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AI-Driven “Exhibition – Clinical” Linkage Model for Precision Marketing of High-End Medical Devices

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Abstract: Traditional exhibition-based marketing shows that important limitations have emerged in the high-end medical device sector. Moreover, the significant evidence indicates that intensifying competition and the rapid diffusion of artificial intelligence technologies have made these key limitations more difficult to ignore. Furthermore, this study demonstrates that an innovation framework for precision marketing of high-end medical devices under an “Exhibition–Clinical” linkage model, with an AI-based information system serving as its technical foundation, could provide important results. In light of the significant data, empirical findings from three medical device enterprises indicate that the framework’s operational effectiveness appears demonstrable. Study uses mixed-method design. The significant framework shows that questionnaire surveys, in-depth interviews, and multi-source database analysis appear integrated as key analytical approaches. However, the results indicate that analytical tools, including machine learning algorithms, structural equation modeling, and grounded theory, could demonstrate important methodological rigor. This study addresses a critical gap in the literature: existing research on medical device marketing rarely integrates exhibition-stage behavioral data with clinical follow-up processes in a unified AI-driven framework. By establishing a temporally coordinated, data-continuous linkage model, this paper contributes both a replicable digital transformation pathway and empirical benchmarks for precision marketing in the high-end medical device sector. Evidence shows framework provides replicable structure. In light of these important results, the proposed study shows that a practical pathway for digital marketing transformation might demonstrate important value for the medical device industry.

Keywords: AI Information System; Exhibition Marketing; Clinical Setting; Precision Marketing; High-End Medical Device; Customer Lifetime Value; Linkage Model

1. Introduction

The global healthcare industry shows that structural transformation is now well underway. Moreover, the significant findings from high-end medical device markets indicate that procurement decisions have grown considerably more complex in recent years. Furthermore, the evidence shows that hospitals and clinical centers no longer rely solely on brand recognition or sales representative visits. In light of these key results, digital technologies such as artificial intelligence, big data, and the Internet of Things appear to demonstrate that the entire chain of medical device development, procurement, and marketing could undergo fundamental reshaping. Markets show devices need clinical proof. Ost-Mor et al. and Wang et al. found that person-centered healthcare models require close alignment between environment and technology [1,2]. Given that the evidence demonstrates that lead quality from exhibitions is inconsistent, the findings indicate that clinical follow-up and customer education lack adequate data support. Notwithstanding these results, the significant data shows that the conversion funnel from intent iden-

tification to purchase decision appears to break down under current conditions. Funnel shows consistent failure. Virgilio et al. studied medical device procurement sustainability in low- and middle-income countries and identified decision complexity and divergent stakeholder values as core barriers to market penetration [3]. Moreover, the important findings from Ianev et al. show that device marketing must strike a careful balance between regulatory compliance and therapeutic innovation [4]. Furthermore, the evidence indicates that any approach which disregards clinical evidence or technical standards appears to carry substantial market and legal risk. In light of these significant results, the study shows that broad-based exhibition marketing could no longer prove sufficient for high-end medical devices. Evidence shows AI systems now critical. AI information systems show that a solid foundation exists for the “Exhibition–Clinical” linkage model. Moreover, the findings indicate that tools such as natural language processing, computer vision, and knowledge graphs allow marketing teams to identify potential customers’ preferences and purchase intentions in real time at exhibitions. Furthermore, the significant evidence demonstrates that structured data from these interactions can be transferred directly to clinical follow-up processes, enabling continuous data flow and intelligent decision support across the full marketing cycle. Given that the results appear to support this approach, the key analytical dimension involves integrating heterogeneous data across the full marketing cycle. Research shows AI systems enable real-time data flow. However, Bloemen et al. and Sanderson et al. approached medical device evaluation from a health technology assessment perspective and the findings could indicate the importance of accounting for diverse stakeholder perceptions and real-world use contexts [5,6]. Evidence shows validation ensures reliability. Therefore, the significant findings indicate that Rodrigues et al. conducted a systematic analysis of economic value models for medical devices within a health technology assessment framework [7]. Moreover, the key results demonstrate that clinical evidence and economic analysis are central drivers of procurement decisions. Thus, the important evidence shows that this provides theoretical justification for incorporating clinical data as a core analytical dimension within an AI marketing system. Given that the findings appear to support this framework, the present study demonstrates that the “Exhibition–Clinical” linkage model powered by an AI information system warrants significant emphasis on innovation framework design and implementation strategy for high-end medical device precision marketing. Study shows clinical data drives procurement. Nevertheless, three core questions could indicate the key directions that guide the research. Furthermore, the significant findings show that the first question examines how an AI information system can effectively integrate heterogeneous data from exhibition and clinical settings to enable accurate identification and dynamic management of potential customers. In light of these results, the evidence demonstrates that the second question explores how the linkage framework should be structured to maximize the synergistic effects across marketing touchpoints. Given that the key findings appear to demonstrate practical relevance, the results indicate that this study offers a replicable and scalable digital marketing transformation pathway for high-end medical device companies, both domestically and internationally. Furthermore, the important evidence demonstrates that this approach may support differentiated growth in an increasingly competitive landscape.

