualitative studies, researchers can uncover the "why" and "how" aspects behind algorithm performance figures.

Selection of Informants

Research informants were selected using purposive sampling techniques to ensure that the individuals interviewed had epistemic authority and practical experience relevant to the research object. Informant inclusion criteria included (Davenport & Ronanki, 2018):

1. Holds a managerial position (Supply Chain Manager, Operations Director, Head of Data/Analytics Division) or senior analyst directly responsible for the demand forecasting function.
2. Work for a company operating in the digital business sector (e-commerce, omni-channel integrated modern retail, or technology-based distribution company) in Indonesia.
3. The company where I work has implemented AI technology for at least the last 2 (two) years in their demand forecasting process.

Data Collection Techniques

Primary data were collected through semi-structured *in-depth interviews.* The interview guide was based on the conceptual pillars identified in the literature review, yet remained flexible to respond to the dynamics of findings in the field. Interviews lasted 45 to 90 minutes per session, conducted either face-to-face or virtually via video conferencing for the convenience of the informants. All interview sessions were recorded with the informants' *informed consent* and confidentiality was guaranteed through data anonymization procedures. In addition to the interviews, the researchers also triangulated data sources by collecting relevant declassified internal company documents (such as anonymized operational performance metrics reports, forecasting workflow SOPs, and forecasting system data architecture diagrams) to validate the informants' verbal statements (Kuhn & Johnson, 2013).

Data Analysis

The qualitative data analysis process was carried out interactively following the flow analysis model from Miles, Huberman, and Saldaña (2014), which consists of three simultaneous stages:

1. **Data Reduction**: Interview transcripts were transcribed verbatim. The data were then selected, focused, and simplified. Statements irrelevant to the

research focus were eliminated, while key phrases were given initial codes (*open coding)*.

2. **Data Display *:* Similar** codes are grouped into larger conceptual categories (*axial coding)*. These categories are then arranged in the form of comparative matrices and narrative networks to show causal relationships and consistent patterns between informants.
3. Conclusion Drawing and Verification: The researcher conducts in-depth interpretations of the emerging patterns, confronts them with established theories in the literature review, and formulates a solid final theoretical proposition.

To ensure the validity of the data (*trustworthiness)*, the researcher applied credibility criteria through member checking (returning draft transcripts to informants to ensure accuracy of meaning) and method triangulation (comparing interview results with internal company documentary evidence) (Carbonneau et al., 2008).

RESULTS AND DISCUSSION

Practical Implementation of AI in Digital Business Operations in Indonesia

Based on interview data, the use of AI in demand forecasting in Indonesia's digital business ecosystem has shifted from a mere cosmetic technology experiment to an absolutely essential core infrastructure. Informants revealed that the variety of AI algorithms adopted is highly correlated with the data characteristics and supply chain complexity of each industry.

Informant INF-02 (*Head of Data Analytics)* explained their system architecture: "We have completely abandoned traditional univariate statistical models. On our marketplace platform, daily transaction volumes exceed millions of entries. We combine *Gradient Boosting algorithms* such as *Light* GBM and XG *Boost* for daily short-term forecasting, as well as LSTM neural network models to capture long-term seasonal trends. Our AI ingests historical sales data, internal promotion performance, real-time competitor pricing through web scraping, and external metrics such as people's *paydays* and national holidays."

This statement confirms the theory proposed by Soust-Verdaguer et al. (Rialti & Filieri, 2024) regarding the superiority of multivariate analysis in AI. In *the omni-channel fashion sector,* the use of AI extends to *computer vision* and *natural language processing* (NLP). INF-03 explained that their AI model parsed thousands of popular social media posts and customer app reviews to identify emerging trends in clothing colors and cuts before they materialized in official sales figures.

The results of this unstructured data processing are converted into sentiment scores that are injected into a quantitative forecasting model as a control variable. Furthermore, in the *Grocery Commerce sector,* which handles fresh products with a very short shelf life (perishable goods), micro-level forecasting accuracy is crucial. INF-09 (*Co-Founder* /CEO) emphasized: "For us, missing the mark on vegetable or meat demand by just one day means direct losses due to product spoilage. We use AI that integrates local weather forecast data from the BMKG.

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If AI predicts heavy rain tomorrow in the South Jakarta area, the system automatically lowers the estimated demand for fresh produce in physical stores due to reduced public mobility, but increases stock quotas in online delivery warehouses (*dark stores)* to anticipate a surge in orders from home. This dynamic, contextual data integration demonstrates that AI capabilities go beyond static time series analysis, providing businesses with high operational agility in responding to external environmental anomalies (Sakib et al., 2025).

