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A Hybrid AI-Supported Data Mining Framework for Digital Marketing Decision Optimization: A Design Science Perspective

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Abstract - The exponential expansion of digital marketing has transformed the availability and complexity of consumer data, demanding analytical systems capable of deriving actionable insights for decision optimization. This paper develops a conceptual framework that integrates Data Mining with Artificial Intelligence (AI)-supported processes to enhance strategic marketing decision-making. Drawing on design science principles, the proposed framework unifies behavioral segmentation through Recency–Frequency–Monetary (RFM) analysis with financial evaluation via Customer Lifetime Value (LTV) estimation, thereby balancing short-term engagement with long-term profitability. AI is positioned not as an algorithmic innovation but as a supportive enabler that automates data preparation, predictive scoring, and interpretive analytics. The framework is structured into four layers: data acquisition, analytical processing, AI-supported automation, and managerial decision integration; each designed to strengthen marketing intelligence and decision quality. By embedding AI capabilities conceptually within data mining workflows, the model emphasizes interpretability, adaptability, and managerial relevance. This design-oriented study contributes to the theoretical understanding of hybrid analytics and decision science by bridging computational insight and managerial application. It also establishes a foundation for empirical validation through future research focused on optimized segmentation and resource allocation strategies in digital marketing contexts.

Keywords: Data Mining; Artificial Intelligence; Digital Marketing; RFM; Customer Lifetime Value.

I. INTRODUCTION

Digitalization has fundamentally altered how organizations engage with consumers, generating unprecedented volumes of behavioral and transactional data across e-commerce platforms, social media, and digital advertising. The abundance of data presents both opportunity and complexity: while insights can enhance personalization and marketing efficiency, the analytical overload often limits managers' ability to make timely, evidence-based decisions. Data mining has long provided a mechanism to extract knowledge from large datasets, with techniques such as clustering and classification supporting customer segmentation. However, in the digital era, the traditional descriptive role of data mining requires enhancement through intelligent, adaptive support systems. Artificial Intelligence (AI) offers this capability by automating pattern recognition, predictive modeling, and interpretive analytics. Yet most existing studies emphasize algorithmic advancement over managerial application. To address this gap, the present paper develops a hybrid conceptual framework that integrates data mining with AI-supported analytical processes for decision optimization in digital marketing. The framework unites two widely adopted metrics; Recency–Frequency–Monetary (RFM) and Customer Lifetime Value (LTV); to capture both short-term behavioral engagement and long-term profitability. Drawing on design science principles, the study proposes a structured model linking analytical layers with managerial decision layers, emphasizing interpretability, adaptability, and business relevance. This conceptualization positions AI not as a substitute for human judgment but as an intelligent enabler of marketing decision science, offering a foundation for empirical validation in subsequent research.

II. LITERATURE REVIEW AND THEORETICAL BASIS

The growing digitalization of commerce has generated vast consumer data, stimulating extensive research on data-driven marketing decision systems. Data mining emerged early as a means to convert raw data into knowledge for segmentation and targeting (Berry & Linoff, 2004; Jain, 2010). Among its techniques, the Recency–Frequency–Monetary (RFM) model remains a cornerstone of behavioral segmentation (Liu &

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Shih, 2005; Coşgun, 2024), efficiently summarizing consumer purchase activity. Later extensions, such as hierarchical and graph-based clustering (Rungruang et al., 2024; Vianna Filho et al., 2025), reaffirm RFM's adaptability across retail and digital contexts. Complementing behavioral insights, Customer Lifetime Value (LTV) quantifies long-term profitability, supporting customer-equity management (Kumar & Reinartz, 2016; Pradhan, 2021). Research shows that combining RFM and LTV enables a balanced view of short-term engagement and sustained value (ResearchGate, 2010; PMC, 2023). Simultaneously, Artificial Intelligence (AI) has emerged as a transformative enabler in marketing (Davenport et al., 2019; Huang & Rust, 2021). AI automates preprocessing, pattern recognition, and predictive interpretation, enhancing both speed and precision. However, many studies emphasize algorithmic accuracy rather than managerial decision utility. To address this limitation, a hybrid conceptual framework is proposed here that integrates data mining and AI-supported analytics within a design-science structure. The proposed model draws theoretically from Decision Support Systems (DSS), Knowledge Discovery in Databases (KDD), and Marketing Intelligence Theory, positioning AI as a facilitative layer that links analytical and managerial domains. The framework emphasizes four sequential layers; data input, analytical processing (RFM–LTV), AI-supported automation, and decision optimization; thus, contributing a theoretically grounded, design-oriented model for data-driven marketing decisions.