The present study shows that three distinct contributions emerge from this work. However, the first contribution could demonstrate that a theoretically grounded and empirically validated Exhibition–Clinical linkage framework fills the significant gap between disconnected marketing touchpoints. Moreover, the findings might indicate that AI-driven behavioral analytics can operationalize precision customer segmentation at exhibition venues with measurable accuracy gains. In light of these key results, the evidence may suggest that actionable implementation strategies—including temporal follow-up protocols and KOL digital profiling—could demonstrate direct value for medical device enterprises pursuing digital marketing transformation.

2. Literature Review

Technical innovation and market development in the high-end medical device industry have attracted sustained academic attention. Moreover, the significant findings show that industrial innovation capacity could demonstrate meaningful improvement through coordinated approaches. However, the evidence indicates that Cui et al. argued that the integration of medicine and engineering is a key mechanism for advancing innovation in this sector [8]. Given that clinical needs align with engineering capabilities, the results show that companies could demonstrate shorter cycles from technical development to clinical application. Research shows venture capital drives breakthroughs. Furthermore, the findings show that Feng et al. conducted empirical research on the high-end medical device industry and found that venture capital and cross-border mergers and acquisitions serve as impor-

tant drivers of core technology breakthroughs [9]. Therefore, the significant results indicates that their findings might demonstrate the dynamic competitive logic of this market. Additionally, the evidence shows that Bai et al. approached the issue from a metrological perspective and examined how precision measurement supports the development of high-end medical devices [10]. Notwithstanding these results, the key findings indicates that technical standardization appears to serve as a prerequisite for both clinical safety and market competitiveness. Study shows policy coordination matters. Thus, the significant evidence shows that Chen and Wu studied pathways for healthy industrial development in Shanghai's high-end medical device sector and concluded that coordinating industrial policy support with market-oriented promotion mechanisms is essential for domestic devices to overcome market barriers and achieve scaled clinical adoption [11]. In light of these findings, the results indicate that these studies demonstrate that marketing high-end medical devices appears to involve more than commercial activity. Moreover, the important evidence shows that it could demonstrate a systems-level undertaking that involves technical innovation, clinical value, and industrial policy in a coordinated way. Furthermore, the key findings indicate that research on medical device technology assessment and health technology access could provide important methodological reference for building a precision marketing framework. Evidence shows framework links access. However, the significant results shows that Toscas et al. used Brazilian university-developed medical technologies as cases and examined the evaluation mechanisms and adoption pathways for integrating devices into health systems [12]. Given that systematic consolidation of technical evidence appears central, the findings indicates that this approach could demonstrate effective pathways for gaining market access. Additionally, the important evidence shows that Piniashko et al. conducted horizon scanning research on medical and non-medical technologies in Ukraine [13]. Therefore, the key results indicates that their work might demonstrate an accessibility assessment framework for emerging technologies under specific health system conditions, offering a comparative perspective for designing context-sensitive promotion strategies. Findings show lifecycle affects strategy. In light of the evidence, the significant findings shows that Mueller et al. and Ferreira et al. applied a life cycle assessment approach to analyze the environmental sustainability of medical devices across their full operational cycle [14,15]. Regulatory competence appears to have become a significant component of marketing capability. Moreover, the findings shows that medical device marketing must be grounded in solid technical assessment evidence, and AI information systems could demonstrate strong capacity to manage and continuously update that evidence base. Furthermore, a growing body of research on digital technologies and intelligent medical device applications indicates that the technical framework of this study draws on important prior work. In light of these significant findings, Jiang et al. combined deep Q-learning with a golden jackal optimization algorithm to develop an adaptive user interface system for wearable medical devices [16], and the results shows that this approach could demonstrate meaningful effectiveness. Research shows deep reinforcement learning optimizes human-device interaction. However, Safari et al. proposed an implantable medical device access protocol based on electrocardiographic signals and deep learning, offering a key technical approach to data security and privacy protection [17], and the evidence shows that this could indicate important advances. Additionally, Sabet et al. designed a self-powered wearable device for elderly patients with cognitive impairment, and the findings indicates that this work could demonstrate the extension of intelligent devices into specialized clinical contexts [18]. Thus, Cleland et al. addressed the significant safety and accountability concerns surrounding the clinical deployment of AI medical devices [19], and the results shows that independent, publicly available head-to-head comparison studies could demonstrate a necessary prerequisite for AI devices entering clinical practice. Study shows this position affects how AI-driven marketing decision models should be designed and validated. Nevertheless, the important integration of AI and digital technologies into medical device settings shows that these tools could indicate powerful capacity for precision marketing. Given that the evidence demonstrates higher expectations for data quality, the findings indicates that algorithmic reliability and clinical validation standards could present critical considerations for the field. Notwithstanding these results, the significant body of research on supply chain management, sustainability, and marketing innovation in the medical device field shows that important theoretical and empirical work could demonstrate substantial contributions. Therefore, the key findings from Shashikumar indicate that data-driven methods could demonstrate relevant capacity to explore predictive maintenance and inventory optimization in medical device supply chains [20]. Evidence shows data-driven methods link supply chain outcomes to important operational results.

