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BRIDGING ACCURACY AND ADOPTION IN AI-BASED PROMOTION FORECASTING IN RETAIL

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ABSTRACT

AI and machine learning–based systems are increasingly used in retail to forecast promotional demand and support complex promotion planning decisions. Yet many retailers continue to rely heavily on managerial intuition and simple performance indicators, indicating a gap between advanced analytical capabilities and their effective use in decision-making. This conceptual paper develops a socio-technical framework for AI-based promotion forecasting in organized retail that integrates technical and organizational perspectives. Drawing on literature on AI-driven promotion analytics, customer segmentation, decision support systems, human–AI collaboration, and AI governance, the framework theorizes how customer segmentation sophistication and machine learning–based forecasting inputs influence managers' perceptions of forecast accuracy and decision support quality. It further proposes that interpretability and managerial trust mediate these relationships, while organizational readiness and governance structures moderate the extent to which AI-generated forecasts shape promotion decisions. Based on this integrated perspective, the paper formulates propositions to guide future empirical research and outlines implications for designing AI-enabled promotion forecasting systems that are technically robust, interpretable, and aligned with managerial and organizational realities in retail.

KEYWORDS: *AI, Promotion Forecasting, Retail Analytics, Customer Segmentation, Decision Support Systems, Interpretability, Trust*

1. INTRODUCTION

Organized retail in emerging economies is becoming increasingly complex and data-intensive, driven by expanding product assortments, omnichannel customer journeys, and intensifying competitive pressures. Promotional campaigns remain one of the most critical levers for influencing short-term demand, managing inventory, and sustaining market share. However, promotion planning is inherently uncertain, as demand response depends on multiple interacting factors, including price sensitivity, cross-category substitution, seasonality, and competitor actions.

In response, retailers have increasingly adopted artificial intelligence (AI) and machine learning (ML) based systems to improve promotion forecasting and decision-making. These systems leverage large volumes of transactional, behavioral, and contextual data to model nonlinear demand patterns, estimate promotional uplift, and simulate alternative promotion scenarios. In parallel, advances in customer segmentation have enabled retailers to identify fine-grained behavioral segments with distinct promotion sensitivities, further enhancing the potential precision of promotion planning.

Despite these advances, a persistent gap remains between the technical capabilities of AI-driven promotion forecasting systems and their effective use in managerial decision-making. Empirical evidence and industry practice suggest that managers frequently rely on intuition, experience, and simplified heuristics, even when sophisticated forecasting tools are available. This disconnect highlights a critical limitation in existing research, which largely treats promotion forecasting as a prediction problem and assumes that improvements in model accuracy translate directly into better decisions.

However, emerging research in human–AI collaboration and decision support systems challenges this assumption. Accurate models do not necessarily lead to better decisions if their outputs are not interpretable, trusted, or aligned with managerial mental models and organizational processes. In practice, AI-generated forecasts may be ignored, overridden, or inconsistently applied due to concerns about transparency, lack of trust, and unclear governance structures.

For example, a large grocery retailer using AI-based promotion forecasting may generate highly accurate uplift predictions for different discount levels across stores. However, category managers may still override these recommendations due to limited understanding of model drivers or lack of trust in the system, highlighting the importance of interpretability and governance in ensuring effective use of AI outputs.

This paper argues that AI-based promotion forecasting should be understood as a socio-technical system, where technical model capabilities interact with managerial perceptions and organizational conditions to shape decision outcomes. Specifically, while customer segmentation sophistication and ML-based forecasting inputs enhance predictive capability, they may also increase model complexity and reduce interpretability, thereby affecting managerial trust and usage.

To address this gap, this paper develops an integrated socio-technical framework that connects technical inputs (segmentation sophistication and ML-based forecasting inputs) with managerial perception constructs (interpretability, perceived accuracy, decision support quality, and trust), and organizational factors (readiness and governance). The framework proposes that interpretability and managerial trust mediate the relationship between technical sophistication and decision outcomes, while organizational readiness and governance moderate the extent to which AI-generated forecasts influence promotion decisions. This study adopts a conceptual research approach based on an integrative review of existing literature.

