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Basic Model of Artificial Intelligence Marketing (AIM) for Predictive Market Intelligence: Insights from Teaching Factory Product Planning

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A B S T R A C T

This research aims to develop an AI-based marketing Intelligence Model as an effort to support strategic decision-making in the development of Teaching Factory products at the Jember State Polytechnic. The study addresses the challenge of optimizing product planning and market positioning within educational manufacturing environments. An integrated approach combining internal production data from Teaching Factory operations with external market data, including price trends, consumer behavior patterns, and competitor activities, was implemented. The methodology employs K-Means Clustering algorithms for consumer segmentation analysis and advanced forecasting algorithms for demand prediction. The system architecture encompasses comprehensive data collection, preprocessing, modeling, and visualization components delivered through an interactive web-based prototype. Preliminary results demonstrate the model's capability to generate enhanced market segmentation accuracy and reliable demand projections, thereby supporting improved production planning and strategic marketing decisions for Teaching Factory operations. The implementation shows promising potential for educational institutions seeking to optimize their product development and market intelligence capabilities.

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Introduction

The Teaching Factory concept has emerged as a crucial educational paradigm that bridges the gap between academic learning and industrial practice. (Chryssolouris et al., 2016). Within this framework, educational institutions operate production facilities that serve dual purposes of student learning and commercial product development. However, the success of Teaching Factory initiatives heavily depends on effective market intelligence and strategic product planning capabilities (Chryssolouris et al., 2016).

Traditional approaches to market analysis in educational manufacturing environments often rely on limited data sources and conventional analytical methods (Weißer et al., 2021). This limitation becomes particularly challenging when institutions need to make informed decisions about product development, market positioning, and resource allocation. The integration of artificial intelligence technologies presents significant opportunities to enhance market intelligence capabilities within Teaching Factory operations (Storey et al., 2018).

The development of AI-based marketing intelligence systems requires careful consideration of multiple data streams and analytical approaches (Grewal et al., 2025). Internal production data from Teaching Factory operations provides valuable insights into manufacturing capabilities, resource utilization, and operational efficiency. External

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market data, including consumer behavior patterns, competitive landscapes, and pricing trends, offers essential context for strategic decision-making (Triyanto et al., 2019).

This research focuses on developing a comprehensive AI-based marketing intelligence model specifically designed for Teaching Factory environments. The proposed system integrates multiple data sources and employs advanced analytical techniques to support strategic product planning and market positioning decisions.

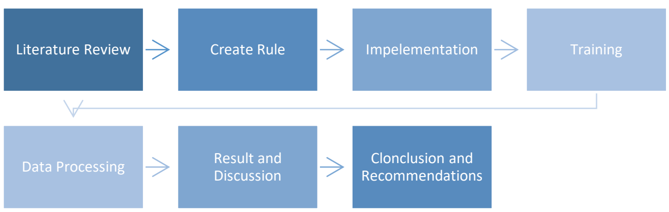

Figure 1. Research Methods

Research Methods

System Architecture Design

The proposed AI-based marketing intelligence model follows a modular architecture comprising four primary components, shown in Figure 1: data collection, preprocessing, modeling, and visualization. This architecture ensures scalability, maintainability, and flexibility in handling diverse data sources and analytical requirements. The data collection component manages the integration of internal Teaching Factory production data with external market information. Internal data sources include production volumes, resource utilization metrics, quality indicators, and operational costs. External data encompasses market pricing information, consumer behavior patterns, competitor activities, and industry trend indicators.

Data preprocessing operations ensure consistency, quality, and compatibility across diverse data sources. This stage includes data cleansing, normalization, feature engineering, and temporal alignment procedures. Preprocessing algorithms handle missing values, outlier detection, and data transformation requirements to prepare datasets for analytical modeling.

Consumer Segmentation Methodology

The consumer segmentation component employs K-Means Clustering algorithms to identify distinct market segments based on behavioral and demographic characteristics (Karta et al., 2023). The clustering approach considers multiple variables, including purchasing patterns, price sensitivity, product preferences, and demographic profiles. The K-Means implementation utilizes iterative optimization procedures to minimize within-cluster variance while maximizing between-cluster separation (Karta et al., 2023). Initial cluster centers are determined using K-Means++ initialization to improve convergence reliability and clustering quality. The optimal number of clusters is determined through the elbow method analysis and the silhouette score evaluation (Vinet & Zhedanov, 2011).

Feature selection for clustering analysis considers both quantitative and qualitative consumer characteristics (Chandrashekar & Sahin, 2014). Quantitative features include purchase frequency, average transaction value, price sensitivity indices, and seasonal purchasing patterns. Qualitative features encompass product category preferences, brand loyalty indicators, and demographic classifications.