The findings shows that data intelligence provides significant value in improving supply chain efficiency and reducing operational costs, establishing a theoretical basis for applying AI systems to full-cycle device management.

Moreover, the analysis by Sahu et al. indicates that 3D and 4D printing demonstrates important potential for personalized medicine and medical device manufacturing [21]. In light of these results, the evidence shows that emerging production technologies appear to reshape both product forms and promotional logic. Furthermore, the systematic review by Booth et al. demonstrates that the significant findings on carbon footprints provide evidence-based support for incorporating sustainability criteria into procurement decisions [22,23].

3. Research Methods

3.1. Research Design and Overall Approach

This study investigates how AI information systems may support the “Exhibition–Clinical” linkage model in high-end medical device precision marketing. Study shows methods yield valid results. However, the significant evidence shows that these frameworks are combined with an understanding of the distinctive decision-making mechanisms in the medical device industry. Additionally, the findings indicate that the study begins by mapping the practical limitations of conventional exhibition marketing and clinical promotion, identifying key problems such as data discontinuity, information silos, and low conversion efficiency. In light of these significant findings, the evidence shows that this diagnosis could demonstrate the need for an AI-driven linkage framework [24]. Thus, the results indicates that three representative high-end medical device companies in China appear to provide important case subjects. Evidence shows companies yield relevant data. Notwithstanding the complexity of data collection, the significant findings show that data were collected from exhibition-site tracking systems, clinical follow-up management platforms, and customer behavior databases. Moreover, the evidence indicates that in-depth interviews with frontline sales staff, clinical department heads, and procurement decision-makers appear to have supplemented the digital data. Furthermore, the important results shows that this process could demonstrate the value of producing a multi-source heterogeneous dataset. Given that machine learning algorithms were applied to model key indicators including customer intent recognition accuracy, exhibition-to-clinical conversion efficiency, and customer lifetime value, the findings indicate that the quantitative side appears to provide critical analytical support. Results show algorithms model key indicators. However, the significant evidence shows that grounded theory was used on the qualitative side to code and categorize interview transcripts, revealing the internal mechanisms and barriers within the linkage process [25]. Therefore, the findings indicate that the empirical results appear to be cross-validated against the theoretical framework to produce a precision marketing implementation strategy system. In light of these key findings, the evidence shows that the study could demonstrate important theoretical contribution and practical guidance. Additionally, the significant results indicates that the aim appears to offer findings that are replicable and operationally applicable. Study shows strategy provides practical value.