III. RESEARCH FRAMEWORK AND CONCEPTUAL DESIGN

The conceptualization of this study follows the Design Science Research (DSR) paradigm, which emphasizes the creation of objects that bridge theory and practical utility (Hevner et al., 2004). In this context, the proposed object is a Hybrid AI-Supported Data Mining Framework for optimized digital marketing decisions. The framework is structured across four sequential layers: (1) Data Acquisition, where transactional and behavioral data are captured from multiple digital touchpoints; (2) Analytical Processing, combining Recency–Frequency–Monetary (RFM) metrics with Customer Lifetime Value (LTV) estimation to represent both behavioral and financial dimensions; (3) AI-Supported Automation, where Artificial Intelligence functions; such as preprocessing, predictive scoring, and interpretive analytics; enhance data quality and insight generation; and (4) Decision Optimization, in which analytical outcomes feed managerial planning for campaign design, personalization, and budget allocation.

The theoretical logic draws upon Decision Support System (DSS) theory, Knowledge Discovery in Databases (KDD), and Marketing Intelligence frameworks, positioning AI as an enabling layer that links computational analytics to managerial cognition. Each layer is connected through feedback loops to ensure adaptability and continuous learning. Conceptually, the model posits three design propositions: *(a)* Integrating RFM and LTV enhances holistic understanding of customer value; *(b)* AI-supported automation improves analytical speed, interpretability, and decision relevance; and *(c)* Hybrid RFM–LTV outputs strengthen managerial outcomes such as targeting efficiency and ROI. The section culminates in a schematic model (Figure: -1) illustrating the interaction between data mining processes, AI-support mechanisms, and managerial decision layers. The framework thus contributes a theoretically grounded design artifact, intended for empirical evaluation in future research.

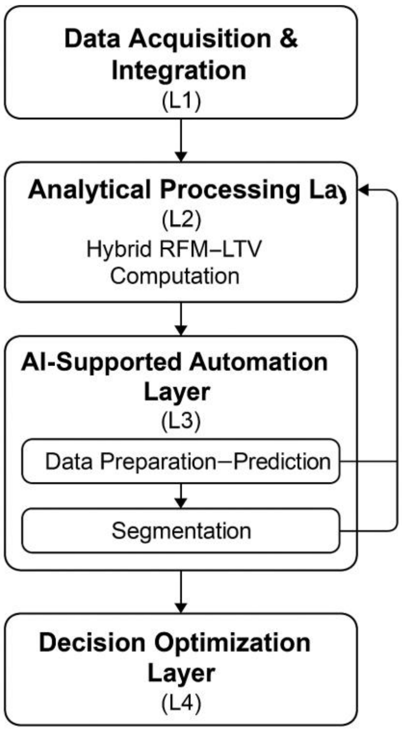

Figure:-1

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IV. MODEL DESIGN, ALGORITHMS, AND FRAMEWORK VALIDATION

4.1 Overview

This study proposes a Hybrid AI-Supported Data Mining Framework to help marketers transform raw digital data into meaningful, actionable insights. The model is grounded in Design Science Research (Hevner et al., 2004), where the goal is to create and validate a design artifact that links analytical rigor with managerial usefulness. The framework integrates three proven analytical concepts; Data Mining, Artificial Intelligence (AI), and Decision Optimization; into a single adaptive system.