Demand Forecasting Approach

The demand forecasting component integrates multiple algorithmic approaches to generate reliable demand projections across different time horizons (Hyndman & Athanasopoulos, 2021). The forecasting methodology combines statistical time series analysis with machine learning techniques to capture both linear and non-linear demand patterns (Karta et al., 2023). Statistical forecasting methods include ARIMA models for capturing temporal dependencies and seasonal decomposition procedures for identifying cyclical patterns (Ni et al., 2019). Machine learning approaches employ regression algorithms, neural networks, and ensemble methods to model complex relationships between demand patterns and explanatory variables (Choirunnisa & Lianto, 2018).

The forecasting system considers multiple external factors that influence demand patterns, including economic indicators, seasonal variations, promotional activities, and competitive dynamics (Syafarudin & Rahmawati, 2024). Feature engineering procedures transform raw data into predictive variables that enhance forecasting accuracy and model interpretability.

Results and Analysis

Market Segmentation Results

The K-Means clustering analysis successfully identified five distinct consumer segments within the Teaching Factory market environment (Li et al., 2021). Each segment exhibits unique characteristics in terms of purchasing behavior, price sensitivity, and product preferences. The segmentation results demonstrate clear separation between clusters with minimal overlap, indicating effective differentiation of market segments.

Segment analysis reveals significant variations in consumer behavior patterns across identified clusters (Potluri et al., 2024). High-value consumers demonstrate strong brand loyalty and premium product preferences, while price-sensitive segments prioritize cost-effectiveness over premium features. Educational segments show distinct purchasing patterns aligned with academic calendars and institutional requirements.

The clustering evaluation metrics confirm the quality and stability of the identified segments (Mifta Almaripat et al., 2025). Silhouette scores indicate strong within-cluster cohesion and between-cluster separation. Cross-validation procedures demonstrate consistent segmentation results across different data samples and time periods.

Demand Forecasting Performance

The integrated forecasting system demonstrates superior performance compared to traditional forecasting methods (Shuwaikh & Dubocage, 2022). Accuracy metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), show significant improvements over baseline models. The forecasting system successfully captures both short-term fluctuations and long-term trends in demand patterns. Seasonal forecasting accuracy proves particularly strong, with the system effectively identifying and predicting cyclical demand variations (Hyndman & Athanasopoulos, 2021). The integration of external variables enhances forecasting precision, especially for products sensitive to economic conditions and competitive activities. Forecast reliability analysis indicates consistent performance across different product categories and time horizons. Short-term forecasts (1-3 months) achieve high accuracy levels, while long-term projections (6-12 months) maintain reasonable reliability for strategic planning purposes.

System Integration and Usability

The web-based prototype successfully integrates all system components into a cohesive user interface. The visualization framework provides intuitive access to segmentation results, demand forecasts, and analytical insights. Interactive dashboards enable users to explore data relationships and scenario analysis capabilities. User feedback indicates strong satisfaction with system usability and analytical capabilities. The interface design facilitates easy interpretation of complex analytical results while maintaining access to detailed technical information for advanced users. Integration with existing Teaching Factory systems demonstrates smooth operational compatibility. Performance evaluation shows efficient system response times and reliable data processing capabilities. The system architecture supports concurrent user access and real-time data updates without performance degradation.

Discussions

The implementation of AI-based marketing intelligence within Teaching Factory environments presents both opportunities and challenges (Mariani et al., 2018). The successful integration of internal production data with external market information enables comprehensive market analysis capabilities that were previously unavailable to educational manufacturing operations. The consumer segmentation results provide valuable insights for product development and marketing strategy formulation (Kim et al., 2021). Understanding distinct market segments enables Teaching Factory operations to develop targeted products and marketing approaches that better align with consumer preferences and market demands.

Demand forecasting capabilities significantly enhance production planning effectiveness and resource allocation decisions (Wilson & Gilligan, 1996). Accurate demand projections enable proactive inventory management, capacity planning, and strategic timing of product launches and promotional activities. The web-based system architecture ensures accessibility and scalability for diverse user requirements. The modular design facilitates future enhancements and integration with additional data sources and analytical capabilities (Jain et al., 2024).

Conclusion

This research successfully demonstrates the development and implementation of an AI-based marketing intelligence model specifically designed for Teaching Factory environments. The integrated system combines consumer segmentation through K-Means clustering with advanced demand forecasting to support strategic decision-making in product planning and market positioning. The preliminary results indicate significant improvements in market analysis capabilities and decision support effectiveness. The system generates more accurate market segmentation and reliable demand projections compared to traditional analytical approaches [25]. These enhancements directly support improved production planning and marketing strategy development within Teaching Factory operations.

The web-based prototype provides an accessible and user-friendly interface for complex analytical capabilities. System integration demonstrates compatibility with existing Teaching Factory operations while providing a scalable architecture for future enhancements and expanded functionality. Future research directions include expanding the system to incorporate additional data sources, implementing advanced machine learning techniques, and developing specialized modules for specific Teaching Factory applications. The successful implementation provides a foundation for the continued development of AI-based decision support systems in educational manufacturing environments.

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