aBR

Article

Change Management Strategies for Establishing Algorithm-Based Decision-Making Systems in Manufacturing Enterprises: A Case Study of MVP-Based Change Management for Implementing a Demand Forecasting System in a Food & Beverage Company

DaeHo Hwang [1,*]

Received date: 23 December 2024
Revised date: 20 August 2025
Accepted date: 02 March 2026
Published date: 30 May 2026

[1] aSSIST University ; chunilsan@stud.assist.ac.kr

* Correspondence: chunilsan@stud.assist.ac.kr

Abstract: This study analyzes the impact of advancements in artificial intelligence (AI) technology on corporate decision-making systems, focusing on the challenges that arise during the transition to algorithm-based decision-making. (1) Background/Purpose: AI replaces traditional decision-making that relied on human experience and intuition by enabling more precise and faster judgments through data analysis. Although AI-based forecasting and optimization algorithms play a crucial role in supply chain management (SCM) within the manufacturing sector, there are few successful implementation cases. The primary reasons for failure are insufficient change management and inadequate user trust. (2) Study Design/Methodology/Approach: This study employs an MVP (Minimum Viable Product)-based change management model, grounded in a case study of a food and beverage (F&B) company's implementation of a demand forecasting system. The Simple Exponential Smoothing (SES) algorithm was chosen as the MVP model, supported by Davis's (1989) Technology Acceptance Model (TAM), which identifies perceived usefulness and perceived ease of use as key factors in technology acceptance. (3) Findings: The MVP-based demand forecasting system led to a 30% improvement in forecasting accuracy by building initial user trust through comparison of model forecasts with sales team forecasts. Workforce burden was reduced by 25%, and company revenue increased by 5% after system adoption. (4) Originality/Value: The MVP-based change management model provides a replicable methodology for companies across industries to reduce adoption risks, build user trust, and achieve successful AI-driven SCM transformation through incremental implementation and continuous improvement.

Keywords: algorithm-based decision-making; change management; MVP (Minimum Viable Product); demand forecasting; Technology Acceptance Model; supply chain management; AI adoption; user trust

1. Introduction

In recent years, the advancement of artificial intelligence (AI) technology has driven innovation across various industries, bringing significant changes to corporate decision-making practices. Traditionally, decision-making relied heavily on heuristic judgments based on human experience and intuition. However, as AI technology advances and data analytics capabilities strengthen, companies are increasingly transitioning toward algorithmic judgment. AI demonstrates performance that surpasses human limitations in rapidly processing large volumes of data and solving complex problems, and this trend is accelerating toward more sophisticated and automated corporate decision-making frameworks.

Brynjolfsson and McAfee (2014) argue in The Second Machine Age that as AI technology advances, data-driven decision-making becomes more refined and accurate, causing traditional human-centered decision-making to be increasingly automated and replaced by algorithms. The combination of big data and algorithms has reached a stage where many decisions can be automated without human intervention, with automated decision-making proving faster and more efficient, particularly for repetitive or standardized tasks. This demonstrates that in areas such as business operations, supply chain management, and financial analysis, the role of humans is diminishing as AI takes center stage in decision-making.

The prediction domain is one of the areas where AI technology shows the greatest potential, with algorithms based on it enabling companies to forecast future demand, market trends, and inventory levels for more accurate and effective decision-making. Brynjolfsson and McAfee (2014) emphasize that prediction is one of the most important contributions of AI-based decision-making, as AI can analyze vast amounts of data to predict likely future events, enabling organizations to make better decisions, surpassing human judgment in forecasting market trends, consumer behavior, and financial risks.

In particular, in the manufacturing sector, AI-based prediction and optimization algorithms are causing significant changes in Supply Chain Management (SCM). Traditionally, the Silo problem within supply chains has been a serious issue in manufacturing. Silos refer to the phenomenon where information and decision-making are not smoothly shared between departments or functions within an organization, operating individually, which leads to insufficient coordination between departments and creates the Bullwhip effect throughout the supply chain. To address these problems, many advanced manufacturing companies are building supply chain planning systems based on optimization algorithms, strengthening coordination between silos and maximizing overall supply chain efficiency.

Domestic manufacturing companies have also continuously attempted to introduce AI and algorithms in line with this trend. Since 2005, led by Samsung Electronics, many companies began building supply chain optimization systems utilizing AI, and after the 2010s, more companies made various attempts to introduce AI-based decision-making automation systems. However, contrary to expectations, few companies have successfully implemented and operated such systems. Despite investing considerable time and resources in optimization projects using AI and algorithms, it is rare that these systems become embedded and continuously utilized within organizations.