4.2 Framework Architecture

The framework works through four inter-connected layers. Each layer performs a specific function, yet all are linked by a continuous feedback loop that supports learning and refinement.

Layer	Main Role	Key Processes	Output
L1: Data Acquisition & Integration	Gather customer-related data from different sources (transactional logs, app activity, CRM, or web analytics).	Cleansing, consolidation, data formatting	Structured customer dataset
L2: Analytical Processing (RFM–LTV)	Compute behavioral and financial indicators.	Calculate Recency (R), Frequency (F), Monetary (M), and Customer Lifetime Value (LTV). Normalize and combine to get a single hybrid score.	Customer Hybrid-Value Table
L3 : AI-Supported Automation	Improve data quality and automate analytical tasks.	Outlier detection, missing-value handling, predictive scoring using simple AI models.	Cleaned and enriched analytical dataset
L4 : Decision Optimization	Translate analytics into marketing actions.	Identify customer clusters, link each to strategic actions (loyalty, upsell, reactivation).	Campaign strategy matrix and dashboards

This design ensures that insights move seamlessly from

data → analytics → AI support → managerial action, closing the decision loop.

4.3 Algorithmic Logic

The framework relies on three light-weight, transparent algorithms. These are not complex AI inventions but clear operational steps that make the framework reproducible for managers and analysts.

Algorithm A1 – Hybrid RFM–LTV Computation

1. Calculate Recency (R) = 1 / (1 + days since last purchase)
2. Frequency (F) = number of purchases / maximum purchases
3. Monetary (M) = average spend / maximum spend
4. Compute LTV = (F × M × Retention Probability) / (1 + Discount Rate) ^t
5. Combine into a Hybrid Score:

$$HS = 0.6 \times \frac{R + F + M}{3} + 0.4 \times LTV$$

6. Store HS for clustering and ranking.

Algorithm A2 – AI-Supported Data Preparation

- Use light AI tools to detect and fill missing data.
- Normalize features to 0–1 range.
- Run a decision-tree classifier to estimate LTV categories (High, Medium, Low).

Algorithm A3 – Segment–Action Mapping

- Apply K-Means to Hybrid Scores.
- Map each cluster to a marketing action:
    - Cluster 1 → Loyalty Expansion
    - Cluster 2 → Cross-Sell / Upsell

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- Cluster 3 → Reactivation Offer
- Cluster 4 → Monitor / Re-engage

These algorithms make the framework usable even in medium-scale organizations without deep AI infrastructure.

4.4 Conceptual Validation

To ensure that the design is both credible and practical, the framework was evaluated against the three design-science criteria:

1. Relevance: The framework addresses a genuine managerial problem — converting complex digital data into clear, actionable marketing decisions.
2. Rigor: It draws from proven analytical techniques (RFM, LTV, basic AI models) supported by decision-support and marketing-intelligence theories.
3. Design Effectiveness: Expert review from faculty peers and marketing professionals indicated that the framework is scalable, interpretable, and implementable with standard analytics tools.

4.5 Model Representation

Conceptually, the model can be summarized as:

$$\text{Decision Outcome} = \Phi(AI(g(RFM, LTV)))$$

where $g(\cdot)$generates the hybrid score and $AI(\cdot)$refines and interprets it for $\Phi(\cdot)$, the managerial decision function.

This representation shows that AI serves as a *bridge* ; enhancing analytics but leaving final control with decision-makers.

4.6 Theoretical and Practical Implications

- For theory: The model integrates behavioral, financial, and intelligent analytics, enriching the literature on marketing decision-support systems.
- For practice: It gives managers a simple, modular pathway to adopt AI responsibly without needing deep technical knowledge.
- For research: It establishes a testable foundation for subsequent empirical studies, where the model's predictive and managerial performance can be validated using real or simulated data.