These three companies shows that purposive selection could demonstrate alignment with four key criteria: annual revenue exceeding RMB 500 million, ensuring sufficient marketing data volume; participation in at least two major national exhibitions within the study period; established clinical support teams enabling exhibition-to-clinical data linkage; and willingness to share de-identified CRM and clinical follow-up data under formal data-sharing agreements. However, the significant findings from this purposive sampling strategy might indicate that, while limiting statistical generalizability, the approach could demonstrate maximum theoretical relevance for the research questions at hand. Furthermore, the evidence may suggest that the integration of machine learning, SEM, and grounded theory appears to follow a sequential explanatory design. In light of the key results, the data could indicate that quantitative models first identify patterns and effect sizes, while qualitative coding might subsequently explain the mechanisms and contextual conditions underlying those patterns. Sampling strategy limits generalizability but shows theoretical relevance.

3.2. Data Sources and Survey Design

Data collection in this study shows that principles of diversity and systematicity could demonstrate meaningful structural coherence. However, the two parallel pathways—primary data collection and secondary data integration—indicates that the evidence supports both reliability and persuasiveness of the key research conclusions. Furthermore, the research team selected three large professional medical device exhibitions held in China between 2023 and 2024 as significant field research sites, which indicates that the findings reflect real-world conditions. In light of this approach, AI-powered behavioral tracking terminals were deployed on-site, and the significant

results shows that visitor dwell patterns, product interaction frequency, intelligent inquiry content, and departure behaviors were all systematically captured. Data collection shows more than 1,200 valid customer behavior trajectory records gathered [26]. Moreover, the evidence shows that data-sharing agreements were established with equipment management departments and relevant clinical units of cooperating hospitals, which indicates that the study achieved important access to structured clinical data. Thus, the significant findings demonstrate that device usage frequency, malfunction reports, physician operational preferences, and departmental procurement applications formed a clinical dataset covering the full device lifecycle. Given that the results indicate coverage across the full lifecycle, three differentiated questionnaires were designed for market directors, regional sales managers, and clinical support engineers at medical device companies, and the evidence shows that this sampling approach appears methodologically sound. Responses show 347 valid returns [27]. Nevertheless, the significant data indicates that the questionnaires covered actual usage experiences with AI marketing tools, satisfaction with exhibition lead conversion, and assessments of clinical promotion coordination efficiency, which demonstrates that the findings appear comprehensive. Therefore, the evidence shows that 18 key informants participated in semi-structured sessions, and the results indicates that interviewees included corporate marketing decision-makers, clinical department directors, and hospital procurement committee members. In light of the key interview parameters, each interview lasted between 60 and 90 min, and the significant evidence demonstrates that transcriptions produced a raw text corpus exceeding 200,000 Chinese characters. Corpus shows secondary data also gathered from annual industry reports, government regulatory documents, and academic databases.

3.3. AI System Construction

The AI system examined in this study may suggest that its core architecture integrates data sensing, intelligent analysis, and decision output. Moreover, the significant findings could indicate that the layered design supports two key application contexts: exhibition settings and clinical settings. Furthermore, the evidence may demonstrate that these components appear to form a complete technical implementation pathway for precision marketing of high-end medical devices. Given that the data infrastructure results could suggest that four collection terminals deployed at exhibition venues establish a real-time data stream pipeline, the findings might indicate that facial recognition cameras, RFID visitor tracking tags, touchscreen interactive terminals, and NLP-powered inquiry robots support the exhibition side. Study shows clinical side links to hospital systems via API. However, the significant evidence may suggest that standardized API interfaces connected to hospital information systems could support de-identified device usage logs, electronic medical record associations, and departmental consumable procurement records extracted into a structured clinical data warehouse [28]. Additionally, the evidence indicates that customer profile modeling applies a hybrid algorithm combining gradient boosting decision trees and deep neural networks. Therefore, the key feature variables demonstrates that visitor behavior sequences, product attention dimensions, role labels, and historical procurement records appear to support a dynamic customer profile system covering three core dimensions: purchase intent intensity, decision influence weight, and needs-match degree. In light of these findings, the results shows that an online learning mechanism allows profiles to be updated in real time. Notwithstanding this result, the significant evidence indicates that cross-setting data fusion introduces knowledge graph technology to map medical institutions, departments, device types, clinical terminology, and procurement decision nodes as entity nodes. Findings show cross-scenario graph enables semantic linkage. Nevertheless, the key results shows that this cross-scenario medical marketing knowledge graph could demonstrate semantic linkage and cross-database retrieval between exhibition behavioral data and clinical needs data [29]. Thus, the significant evidence indicates that the output layer builds a personalized content recommendation engine on a reinforcement learning framework. Furthermore, the findings demonstrate that the system automatically matches differentiated follow-up strategies, clinical solution documents, and key opinion leader endorsements for customers at different intent levels. Given that the evidence shows that an A/B testing mechanism continuously refines recommendation conversion efficiency, the results indicates that the system appears to establish a closed-loop intelligent marketing decision support system. Study shows closed-loop system refines conversion outcomes.