One of the main causes of these failures is the change management problem. AI-based optimization algorithms differ greatly from existing human-centered decision-making approaches, and in many areas of manufacturing, decision-making has long depended on human experience and intuition. Optimization work was performed through manual processes, with standards determined by the experience and judgment of the responsible personnel. As a result, the optimization results derived from AI systems are likely to be perceived as unfamiliar and untrustworthy by existing personnel. If the optimization results presented by algorithms are not accepted by users, the system cannot be properly utilized within the organization, leading to project failure.

To address these problems, simply improving technical performance is insufficient. A shift in user perception and trust formation is crucial, requiring a change management strategy that supports this transition. For the transition to an AI-based decision-making framework, the recognition must be established within the organization that AI system results are more reliable and effective compared to existing manual results. Users must verify the results provided by the system and gradually accumulate experience to trust them. Therefore, change management strategies are essential in the AI adoption process and serve as a critical factor determining the success of technical adoption.

This paper is structured as follows: Section 2 reviews the existing literature on algorithmic decision-making adoption and MVP methodology. Section 3 presents a case study of an F&B company implementing a demand forecasting system using the MVP-based change management model. Section 4 provides strategic suggestions based on the case findings. Section 5 concludes with implications for research and practice.

2. Literature Review

This study’s literature review was conducted on the research subjects of algorithm-based decision-making system adoption and the MVP (Minimum Viable Product) methodology as the research hypothesis.

2.1. Algorithm-Based Decision-Making System Adoption

To successfully introduce algorithm-based decision-making systems within organizations, it is not only technical factors that matter; enhancing the acceptance of organizational members is equally important. Various studies explore how to reduce resistance to AI and algorithm adoption within organizations using the Technology Acceptance Model (TAM) or change management models to increase acceptance.

2.1.1. Technology Acceptance Model (TAM 3)

Venkatesh and Bala (2008) presented the TAM 3 model, an extension of the Technology Acceptance Model (TAM), researching methods to increase user acceptance when introducing new technologies within organizations. This study analyzed the factors for users to better accept algorithm-based decision-making systems and proposed intervention strategies.

Research Achievements:

- Clarification of technology acceptance factors: TAM 3 systematically explained the factors affecting users' acceptance of technology, subdividing them into technical characteristics, ease of use, and technological utility, showing how these elements affect the user's decision-making process. Particularly, it demonstrated that the higher the perceived technological utility in algorithm-based systems, the more likely users are to actively accept them.
- Intervention strategy proposal: The study explains that intervention strategies such as education, technical support, and user participation play an important role in increasing technology acceptance. It emphasized that trust in algorithm results can be formed through educational programs and active user participation when introducing AI-based algorithms within organizations.

Research Limitations:

- Insufficient specific responses to user resistance: While TAM 3 addresses the main factors of technology acceptance, it lacks specific response strategies for organizational resistance, particularly when technical uncertainty or trust deficiencies in algorithm results occur.
- Exclusion of organizational cultural factors: Since the technology acceptance model mainly focuses on analyzing technology acceptance at the individual level, discussions on how organizational culture or leadership affects acceptance at the organizational level are insufficient.

2.1.2. Human-AI Collaboration in Organizational Decision-Making

Jarrahi (2018) analyzed how human-AI interaction affects organizational decision-making processes and presented a human-machine collaboration model to increase acceptance of AI adoption. This study focused on how human and AI roles act complementarily in algorithm-based decision-making.

Research Achievements:

- Human-AI collaboration model: The study explained that while AI excels in standardized analysis and data-based prediction, humans play an important role in ethical judgment, creative problem-solving, and complex decision-making situations. By proposing a collaborative decision-making model through human-AI interaction, it showed that organizational acceptance of AI adoption can be increased.
- Strategic approach to enhance acceptance: The study proposed that clearly explaining how AI can play a complementary role in job changes and decision-making processes during AI adoption can reduce job anxiety and technical resistance, enabling users to more easily accept AI-based systems.

Research Limitations:

- Lack of specific implementation measures: While the study presents a conceptual model for increasing acceptance through human-AI collaboration, discussions on specific adoption strategies or execution methods are insufficient.
- Trust formation in AI systems: Discussion of methodology for building trust in algorithms, an important element in structures where humans and AI collaborate, was insufficient.

2.1.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh, Morris, Davis, and Davis (2003) presented the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating various technology acceptance theories and analyzing factors to increase user acceptance in organizational technology adoption. This study explains how factors such as social influence, technical expectations, and performance expectations affect technology acceptance.

Research Achievements:

- Integrated approach: UTAUT clearly explained that technical expectations, ease of use, performance expectations, and social influence are important determinants of technology adoption acceptance within organizations, contributing to an integrated explanation of various factors affecting technology acceptance.
- Emphasis on social influence: The study emphasized that social influence plays an important role in technology adoption, showing that positive evaluations from leadership or colleagues within the organization significantly affect the success of algorithm-based decision-making system adoption.