This paper makes three key contributions. First, it shifts the focus of promotion forecasting research from algorithmic accuracy to a socio-technical perspective that incorporates managerial and organizational factors. Second, it introduces interpretability and managerial trust as central mediating mechanisms linking technical model characteristics to decision outcomes. Third, it highlights the moderating role of organizational readiness and governance in determining whether AI-generated forecasts are effectively integrated into promotion planning. Together, these contributions provide a more holistic understanding of how AI can create value in retail decision-making.

2. LITERATURE REVIEW

2.1 AI-Based Promotion Forecasting in Retail

Promotion planning in organized retail is characterized by volatile demand, intense competition, and frequent use of price discounts, bundling, and loyalty incentives. Traditional statistical forecasting methods often struggle to capture nonlinear promotion effects, cross-category substitution, stockpiling behaviour, and external shocks. AI- and machine learning–based promotion forecasting systems address these limitations by processing large volumes of transactional and contextual data, detecting complex patterns, and generating uplift estimates and scenario simulations. Such systems typically integrate data on prices, promotion depth and duration, store attributes, historical sales, seasonality, and macro-environmental factors to support promotion planning decisions.

Beyond point forecasts, contemporary AI-enabled promotion forecasting tools provide scenario analysis and prescriptive recommendations to help managers evaluate alternative promotion designs before implementation. Managers can compare expected outcomes for different discounts, timing options, and targeting strategies, potentially improving the quality and consistency of promotion decisions. However, the usefulness of these systems depends not only on technical accuracy but also on how outputs are presented, interpreted, and embedded into existing decision processes.

2.2 Customer Segmentation Sophistication

Customer segmentation is a core input into AI-driven promotion forecasting and personalization. Retailers have moved from simple demographic or rule-based segmentation to data-driven approaches using clustering algorithms, behavioural features, and hybrid models that combine transactional, temporal, and attitudinal data. Sophisticated segmentation approaches can identify segments that differ in price sensitivity, promotion responsiveness, and channel preferences, enabling more precise targeting of promotional offers.

In many cases, segment information is embedded within forecasting and recommendation models, influencing elasticity estimates and uplift predictions without being explicitly communicated to managers. While such embedded segmentation can improve predictive performance, it may also reduce transparency for decision-makers, who may not fully understand how segments are defined or why certain promotions are recommended. As segmentation sophistication increases, the risk arises that managers perceive AI systems as “black boxes”, potentially limiting trust and adoption despite technical improvements.

2.3 Managerial Perception, Decision Support, and Governance

AI-based promotion forecasting systems function as decision support tools rather than fully automated decision-makers in most organized retail settings. Research on decision support and human–AI collaboration highlights that managers’ perceptions of system outputs—such as perceived forecast accuracy, relevance, interpretability, and usefulness—strongly influence whether AI recommendations are followed or overridden. Opaque models, complex interfaces, or misalignment with managerial mental models can undermine trust, even when technical performance is high.

Organizational factors further shape AI adoption in promotion planning. Promotion decisions often involve cross-functional coordination among merchandising, marketing, finance, and analytics teams, creating ambiguity around decision rights and accountability. Governance structures that clarify roles, define when and how AI recommendations should be used, and address issues such as algorithmic bias and fairness are critical for building confidence in AI systems. Organizational readiness—skills, infrastructure, leadership support, and a data-driven culture—also affects the extent to which AI insights are integrated into routine promotion decisions.

Existing literature on AI in retail and marketing has predominantly emphasized improvements in predictive accuracy, model performance, and algorithmic sophistication. However, this stream of research often assumes a direct link between prediction quality and decision effectiveness, overlooking the socio-cognitive and organizational processes through which AI outputs are interpreted and used. At the same time, research on human–AI collaboration and decision support systems highlights the importance of interpretability, trust, and alignment with managerial mental models, but does not explicitly integrate these factors with the technical design of promotion forecasting systems. This fragmentation creates a conceptual gap in understanding how technical sophistication translates into actual decision impact in retail promotion planning. The present study addresses this gap by integrating these perspectives into a unified socio-technical framework.

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3. CONCEPTUAL FRAMEWORK

3.1 Key Constructs

This paper focuses on several key constructs within AI-based promotion forecasting in organized retail.

Customer segmentation sophistication refers to the extent to which a retailer uses advanced, data-driven methods (for example, behavioural clustering, hybrid models) to identify and operationalize customer segments in promotion planning.