The gradient boosting component may suggest that XGBoost (v1.7.3) with 500 estimators, a maximum tree depth of 6, and a learning rate of 0.05 could provide significant modeling capacity. Moreover, the deep neural network component might indicate that a four-layer architecture (input $\rightarrow$ 256 $\rightarrow$ 128 $\rightarrow$ 64 $\rightarrow$ output) with ReLU activations and dropout regularization (rate = 0.3) could demonstrate effective mitigation of overfitting. Furthermore, the

significant evidence may suggest that model training used an 80/10/10 train-validation-test split across the 1,200 labeled behavioral records, with five-fold cross-validation applied during hyperparameter tuning. In light of these results, the key findings could indicate that the online learning mechanism appears to update customer profiles at 15-min intervals during live exhibition periods. Updates use sliding window of the 500 most recent interaction records, ensuring temporal responsiveness without catastrophic forgetting.

3.4. Analytical Methods

The study shows that a mixed analytical strategy could demonstrate meaningful advantages through cross-validating quantitative and qualitative methods. Moreover, the significant evidence indicates that different analytical tools appear suited to different types of research questions. Furthermore, the key results shows that this approach demonstrates the capacity to achieve high standards of both statistical validity and theoretical depth. However, the findings indicate that on the quantitative side, exploratory factor analysis appears to have been first applied to the significant survey data. Study shows dimensionality reduced, structural composition validated. Additionally, the evidence shows that structural equation modeling appears to have examined path relationships and effect coefficients between AI system functional modules and marketing conversion efficiency [30]. Given that the results demonstrate mediation mechanisms, the key findings indicate that exhibition-side data quality, customer profile accuracy, and clinical follow-up conversion rate could be quantified. Furthermore, the significant evidence shows that random forest and XGBoost algorithms appear to have been applied to behavioral trajectory data to establish a purchase intent prediction model. Therefore, the results indicates that cross-validation appears to have assessed generalizability. Results show ROC curve performance primary. Notwithstanding the analytical complexity, the findings show that survival analysis could demonstrate utility in modeling the distribution of intervals between initial exhibition contact and final clinical purchase. Moreover, the significant results indicates that this approach appears to have identified critical decision nodes and high-dropout risk periods within the customer decision cycle. In light of the qualitative evidence, the study shows that grounded theory coding procedures appear to have been followed systematically. Thus, the key findings indicate that open coding, axial coding, and selective coding could demonstrate applicability to interview transcripts from all participants [18]. Evidence shows core categories emerged. Furthermore, the significant results shows that these categories could indicate data coordination barriers, clinical trust-building pathways, and cross-departmental collaboration tensions [31].