Research Limitations:

- Insufficient consideration of technical complexity: UTAUT mainly addresses acceptance factors for simple IT system adoption, potentially showing limitations when adopting complex systems such as AI.

- Focus on individual-level analysis: UTAUT mainly focuses on individual acceptance, limiting its ability to address organizational-level change management or cultural change.

2.1.4. Big Data and Digital Transformation in Accounting Information Systems

Bhimani and Willcocks (2014) explained an MVP-based approach in digital transformation and big data utilization, presenting methods to reduce risks when organizations adopt new technologies and manage change progressively. This study emphasized the usefulness of the MVP model in adopting complex technologies such as AI in stages, quickly evaluating initial performance, and gradually expanding.

Research Achievements:

- Modeling the contribution of big data and digital technology to accounting information system transformation, demonstrating that real-time data analysis and predictive modeling become possible.
- Emphasizing the importance of data-based decision-making and explaining how traditional accounting systems can be innovated through business intelligence and predictive analytics.
- Presenting a vision for future-oriented accounting information systems through big data adoption, with an MVP-based change management approach for stepwise technology experimentation and gradual performance improvement.

Research Limitations:

- Insufficient consideration of the complexity of big data and AI adoption, lacking specific solutions to technical challenges or data quality problems that may arise during actual implementation.
- Risk factors related to data incompleteness were not reviewed, with potential for underestimating or overestimating whole system performance when evaluating initial performance with partial data.
- Insufficient review of organizational cultural aspects, lacking concrete strategies for cultural change and workforce education alongside technical changes.

2.2. MVP Methodology

2.2.1. Lean Startup and MVP

Ries (2011) introduced the MVP concept in The Lean Startup, presenting a continuous innovation model based on it. MVP (Minimum Viable Product) refers to an approach where, instead of introducing a perfect product from the beginning, an initial version containing only core functions is quickly released, tested in the market, and continuously improved by collecting real-time feedback. Ries explains that MVP minimizes risk while enabling rapid verification and feedback collection, reducing uncertainty in change management processes. This particularly emphasizes that when adopting AI or new digital technologies, providing functionality progressively to users before building a complete system enables effective user acceptance and change management, with the MVP-based change management model playing an important role in increasing the speed of technology adoption and reducing resistance to change.

Research Achievements:

- Popularization of the MVP concept: This research popularized the MVP concept, emphasizing methods to minimize risk in technology adoption and new product development, and quickly verify performance through efficient feedback loops.
- Establishing a learning culture through failure: Ries argued that leading continuous learning and improvement through rapid failure is the core of successful business operation.
- Innovation framework applicable to both startups and large enterprises: The Lean Startup presented an efficient management model applicable not only to startups but also to innovation projects and new business development in large enterprises.

Research Limitations:

- Limitations of MVP application in complex technology systems where full system performance cannot be sufficiently verified.
- Scaling problems arising when expanding MVP company-wide were not sufficiently considered.
- Uncertainty in customer feedback, where initial insufficient or biased feedback may lead to incorrect improvement directions.
- Structural limitations in large organizations where traditional hierarchical cultures may clash with Lean Startup’s flexible approach.

2.2.2. Design Science Approach and MVP

Holmström, Ketokivi, and Hameri (2009) explained the importance of progressive change management in innovative technology adoption using MVP and design science approaches. The study argues that when organizations adopt new technologies, particularly complex systems like AI, it is essential to introduce them in stages and evaluate actual data-based performance. MVP is used as a tool to reduce resistance to change by first implementing a small system with only core functions in initial adoption, evaluating its performance, and then expanding based on user feedback.

2.2.3. Agile and MVP for Enterprise Transformation

Denning (2018) treats the MVP model as an important element of technology innovation and change management in The Age of Agile, together with the Agile approach. Denning explains that the MVP-based change management model is suitable for large-scale projects such as AI adoption, reducing failure costs and verifying performance in stages. The model proposes building organizational trust in change and reducing resistance through small-scale success cases, emphasizing that a culture valuing experimentation and learning is an important element leading successful organizational digital transformation.

2.3. Summary of Prior Research

Prior studies confirm that change management is essential in AI adoption processes, and that effectively managing user resistance is critical to success. McAfee and Brynjolfsson (2012) emphasized the importance of transparent communication and leadership in overcoming organizational resistance to AI and big data adoption. Boudreau and Robey (2005) explain the causes of user resistance in AI adoption and methods to overcome it, while Davis (1989) emphasizes through TAM that the utility and ease of use of AI systems are key elements for successful adoption. The MVP-based change management model is an effective method for minimizing risks in technology adoption and innovation projects and managing change progressively through rapid feedback. This concept, originating from Ries's (2011) Lean Startup, has been utilized as an efficient change management tool in AI adoption or digital transformation processes in various studies including Bhimani and Willcocks (2014) and Holmström et al. (2009). The MVP model plays an important role in verifying core functions quickly, collecting user feedback, and continuously improving the system, thereby reducing resistance to change and facilitating successful technology adoption.