Impact of AI Efficiency and Accuracy on Financial Performance

The application of AI in the demand forecasting process has had a significant impact on the company's operational and financial *key performance indicators (KPIs). All informants reported a* drastic reduction in prediction error rates *after migrating to an AI-based system.*

The performance metrics reported by the informant companies are summarized in the comparative table below:

Tabel 1. Performance Metrics company's operational and financial key performance indicators (KPIs)

Operational Performance Dimensions	Before AI Implementation (Traditional Statistical Models)	After AI Implementation (Machine Learning/Deep Learning Model)	Direct Financial & Operational Impact
Average Accuracy Rate	60% – 70% (MAPE: 30% – 40%)	85% – 95% (MAPE: 5% – 15%)	Drastic reduction in procurement planning deviation.
Forecasting Cycle Duration	Weekly / Monthly (Manual Process-Section)	Real-Time / Daily (Full Automation)	Reduced response time to sudden market changes.
Stockout Rate	8% – 12% of total demand	< 2% of total demand	Increasing customer lifetime value and saving potential turnover.
Excess Inventory (Overstock)	High (Requires aggressive clearance discounts)	Optimal (According to market absorption capacity)	Savings on warehouse storage costs (holding costs) of 15% – 25%.

INF-04 (*Senior Demand Planner)* provides a critical analysis of how the decline in MAPE values transformed working capital efficiency: "Previously, with ARIMA, during shopping campaigns such as National Online Shopping Day (*Harbolnas)*, our predictions were often off by up to 35% (Herawatie et al., 2024). As a result, we were forced to stockpile huge amounts of *safety stock in the warehouse, which locked up the company's cash flow and increased the cost of cold storage rental. After the ML system was implemented, our error has stabilized below 10%. Inventory management is now closer to the Just In Time* (JIT) principle, freeing up working capital liquidity to be allocated to marketing expansion." On the other hand, eliminating *the stockout phenomenon* has significantly contributed to maintaining brand reputation in the digital world (Jafari-Sadeghi et al., 2021).

In Indonesia's digital business ecosystem, where competitors are just a click away, the lack of inventory on one platform can quickly drive consumers to a competitor's store. AI successfully recovers potential hidden revenue *by* ensuring the right products are in the right regional warehouse at the right time.

Transformation of Managerial Decision Making: Between Intuition and Algorithms

Field findings indicate a profound shift in the dynamics of managerial decision-making, reflecting the strengthening of Herbert Simon's theory of Bounded Rationality.

The presence of AI acts as a catalyst that expands the boundaries of managers' cognitive capacity in processing complex information that was previously impossible to analyze manually. However, the transition from intuition-based to data-driven decision models does not occur without psychological and cultural clashes. INF-07 (*Supply Chain Manager)* recounts his experience: "In the early phases of the AI rollout, there was a sharp internal conflict between the senior planning team that had relied on business instincts for decades and the recommendations issued by the computer system. Often, the AI produced procurement predictions that did not seem intuitively reasonable, for example, recommending stock cuts on popular products.

However, upon further investigation, the AI detected a decline in the product's search trend on Google and a global decline in consumer engagement a week before the sales decline occurred. Managers who overrode the AI's decisions and continued to order goods based on their instincts ultimately suffered significant losses as the products piled up in warehouses. "Empirical events like this are slowly undermining the arrogance of intuition." This phenomenon illustrates the transition to balanced *Augmented Intelligence* (Ali et al., 2022). Informant INF-01 emphasized that the role of human managers was not eliminated, but rather experienced an elevation in strategic value. Managers no longer spent hours in front of Excel spreadsheets calculating statistical formulas, but instead focused on monitoring the algorithm's macro parameters. Managers intervened in AI decisions only when extraordinary events (*black swan events)* occurred that were not recorded in historical data, such as sudden changes in government import regulations or emergency mobility restrictions due to a global health crisis (Ananda et al., 2023).

This demonstrates the harmony between the computational acumen of machines and the contextual wisdom of humans (Arief & Brabo, 2025).

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Structural Challenges and Barriers to AI Implementation in Indonesia

While the financial and operational benefits of AI are enticing, this qualitative study identified a complex spectrum of barriers that are slowing the widespread adoption of AI across Indonesia's digital business landscape.