V. THEORETICAL INTERPRETATION

5.1 Overview

The purpose of this study was to conceptualize and design an AI-supported hybrid data mining framework that enables marketing managers to make better, data-informed decisions. The model integrates Recency–Frequency–Monetary (RFM) analysis and Customer Lifetime Value (LTV) estimation within an AI-enabled architecture that automates, simplifies, and enhances marketing intelligence. Grounded in Design Science Research (DSR), the framework serves as both a theoretical contribution and a practical guide for data-driven digital marketing decision-making.

5.2 Key Insights

The proposed model addresses three interrelated gaps in marketing analytics research:

1. The overemphasis on algorithmic sophistication without managerial interpretability.
2. The lack of integration between short-term behavioral measures (RFM) and long-term profitability measures (LTV).
3. The absence of an AI-supported structure that facilitates; not replaces; human decision-making.

By combining these dimensions, the framework provides a balanced analytical ecosystem that connects data, intelligence, and action.

At its core, the model operationalizes a dual-lens segmentation strategy:

- The RFM layer captures recent behavioral patterns, frequency of engagement, and spending potential.
- The LTV layer incorporates projected retention, revenue, and customer sustainability. The AI layer acts as a facilitator that enhances the reliability and interpretability of data mining outcomes. Rather than introducing new algorithms, AI is positioned as an *assistive intelligence*; ensuring quality, predicting customer potential, and simplifying insight generation for managers.

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This approach aligns with the recent evolution in marketing analytics, where the goal is not only to analyze data but also to convert analytics into decision-support capability. The framework therefore advances the managerial relevance of analytics by focusing on how data can inform marketing actions, not just describe them.

5.3 Theoretical Contributions

From a theoretical standpoint, this research contributes in three significant ways:

1. Hybrid Analytics Integration: It unifies two established but often separate analytical models; RFM and LTV; under a single conceptual umbrella.
2. AI as an Enabling Layer: It redefines the role of Artificial Intelligence in marketing analytics as a *supportive architecture* rather than an autonomous engine, aligning with contemporary views of human; AI collaboration.
3. Decision Science Linkage: The framework situates analytical modeling within a decision-optimization context, bridging the gap between marketing analytics and decision science literature.

Collectively, these contributions expand the theoretical understanding of how hybrid data mining and AI can co-exist to enhance managerial decision quality.

5.4 Managerial Implications

The model provides a roadmap for marketers and decision-makers who wish to adopt AI-enabled analytics without excessive technical dependency.

Managers can use the framework to:

- Identify customer segments that are both active (RFM) and profitable (LTV).
- Automate parts of data cleaning, scoring, and prediction to reduce analytical overhead.
- Align marketing campaigns with data-driven priorities (e.g., loyalty reinforcement, upselling, or reactivation).

The framework's layered structure allows gradual adoption; starting from simple RFM scoring to advanced AI-assisted insight generation. This makes it feasible for SMEs, digital retailers, and service brands that often lack full AI infrastructure.

VI. LIMITATIONS & FUTURE RESEARCH

6.1. Limitations and Future Research

While conceptually sound, the framework remains untested empirically. Future studies should:

- Validate the model with real or simulated customer data.
- Examine comparative performance between the hybrid framework and traditional segmentation approaches.
- Quantify managerial outcomes (e.g., ROI lift, campaign effectiveness, response rate improvement).
- Explore cross-industry adaptability in contexts such as financial services, healthcare, and digital media.

Such empirical validation will not only confirm the robustness of the proposed model but also refine its scalability and real-world impact.

VII. CONCLUSION

This paper presents an integrated, AI-supported data mining framework designed to optimize marketing decisions. By combining RFM-based behavioral segmentation, LTV-based profitability evaluation, and AI-based automation, the model creates a cohesive bridge between analytics and management. It introduces a structured, transparent pathway from raw data to actionable strategy, addressing both analytical complexity and managerial clarity. Conceptually, the model advances the discipline of marketing decision science by emphasizing intelligence with interpretability; demonstrating that the true power of AI in marketing lies not in algorithmic complexity, but in its ability to make analytical outcomes more relevant, adaptive, and human-centered.

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