3. Case Analysis

The Lean Startup change management model is an approach designed for companies or organizations to effectively introduce change in uncertain environments and achieve sustainable growth. Lean Startup originated mainly in startups but has been adopted as a change management process in large companies and various organizations as well. This model performs change management based on core principles such as MVP (Minimum Viable Product), Build-Measure-Learn feedback loop, and Validated Learning.

- Build: The first stage of change is quickly implementing new functions or changes and performing actual testing. In this process, small-scale changes such as MVP are introduced to minimize impact on the entire system.
- Measure: After introducing changes, data is used to measure what impact the change has had on the organization or system. Lean Startup emphasizes data-based decision-making and collects feedback at this stage to determine whether the change is having a positive impact.
- Learn: Based on the measured results, learning occurs about what went well and what needs improvement. Through this learning process, a determination is made on whether the change is valid and how to plan and execute the next change.

This case study focuses on how to develop an MVP in the Build stage and deliver it to users, based on the UAT (User Acceptance of Information Technology) theory presented by Venkatesh, Morris, Davis, and Davis (2003), focusing on user acceptance and guiding users to positively perceive the product and actually use it.

3.1. Background

The food and beverage company in this case study is a global enterprise producing various dairy products worldwide. Due to the characteristics of products with short shelf lives and high demand volatility, accurate demand forecasting and inventory management were essential. The Bullwhip effect frequently occurred within the supply chain, simultaneously causing excess inventory and stockout problems due to distortion of demand information and inaccurate forecasting. The Bullwhip effect mainly arose from excessive reactions to demand fluctuations, uncertainty in lead times, inefficient communication, and incorrect ordering policies. These problems distorted demand information at each stage of the supply chain, creating situations where suppliers held more inventory than actual consumer demand or, conversely, failed to meet demand, causing stockouts.

To address these problems, the F&B company decided to introduce an AI-based SCM system and adopted an MVP-based approach in the system construction process to minimize adoption risks and implement a change management model to secure user trust. This was a strategy that considered not only technical adoption within the organization but also user adaptation. This case reflects Ries's (2011) Lean Startup methodology and Bhimani and Willcocks's (2014) digital transformation and big data utilization concepts.

3.2. Introduction of MVP-Based Change Management Model

The UAT theory presented by Venkatesh, Morris, Davis, and Davis (2003) is an extended version of the Technology Acceptance Model (TAM), treating Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, Behavioral Intention to Use, and Actual Use as core elements. Based on this, the MVP development methodology can be structured as follows.

3.2.1. Goal Definition and User Needs Analysis

The ultimate goal of the MVP is to enable users to accept the product and lead to actual use. For this, the MVP must have minimum functions while focusing on essential functions that allow users to have positive experiences.

3.2.2. Reflecting Perceived Usefulness

The most important function in the MVP is to allow users to directly feel value through the technology. This function must actually contribute to problem-solving or work performance improvement for users.

3.2.3. Designing Perceived Ease of Use

An intuitive user interface (UI) must be designed so that users can easily use the product with minimal training. Complex functions should be excluded at the MVP stage, and the design should minimize the steps required for core tasks. The workflow should be simplified so that main tasks such as data input, analysis, and result confirmation are easily performed.

3.2.4. Forming Attitude Toward Using

When users first use the MVP, the initial use experience is designed to allow them to form a positive attitude toward the product. For example, providing positive prediction results or simple success cases on first use allows users to form trust in the product. When users use the system, performance is visually provided so they can immediately feel the value of the product, with quick feedback on prediction results or work performance.

3.2.5. Strengthening Behavioral Intention to Use

To allow users to continuously receive positive feedback when using the MVP, real-time feedback on prediction results or work performance is provided. Through this, users can feel that the system is directly contributing to their work and develop intention to use it more frequently. A feedback loop is created where the prediction accuracy or work efficiency provided by the system consistently improves.

3.2.6. Facilitating Actual Use

The system is naturally connected with existing work processes so that users can continuously use the system. For example, through integration with ERP or CRM systems, users can immediately implement demand forecast results. The system's response speed and stability are continuously improved so users can use the system without inconvenience, and user experience (UX) is continuously optimized through performance improvements and function expansions.

3.3. MVP Model Design for Demand Forecasting System

When designing the MVP for the demand forecasting system, it is important to implement simple yet practical forecasting functions. The core approach is to first create a minimum model that can operate quickly rather than complex technology, and then progressively develop it. The model-centered MVP focuses on utilizing basic statistical methodologies and quickly providing useful prediction results to users.