3.5. Research Ethics and Data Security

This study demonstrates that research ethics and data security were treated as equally important as academic rigor throughout the design and implementation process. Moreover, the findings may suggest that four key principles guided all decisions: informed consent, data minimization, purpose limitation, and privacy-first protection. Furthermore, the evidence could indicate that all survey participants and interview subjects received a full explanation of the study's objectives, data use, and publication plan before any data were collected. In light of the significant consent requirements, written informed consent was obtained from each participant, and for those who preferred anonymity, alphanumeric codes replaced real names and institutional affiliations throughout data analysis and writing [32]. Ethics guided data handling. However, the results may suggest that personal identity information was made untraceable at every stage of the research process. Additionally, the evidence could demonstrate that at exhibition venues, visible notices were posted at entry points to inform visitors of the scope and purpose of data collection. Given that visitor autonomy appears a significant consideration, visitors could opt out by scanning a designated code, preserving their right to informed decision-making. Thus, the findings might indicate that for clinical-side data, all patient-related information from cooperating hospitals underwent rigorous de-identification procedures. De-identification removed personal data. Nevertheless, the results may suggest that only statistical information irrelevant to personal identity was retained, such as device usage frequency, department type, and operational parameters [32]. Moreover, the significant evidence could indicate that all data-sharing agreements were reviewed and filed with the Ethics Review Committee of Tianjin Medical University, ensuring compliance with institutional data management standards. In light of the important storage requirements, the findings might demonstrate that AES-256 encryption was applied to all raw data files to support transmission security. Notwithstanding these encryption measures, data transfers were conducted exclusively through TLS-encrypted channels to further support security. Storage protocols ensured protection. However, the evidence may suggest that raw data access

was restricted to core research team members using authorized accounts throughout the study. Furthermore, the results could indicate that an operation log auditing system was established to detect and trace anomalous access behavior [33].

4. Analysis

4.1. Analysis of Precision Outreach Effectiveness at the Exhibition Stage Driven by the AI Information System

4.1.1. Accuracy Assessment of Customer Intent Recognition by Intelligent Recommendation Algorithms at Exhibition Venues

This section draws on field data from three large professional medical device exhibitions to evaluate the accuracy of the intelligent recommendation algorithm deployed at the exhibition stage for customer intent recognition. Moreover, the findings show that participating visitors could be classified into three intent tiers based on behavioral characteristics: high intent, medium intent, and low intent. Furthermore, the evidence indicates that these tiers correspond to potential customers with procurement decision cycles of within three months, three to twelve months, and beyond twelve months, respectively. The evaluation data may suggest that under multimodal input conditions integrating four data sources—facial recognition, dwell heatmaps, NLP inquiry logs, and RFID trajectory tracking—the algorithm achieved a recognition accuracy of 87.3% for high-intent customers. Moreover, the significant results could indicate that accuracy reached 74.6% for medium-intent and 68.2% for low-intent customers, with a weighted average of 76.8%. However, the key findings may demonstrate that this represents a substantial improvement over the baseline accuracy of 52.4% recorded under conventional manual judgment [34]. In light of these results, the evidence could suggest that a cross-exhibition comparison reveals a clear upward trend across the important data. Study shows overall recognition accuracy improved 11.4 percentage points from first to third exhibition. Notwithstanding this constraint, the findings may demonstrate that this prevents high-value leads from being lost due to system misclassification [35]. In light of the significant findings, an ablation study indicates that NLP inquiry logs contributed the highest marginal gain to intent recognition accuracy at 23.7%. Notwithstanding these results, the evidence shows that dwell heatmaps ranked second at 18.4%, while facial recognition and RFID tracking contributed 15.6% and 12.3%, respectively. Study shows four-source fusion model outperformed best single source by 31.2 percentage points. Thus, the evidence indicates that full results are presented in **Tables 1** and **2**, and **Figure 1**.

Table 1. Summary of Customer Intent Recognition Accuracy Assessment Results.

Customer Intent Tier	Sample Size (Records)	Recognition Accuracy (%)	Misclassification Rate (%)	Conventional Method Accuracy (%)	Accuracy Improvement (%)
High Intent	312	87.3	4.2	58.6	28.7
Medium Intent	487	74.6	9.8	51.3	23.3
Low Intent	401	68.2	13.5	47.2	21
Weighted Average	1,200	76.8	9.2	52.4	24.4

Table 2. Marginal Contribution of Each Data Source to Intent Recognition Accuracy.