ML-based forecasting inputs capture the breadth, depth, and quality of data and features used in AI promotion forecasting models, including pricing, promotion attributes, customer histories, and external variables.

Perceived forecast accuracy denotes managers' subjective assessment of how reliable and credible the AI-generated promotion forecasts are, irrespective of objective error metrics.

Perceived decision support quality reflects managers' perceptions of how useful, actionable, and relevant AI forecasts and scenarios are for planning and evaluating promotions.

Interpretability refers to the degree to which managers feel they can understand the logic, drivers, and implications of AI-generated forecasts and recommendations.

Managerial trust denotes managers' willingness to rely on AI-generated forecasts and recommendations in promotion decisions.

Organizational readiness and governance capture the presence of supportive infrastructure, skills, leadership, and formal structures (decision rights, policies, oversight mechanisms) for the responsible use of AI in promotion planning.

3.2 Proposed Relationships

The proposed socio-technical framework positions customer segmentation sophistication and ML-based forecasting inputs as key technical antecedents that shape how managers perceive AI-based promotion forecasts. As segmentation sophistication and the richness of ML inputs increase, AI models are expected to capture customer heterogeneity and promotion effects more accurately, improving perceived forecast accuracy and decision support quality. However, higher sophistication often comes with increased model complexity, which can reduce interpretability for non-technical managers.

Interpretability and managerial trust are therefore proposed as central mediating mechanisms. When AI systems provide clear explanations, intuitive visualizations, and understandable segment-level insights, managers are more likely to interpret forecasts correctly and develop trust in the system. Higher interpretability supports stronger perceived forecast accuracy and decision support quality, which in turn increases the likelihood that AI recommendations will influence promotion decisions.

Organizational readiness and governance are positioned as moderators of these relationships. In organizations with strong analytics capabilities, supportive leadership, and clear governance around AI use, managers are more likely to integrate AI forecasts into promotion planning and to balance AI recommendations with their own judgment. In contrast, in organizations with weak readiness or unclear governance, even technically strong AI systems may be underutilized or inconsistently applied. The framework thus links technical sophistication with managerial perceptions and organizational conditions to explain when AI-based promotion forecasting systems are likely to improve decision-making in organized retail.