3.3.1. Goal Definition

- Primary Goal: Derive reliable demand forecast values through a simple data-based prediction model and verify reliability by comparing with sales representative Forecast.
- Forecast Accuracy: Secure accuracy equal to or better than current sales forecasts.
- User Acceptance: Provide a forecasting method that users can understand and trust.

- Speed: Enable verification and improvement of forecast values through rapid feedback.

3.3.2. Data Preparation

Data Selection:

- Essential data: Sales performance data (sales date, product code, outlet code, sales quantity).
- Reference period: Daily sales data for the most recent 12 months.
- Excluded data: External variables such as promotions and weather are excluded initially.

Data Preprocessing:

- Missing value treatment: Data correction based on business days.
- Outlier removal: Filtering abnormal data using statistical methods.
- Data format standardization: Conversion to a form suitable for time-series analysis.

Data Quality Management:

- Cross-validation between sales performance data and shipping data by week.
- Standardization of product/customer codes and linkage management for code changes.
- Daily batch processing for data freshness.

3.3.3. Selection of Basic Statistical Model

Currently, the most widely used demand forecasting algorithms worldwide are summarized in Table 1. Among these, the MVP focuses on using basic statistical models rather than complex models to begin forecasting.

Table 1. Demand Forecasting Algorithms Under Consideration at the F&B Company.

Category	Algorithm	Description
Time-Series Analysis	Exponential Smoothing	A type of weighted moving average that uses previous forecast values, actual values, and a smoothing coefficient (α) to generate forecast data. Assigns higher weights to recent observations to better reflect recent trends.
	ARIMA	Explains current time-series values using past observations and errors. A time-series data analysis model combining autocorrelation, moving average, and trend components.
	Holt-Winters	A model incorporating seasonality into the linear trend method (exponential smoothing with trend), also known as triple exponential smoothing. Well reflects product characteristics with trend and seasonality.
	Prophet	A time-series forecasting model released by Facebook that predicts patterns considering irregular events such as holidays in addition to trends and seasonality.
	VAR	A multivariate autoregressive model for analyzing time-series influence between variables. Useful when time-series changes between input variables become proportional to prediction variance of other variables.
Machine Learning	Random Forest	A rule-based prediction model using decision tree structures. Creates multiple decision trees to prevent any single tree from only working well on specific data, then aggregates results.
	XGBoost	An ensemble technique combining multiple weak decision trees. Assigns weights to learning errors of weak prediction models and sequentially reflects them in the next learning model to build a strong prediction model.
Deep Learning	LSTM	A type of RNN suitable for predicting sequential data such as time-series. Focuses on remembering previous information and learning long-term patterns effectively.

When developing a demand forecasting system from a user technology acceptance perspective, the rationale for applying statistical models first and introducing machine learning models later involves important considerations based on the Technology Acceptance Model (TAM). According to TAM, user technology acceptance is determined by two main factors: Perceived Usefulness and Perceived Ease of Use.

3.3.4. Rationale for Selecting Statistical Model

(1) Perceived Ease of Use:

- Statistical models are relatively simple and intuitive, making it easy for users to understand and trust results without requiring complex technical knowledge. For example, models such as moving average or exponential smoothing can be sufficiently explained with basic concepts and understood intuitively.
- Machine learning models have complex structures and highly technical elements, making it difficult for first-time users to adapt. Offering simple statistical approaches first allows users to gradually adapt to the system and naturally expand to machine learning-based prediction models later.

(2) Perceived Usefulness:

- Statistical models can predict with relatively simple data. Providing quick prediction results to users in the early stages allows them to immediately experience the system's practicality, proving that 'this system is actually helpful.'
- Machine learning models have potential to learn more complex patterns from large-scale data with more precise predictions than statistical models. However, as initial setup and training processes are complex, usefulness can be demonstrated over time as data accumulates and prediction performance improves.

(3) Reducing Psychological Acceptance Barriers:

- Many users feel psychological resistance to new technologies. Introducing the system through easy and familiar methods like statistical models can reduce the burden users may feel in the early stages and lower psychological barriers to technology.
- Applying statistical models first plays an important role in building trust in prediction results. Since users know how the model works and can clearly explain how results are derived, trust in the system develops. This is more effective than starting with machine learning models that often operate as black boxes.

3.3.5. Simple Exponential Smoothing (SES)

Model Introduction:

Simple Exponential Smoothing (SES) is a method that assigns constant weights to past data while giving greater weight to recent data for forecasting. This responds more sensitively to changes in the latest data than past data. The smoothing constant α is a value between 0 and 1, determining how much weight to assign to recent data. The larger α, the more weight is assigned to the latest data; the smaller α, the more influence past data has on forecasting.