Data Quality Issues (Garbage In, Garbage Out)

The most fundamental obstacle voiced by all informants was poor data governance at the internal company level (*data silos)*. INF-06 (*Data Science Lead)* stated: "Even the most sophisticated AI model will be useless if the input data is dirty. In many Indonesian companies, physical store sales data, *e-commerce transaction data,* and logistics data are in separate systems and managed by different teams with different format standards. The process of cleaning data (*data cleansing)* and unifying data pipelines (*data pipeline)* takes up to 70% of the total duration of the AI project. Without a commitment to data hygiene, AI systems will actually amplify prediction errors exponentially."

Multidisciplinary Digital Talent Deficit

Another challenge is the scarcity of human resources with skills at the intersection of data science *and* practical supply chain business understanding (Irwan et al., 2022). INF-08 noted that many young graduates are technically proficient in coding AI algorithms, but fail to translate the mathematical output into actionable commercial recommendations for warehouse operations teams. This communication gap often leads to frustration on both sides (Lähteenmäki et al., 2022).

***Acceptability Problems* and the " *Black Box* " Phenomenon**

The inability of most Deep Learning models to explain the logical structure of their decision-making *(explainability)* has sparked skepticism among corporate directors. As *Davenport* and Ronanki (2018) observed, high-level decision-makers are reluctant to invest large sums of capital in operational systems whose internal mechanisms they cannot transparently understand. This calls for the urgent development of *Explainable* AI (XAI) methodologies in future business applications.

CONCLUSION

This qualitative research concludes that the use of *Artificial Intelligence* (AI) in demand forecasting has transformed the operational paradigm of digital businesses in Indonesia from a merely *reactive administrative function* to a proactive strategic navigation tool. The integration of *Machine Learning* and *Deep Learning technologies* has been empirically proven to surpass the limitations of conventional linear statistical models by simultaneously assimilating hundreds of complex, dynamic, and non-linear external variables.

The tangible impact of AI adoption is manifested in increased forecasting accuracy of up to 90%, a drastic reduction in inventory holding costs due to inventory optimization, and the elimination of potential revenue losses due to stockouts. From a theoretical perspective, AI is redefining the boundaries of managerial decision-making theory by shifting the supremacy of pure intuition toward an ecosystem of objective, data *-driven decisions.* Within the framework of *Augmented Intelligence,* AI functions as a tool to expand managers' cognitive capacities, mitigating subjective human biases without negating the significance of human expertise in strategic interpretation and macro-level contextual decision-making. However, the acceleration of AI utilization in Indonesia is still hampered by structural challenges rooted in poor internal data integration, limited supply of hybrid talent mastering both technology and business domains, and organizational cultural resistance to black- *box technology.*

The success of this digital transformation ultimately depends not only on the superiority of the purchased computing technology, but also on the maturity of data governance and the readiness of human cultural adaptation.

Suggestions and Policy Implications

Based on the research findings and critical analysis conducted, several strategic recommendations can be considered by various parties. For practitioners and business owners, the primary step that needs to be prioritized is investment in data infrastructure. Before adopting complex artificial intelligence (AI) algorithms, companies must first eliminate internal information silos and build an integrated data management system, or Unified Data Platform. This aims to ensure the availability of clean, valid, and real-time data to support optimal AI performance.

Furthermore, the cultural aspects of the organization also require serious attention through the implementation of a change management program. Top management plays a crucial role in reducing employee resistance to adopting new technologies by providing inclusive data literacy training. It is crucial to instill the understanding that AI is not a threat that will replace humans, but rather a partner that can improve the efficiency and quality of work, especially for traditional analyst staff.

On the other hand, companies are also advised to begin exploring the concept of *Explainable* AI (XAI). This approach allows AI models to be more transparent and understandable, especially for managers without a technical background. By using methods such as SHAP or LIME, AI prediction results can be explained more clearly, thereby increasing trust in the strategic decision-making process.

Meanwhile, academics and future researchers have the opportunity to expand this research with a broader and more in-depth approach. Given that this research is still *qualitative and exploratory* with a limited sample size, further studies are recommended using large-scale quantitative methods, such as *Structural Equation Modeling* (SEM), to test the relationship and statistical significance between AI competency and corporate competitive advantage.

Furthermore, future research could also examine cross-sector comparisons to gain a more comprehensive understanding. Comparative studies between digital -*native companies and legacy* manufacturing companies undergoing digital transformation could provide insights into the differences in challenges, obstacles, and success factors in the AI adoption process. Thus, research findings are expected to provide more specific and applicable contributions to business strategy development in the digital era.

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