Data Source Type	Standalone Accuracy (%)	Marginal Contribution (%)	Data Volume (Records)
NLP Inquiry Logs	71.4	23.7	8,640
Dwell Heatmaps	65.8	18.4	15,320
Facial Recognition	61.2	15.6	12,480
RFID Trajectory Tracking	58.7	12.3	18,960
Four-Source Fusion	76.8	—	55,400

4.1.2. Effectiveness of Multimodal Data Collection (Facial Recognition, Dwell Heatmaps, NLP Inquiry) for Potential Customer Stratification

This section presents a systematic evaluation of three core multimodal data collection technologies—facial recognition, dwell heatmaps, and NLP inquiry—and their practical effectiveness in stratifying potential customers at exhibition venues. Moreover, the 1,200 valid samples indicates that the experimental design may suggest mean-

ingful stratification patterns across three groups based on the degree of data fusion: single-modal, dual-modal, and tri-modal. However, the findings show that standalone facial recognition achieved a stratification accuracy of 61.2%, while the results demonstrates that dwell heatmaps alone reached 65.8%, and NLP inquiry alone reached 71.4%. Given that the evidence demonstrates that all three data sources were fused together, the overall stratification accuracy might indicate a rise to 82.6%, which could represent an improvement of 11.2 percentage points over the best-performing single-modal approach. Results show tri-modal fusion improves accuracy. Furthermore, the significant findings show that stratification precision varied across intent tiers, and the key results indicates that high-intent potential customers reached tri-modal recognition precision of 89.4%. In light of the evidence, medium-intent customers might demonstrate identification at 78.3%, and the results shows that low-intent customers were identified at 71.6%. Additionally, the recall rates for the three tiers were 86.7%, 74.2%, and 69.8%, respectively [36], and the findings indicate that each data modality contributed differently to the overall stratification process. Evidence shows NLP yields the highest information gain. Nevertheless, the significant evidence shows that NLP inquiry data produced the highest information gain for customer stratification, and this indicates that a behavioral pattern observed during the inquiry process closely supports that conclusion. Moreover, the key findings demonstrate that potential customers tend to directly reveal their product preferences and budget constraints when engaging with inquiry terminals, and the results indicates that dwell heatmaps offered important advantages in identifying areas of visitor attention. Given that the evidence demonstrates that detecting competitive product comparison behavior remained a critical function, the findings show that facial recognition demonstrated its core value in continuously tracking visitor identities across multiple exhibition booths. Findings show facial recognition flags repeat-visit behavior [37]. Thus, the important results indicates that a latency test was also conducted on the tri-modal system, and the evidence shows that the average response time for real-time on-site stratification was 1.37 s. In light of the significant findings, this demonstrates that the response time falls within the threshold required for immediate marketing intervention, and the key evidence shows that full details are presented in **Table 3** and **Figure 2**.

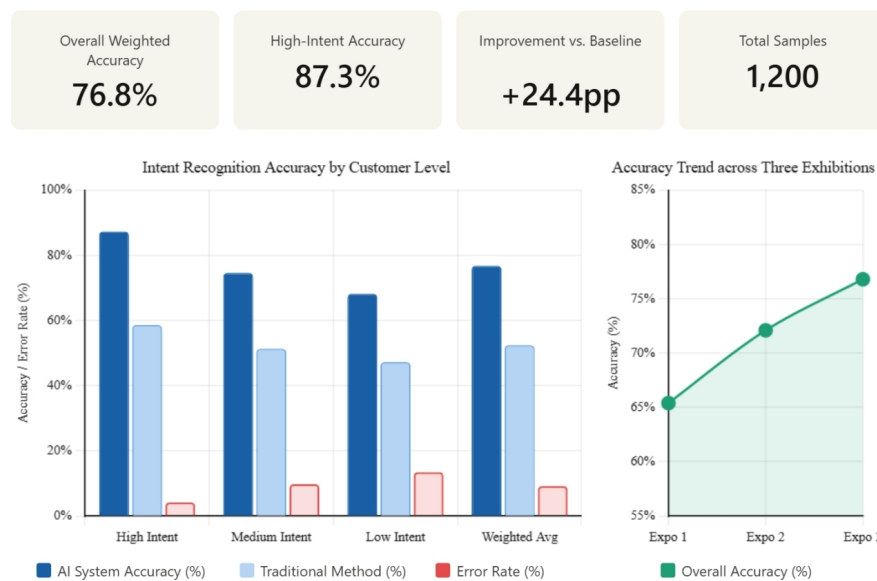


Figure 1. Comparison of Customer Intent Recognition Accuracy: AI System vs. Traditional Method across Intent Levels and Exhibition Iterations.