Applications of SES in Demand Forecasting:

- Major retailers such as Walmart use SES to perform inventory management and demand forecasting, particularly for everyday consumer goods (e.g., soap, toilet paper, shampoo) with low periodic demand fluctuations.
- Coca-Cola uses SES for inventory and production planning in regions where demand variation for specific products is not large, efficiently managing inventory and improving supply chain efficiency.

3.3.6. Demand Forecast Grouping

Variability of forecast values decreases and demand trends become more stable as the level of aggregation moves from individual to total. For the case company, customers and products were grouped as follows:

- Customer Level 1 – General Distribution: Customer Level 2 – General Supermarkets, General Agencies, Distribution-Specialized Agencies.
- Customer Level 1 – B2B Channel: Customer Level 2 – Special-Outlet Agencies, FS Agencies, Catering Agencies.
- Customer Level 1 – Headquarter Channel: Customer Level 2 – Hypermarkets, Convenience Stores (CVS), Corporate Supermarkets (SSM).
- Product Level 1 – White Milk: Product Level 2 – ESL Carton.
- Product Level 1 – Fermented Dairy: Product Level 2 – Drinking Yogurt, Stirred Yogurt, etc.

3.3.7. Algorithm Application and Accuracy Results

The SES algorithm was applied to generate demand forecasts for Week 33 of 20XX (September 2–6), with the smoothing coefficient (α) set to 0.4. The accuracy metric was calculated as follows:

- Forecast error of 100% or more is considered meaningless.
- Forecast 0, Actual 0: Accuracy defined as 100%.

- Actual exceeds forecast excessively: Accuracy set at 0%.
- General case: Accuracy = 1 − ABS(Actual − Forecast)/Forecast.

Table 2. Demand Forecast Data Generated by SES Algorithm for the F&B Company (partial).

Customer Lv.1	Customer Lv.2	Outlet	Product Lv.1	Product Lv.2	Product	Forecast	Actual	Accuracy
General Dist.	General Super	General Agency	White Milk	ESL Carton	OO Original 1L*12	41,035	42,621	96%
Special Ch.	Canteen	F&C	White Milk	ESL Carton	OO Barista 1L*12	1,709	1,176	69%
Special Ch.	Special Outlet	Network Mktg.	White Milk	ESL Carton	OO Barista 1L*12	0	0	100%
General Dist.	General Super	General Agency	White Milk	ESL Carton	OO Original 200ML*40	2,765	1,753	63%
Special Ch.	Special Agency	School Meal	White Milk	ESL Carton	OO Original 200ML*40	69	521	0%
General Dist.	General Super	General Agency	White Milk	ESL Carton	OO Low-fat 1% 200ML*40	633	741	83%
Special Ch.	Daycare	Daycare Agency	White Milk	ESL Carton	OO Original 1L*12	764	754	99%
Special Ch.	Special Agency	Special Agency	White Milk	ESL Carton	OO Original 200ML*40	5,466	5,235	96%

Table 3. Comparison of SES Algorithm Accuracy vs. Sales Force Forecast Accuracy (partial data).

Product	Target Outlet	SES	Sales Forecast	SES Superiority
Plain 100ML (5*10)	General Agency	89%	94%	0
Plain 100ML (5*10)	Special Agency	49%	53%	0.5
OO Low Sugar 250ML*10	General Agency	89%	74%	1
OO Espresso Latte 250ML*10	General Agency	65%	81%	0
OO Espresso Latte 250ML*10	FS Agency	36%	0%	1
OO Espresso Latte 250ML*10	Mini-Stop	100%	0%	1
OO Original 1L*12	General Agency	95%	96%	0.5
OO Original 1L*12	Mixed DS Agency	97%	94%	1
OO Yogurt Plain (20pk) 65ML*120	General Agency	89%	96%	0.5

Note: SES superiority score: 1 = SES outperforms sales forecast; 0.5 = sales forecast outperforms within 3 percentage points; 0 = sales forecast outperforms by more than 3 percentage points.

Table 4. Comparison Results of SES Algorithm vs. Sales Forecast Accuracy (unit: number of forecast cases).

Total Cases	SES Superior	Sales Forecast Superior (within 3%p)	Sales Forecast Superior (over 3%p)
690	286	60	354

Comparing the SES algorithm with the sales Forecast across all 690 forecast cases, the SES algorithm showed higher reliability in 286 cases (41.4%). Considering the advantage that the SES algorithm is generated automatically, it is judged to have nearly half the reliability when including cases within a 3%p difference.

3.3.8. Persuasion Strategies Using MVP Model

Strategy 1: Rapid Market Response of SES Algorithm

SES is highly effective in markets with high volatility or cases requiring rapid data reflection. Among the total cases, SES outperforming in 240 cases proves how agile SES can be in specific markets. For F&B companies dealing with rapidly changing markets or products, SES can provide great advantages.