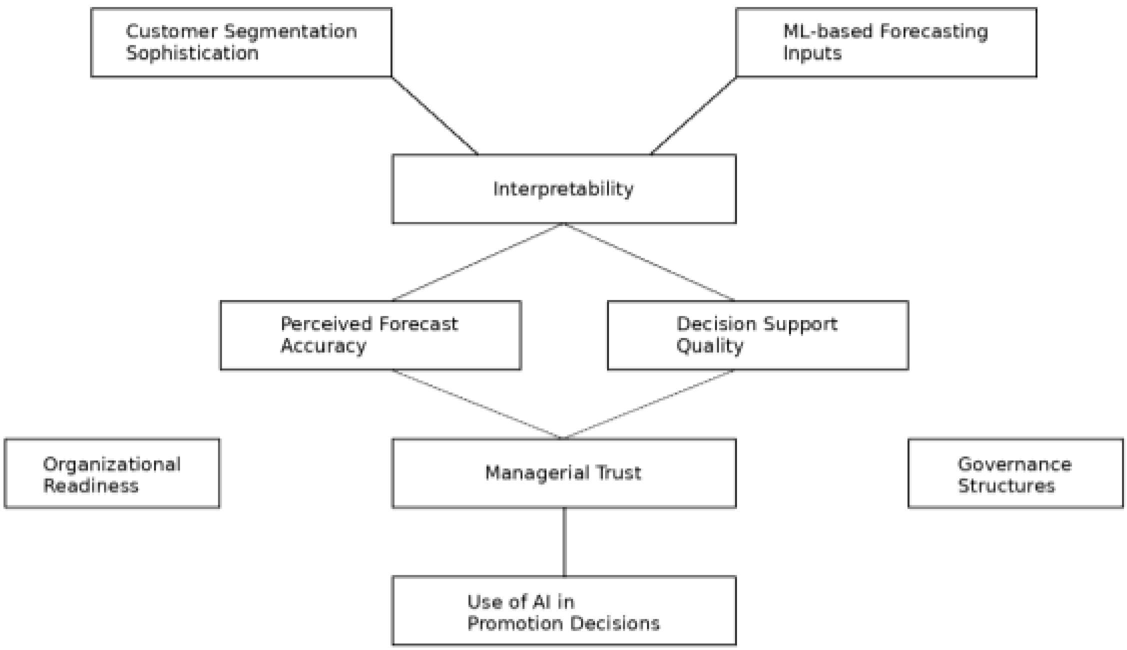

Figure 1: Socio-Technical Framework for AI-Based Promotion Forecasting in Retail

4. PROPOSITIONS

Based on the conceptual framework, the following propositions are advanced to guide future empirical research:

P1: Higher customer segmentation sophistication in AI-based promotion forecasting systems is positively associated with managers' perceived forecast accuracy, provided that key aspects of the segmentation logic are communicated in an understandable manner.

P2: Greater richness and quality of ML-based forecasting inputs (for example, more comprehensive customer and contextual data) are positively associated with perceived decision support quality for promotion planning.

P3: Interpretability of AI-generated promotion forecasts mediates the relationships between (a) customer segmentation sophistication and perceived forecast accuracy and (b) AI-based forecasting inputs and perceived decision support quality.

P4: Managerial trust in AI-based promotion forecasting systems mediates the relationship between perceived forecast accuracy and the extent to which AI-generated forecasts influence promotion planning decisions.

P5: Organizational readiness for AI (in terms of skills, infrastructure, and leadership support) positively moderates the relationship between perceived decision support quality and the use of AI-generated forecasts in promotion planning.

P6: Clear governance structures (including defined decision rights, accountability, and oversight mechanisms for AI use) strengthen the positive effects of interpretability and managerial trust on the use of AI-based promotion forecasts in decision-making.

P7: The relationship between model sophistication and managerial trust is non-linear, such that beyond a certain level, increasing complexity reduces trust due to perceived opacity.

P8: The positive effects of interpretability on trust are stronger for non-technical managers than for analytically trained managers.

5. IMPLICATIONS AND FUTURE RESEARCH

5.1 Theoretical Implications

The proposed socio-technical framework contributes to emerging literature on AI in retail and marketing by moving beyond algorithmic accuracy to emphasize the role of segmentation sophistication, interpretability, trust, and governance in AI-based promotion forecasting. It integrates technical and organizational perspectives by linking model inputs and segmentation design with managerial perceptions and organizational conditions. The propositions offer a basis for empirical studies that can test mediation and moderation mechanisms in different organized retail contexts.

5.2 Managerial Implications

For practitioners, the framework suggests that investments in AI and segmentation must be complemented by efforts to enhance interpretability, trust, and governance to realize decision-making benefits. Retailers should design promotion forecasting interfaces that make segment logic and key drivers of forecasts visible in a simple way, provide explanations for recommendations, and establish clear guidelines on when and how managers should use or override AI outputs. Strengthening organizational readiness—through training, cross-functional collaboration, and leadership support—can help integrate AI forecasts into promotion planning routines.

5.3 Future Research Directions

Future empirical studies can operationalize the constructs in this framework and test the propositions using survey-based structural equation modelling, experiments, or case studies in organized retail. Researchers may examine how different forms of segmentation sophistication (for example, behavioural vs demographic, static vs dynamic) affect perceptions and outcomes, and how explainable AI techniques influence interpretability and trust in promotion forecasting. Comparative studies across sectors and countries can further explore contextual factors that shape the socio-technical dynamics of AI-based promotion forecasting.

6. CONCLUSION

This paper proposes a socio-technical framework for AI-based promotion forecasting in organized retail. By integrating customer segmentation sophistication, ML-based forecasting inputs, managerial perceptions (interpretability and trust), and organizational factors such as readiness and governance, the framework explains the conditions under which AI-driven promotion forecasting can meaningfully influence promotion decisions.

The propositions outlined in this study provide a foundation for future empirical research and offer practical guidance for retailers seeking to design AI-enabled promotion forecasting systems that are not only technically robust but also interpretable, trusted, and aligned with organizational decision processes.

Overall, this study highlights that the effectiveness of AI in retail promotion forecasting depends not only on model accuracy but also on interpretability, managerial trust, and organizational alignment.

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