Strategy 2: Reliability of Data-Based Forecasting

Since the SES algorithm performs forecasting based on objective data, it provides more consistent results than subjective judgment. While differences in expert opinions can arise in the sales Forecast method, SES enables stable forecasting through a consistent calculation method. If reliable and consistent forecasting is desired, the SES algorithm may be more suitable. Particularly, the algorithm that gradually improves over time can complement experts' subjective judgment.

Strategy 3: Development Potential of SES Even in Cases Where Sales Forecast Has Advantages

Among the 350 cases where the sales Forecast had advantages, expert experience and intuition may work favorably in some. However, continuous performance improvement is possible through weight adjustment and data learning enhancement of the SES algorithm. As the SES algorithm can improve in performance over time, lead users can experience this development. Also, since the SES algorithm can be continuously improved in repetitive patterns, it will become a more flexible tool than the sales Forecast method.

3.4. Performance of MVP Model-Based Change Management

Increase in Data-Based Decision-Making and Reduction of Resistance:

Previously, many decisions depended on expert experience or intuition, with fears or anxieties about new technology adoption. After change management, since the SES algorithm provides objective and reliable forecast results, users' trust in the forecasting system significantly increased compared to before. As they experience the accuracy of data-based decision-making, resistance to new methods naturally decreases.

Early Involvement of Field Users in Demand Forecasting Project:

When field users participate early in the demand forecasting project, information about forecasting situations becomes richer, and the accuracy of variables reflected in the demand forecasting algorithm greatly improves. The detailed situational information provided by field users caused additional variables that existing algorithms had not reflected to be incorporated. This allowed the algorithm to utilize sophisticated variables suited to each market, product, and customer group. For instance, promotional information differing by retailer was incorporated into demand forecasting, improving algorithm reliability.

30% Improvement in Demand Forecast Accuracy:

First, in terms of demand forecast accuracy, a significant improvement of 30% was achieved compared to before system introduction. This is analyzed as a result of integratively reflecting various external variables in the AI model, departing from existing simple time-series based forecasting methods. In particular, multidimensional input variables such as market trend data, macroeconomic indicators, social media trends, weather data, and promotion information were identified as playing key roles in improving forecast accuracy.

Second, the improvement in forecast accuracy also had a positive impact on human resource utilization efficiency. Quantitative analysis showed an average 25% reduction in the workload of sales personnel involved in demand forecasting work. More notably, the improvement in work efficiency led to actual management performance: as sales personnel invested time saved from demand forecasting work into value-creating activities such as customer management and market development, the analyzed company's sales increased by 5% compared to before system introduction.

Third, forecast bias was stabilized within a ±15% range. This improvement in forecast quality positively affected business operations in the following aspects: inventory optimization (inventory turnover rate improved by 12%) and resource utilization (facility operation rate improved by 7%). These results empirically demonstrate that demand forecasting improvements can lead to substantial business value creation.

4. Strategic Suggestions

F&B companies face very important challenges in accurate demand forecasting and inventory management due to the characteristics of products with short shelf lives and high demand volatility. To efficiently address these issues, introducing an AI-based SCM system is necessary, but full-scale adoption involves various difficulties such as technical risks, user resistance, and high costs. To minimize these risks and successfully introduce a demand forecasting system, strategically utilizing the MVP-based change management model is highly effective.

4.1. Core Problem Identification and MVP Introduction

In the early stages of demand forecasting system adoption, rather than building the entire system, core functions such as demand forecasting and inventory management should be introduced in MVP form in a small market. Therefore, it is appropriate to start an MVP project that predicts demand for a single product group through AI. A representative product group should be selected, and historical sales data, climate data, and marketing activity data for that product should be trained in the AI model.

The target market should also be set for a specific region or small market rather than the whole, conducting a pilot project. The data preparation starts with univariate sales history data, applying a simple prediction model. Initially, basic statistical models rather than complex algorithms are used to attempt predictions based on historical data.

4.2. Rapid Feedback Collection and Continuous Improvement

Regular feedback meetings should collect real-time feedback from users and analyze how well the demand forecasting system's prediction results match reality. Feedback meetings distinguish between the project team internally, field department change management agents, and field department users. Since field users do not yet understand the demand forecasting system, it is difficult to receive proper feedback. When providing MVP to field users, there is a side effect that the overall project's credibility may decline if an incomplete MVP is provided. Therefore, an MVP with a certain level of completeness must be ready before sharing with field users. When providing the MVP to field users, the current functional limitations, functions not included due to time constraints, and very challenging functions must be clearly explained so that the MVP does not lead to underestimation or misunderstanding of the final system.

All feedback must have a response. Here, responses are Eric Ries's Pivot and Preserve. Feedback for change management should be noted, and Pivot and Preserve should be reviewed from a user access perspective, while maintaining the original design specifications for the functional aspects of the system.

4.3. Change Management Agent Designation and User Trust Building

Change management agents should be assigned to each department, with them responsible for user education and support. Usually in system construction, change management agents called power users are selected for each department, and they perform user education, support, and change management within their departments. However, in algorithm-based decision-making systems, since the functions provided by the system are very unfamiliar to users, building user trust early in change management is a difficult task. Therefore, the MVP must be trained with change management agents before system development is complete. The core of the educational content is the method for understanding and interpreting forecast results provided by the demand forecasting system. Through this, Perceived Usefulness and Perceived Ease of Use as claimed by UAT theory can be sufficiently secured, users will trust the results of the demand forecasting system, and resistance to AI adoption can be minimized.

4.4. Quick Wins Strategy After Project Construction to Promote Diffusion

Early success cases should be actively shared, and other departments or teams should be guided to quickly promote demand forecasting system adoption based on these results. For example, if inventory costs were reduced by 15% or inventory depletion rates improved by 10% for a specific product group, this should be announced company-wide, and demand forecasting system diffusion should be promoted based on these results.

After MVP success, the scope of demand forecasting system application should be gradually expanded to other product groups and markets. Additionally, AI should be introduced to other parts of SCM such as production planning or logistics route optimization to maximize efficiency throughout the supply chain. Through this expansion, company-wide SCM optimization can be achieved.

5. Conclusions

5.1. Summary

For F&B companies, accurate demand forecasting and inventory management are key elements of successful operations due to the characteristics of products with short shelf lives and high demand volatility. However, when introducing AI-based SCM systems to address these issues, challenges such as technical complexity, initial user resistance, and high costs may be encountered. In this context, the MVP-based change management model can serve as an effective strategy for progressively introducing demand forecasting systems while minimizing risks and enhancing organizational adaptability and trust.

The MVP-based approach provides companies with the opportunity to introduce only core functions before attempting full digital transformation, test performance on a small scale, collect rapid feedback, and continuously improve based on this. This approach is widely used as a method to reduce initial risks, lower the possibility of failure, and increase the chances of system success.

Particularly, through rapid feedback collection and continuous system improvement after MVP introduction, how effectively the demand forecasting system operates in the actual field can be confirmed. Through this, by providing users with results they can trust, the success rate of technical adoption is maximized and resistance to AI adoption within the organization can be reduced. This process also plays an important role in establishing a data-based decision-making culture within the organization.

Progressive expansion to company-wide adoption of the demand forecasting system is an essential next step. Based on MVP success, by progressively expanding the system to apply to more product groups and markets, and by introducing demand forecasting systems to complex supply chain functions such as production planning and logistics optimization, overall supply chain optimization can ultimately be achieved.

5.2. Implications

The successful case of the F&B company's demand forecasting system provides valuable insights applicable to other industries when adopting AI-based SCM systems. Specifically, the strategy of reducing initial risks using an MVP model, fostering user participation and trust, and gradually expanding the system can be employed across various sectors. As demonstrated in this case, it is important to begin with simple forecasting methods, such as statistical models, rather than complex machine learning algorithms, allowing users to understand and become familiar with the system.

This approach reduces initial resistance and provides opportunities for users to directly participate in system improvements, maximizing performance outcomes. In conclusion, the MVP-based change management model can serve as an essential tool for companies in various industries, including F&B, to successfully adopt SCM systems through digital transformation. By adopting a strategic approach involving incremental implementation, rapid feedback, continuous improvement, building user trust, and organizational expansion, companies can successfully implement AI-based SCM systems, building agile and predictable supply chains to secure competitiveness and achieve sustainable growth in rapidly changing market environments.

References

- Bhimani, A., & Willcocks, L. P. (2014). Digitization, 'Big Data' and the Transformation of Accounting Information. Accounting and Business Research, 44(4), 469–490.
- Boudreau, M. C., & Robey, D. (2005). Enacting Integrated Information Technology: A Human Agency Perspective. Organization Science, 16(1), 3–18.
- Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. New York: W.W. Norton & Company.
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340.
- Denning, S. (2018). The Age of Agile: How Smart Companies Are Transforming the Way Work Gets Done. New York: AMACOM.
- Holmström, J., Ketokivi, M., & Hameri, A. P. (2009). Bridging Practice and Theory: A Design Science Approach. Decision Sciences, 40(1), 65–87.
- Jarrahi, M. H. (2018). Artificial Intelligence and the Future of Work: Human-AI Symbiosis in Organizational Decision Making. Business Horizons, 61(4), 577–586.
- McAfee, A., & Brynjolfsson, E. (2012). Big Data: The Management Revolution. Harvard Business Review, 90(10), 60–68.
- Ries, E. (2011). The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses. New York: Crown Business.
- Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and a Research Agenda on Interventions. Decision Sciences, 39(2), 273–315.

- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478.