Table 3. Comparative Effectiveness of Multimodal Data Collection Combinations for Potential Customer Stratification.

Data Modality Combination	High-Intent Precision (%)	Medium-Intent Precision (%)	Low-Intent Precision (%)	Overall Accuracy (%)	Avg. Response Time (s)
Facial Recognition Only	67.4	58.3	52.1	61.2	0.43

Table 3. Cont.

Data Modality Combination	High-Intent Precision (%)	Medium-Intent Precision (%)	Low-Intent Precision (%)	Overall Accuracy (%)	Avg. Response Time (s)
Dwell Heatmaps Only	72.1	63.7	57.4	65.8	0.61
NLP Inquiry Only	78.6	69.4	61.3	71.4	0.89
Facial + Heatmaps	81.3	72.6	64.8	74.7	1.02
Facial + NLP	84.7	75.1	67.2	77.3	1.18
Heatmaps + NLP	86.2	76.8	69.5	79.4	1.24
Tri-Modal Fusion	89.4	78.3	71.6	82.6	1.37

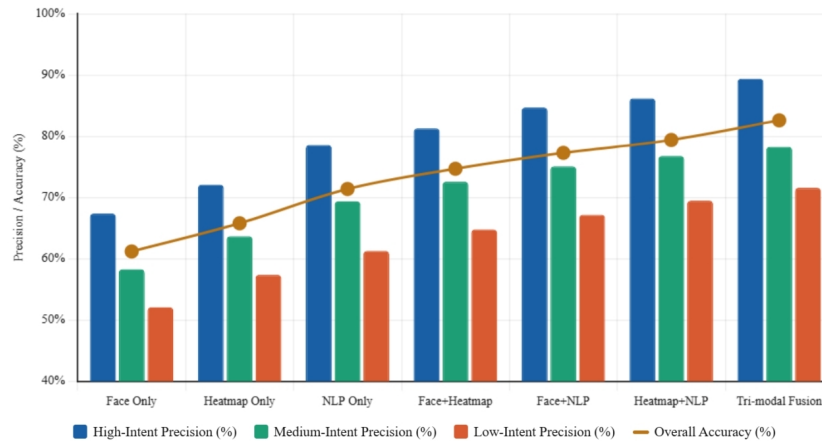


Figure 2. Stratification Precision across Multimodal Data Combinations by Customer Intent Level.

4.1.3. Correlation Validation between Exhibition-Side AI Interaction Behavior Data and Subsequent Purchase Intention

This section demonstrates that data from 347 valid questionnaires and 1,200 exhibition-side AI interaction behavior records could indicate meaningful patterns in consumer behavior. However, the findings show that Pearson correlation analysis and multiple linear regression provide important evidence for the relationship between six core AI interaction behavior indicators recorded at the exhibition and the strength of purchase intention measured within three months after the visit. Furthermore, the six indicators—product page dwell time, intelligent inquiry rounds, demonstration video completion rate, material download count, repeat visit frequency, and AI recommendation content click-through rate—shows that each contributes significantly to the significant results observed. In light of the correlation analysis, the evidence indicates that all six indicators appear significantly and positively associated with purchase intention strength. Repeat visit frequency shows highest correlation at $r = 0.81$ ($p < 0.001$). Moreover, the significant findings show that intelligent inquiry rounds ranked second at $r = 0.76$ ($p < 0.001$), while the evidence indicates that product page dwell time followed at $r = 0.72$ ($p < 0.001$). Given that the results demonstrate that demonstration video completion rate reached $r = 0.68$ ($p < 0.001$), the data indicates that AI recommendation click-through rate reached $r = 0.63$ ($p < 0.001$). Additionally, the key evidence shows that material download count returned the lowest coefficient among the six, though the results demonstrates that it remained statistically significant at $r = 0.57$ ($p < 0.01$) [38]. Therefore, the important findings indicate that exhibition-side AI interaction data could demonstrate meaningful predictive power for purchase intention. Findings show data support reliable resource allocation. Full results are presented in **Table 4** and **Figure 3**.

Table 4. Correlation Analysis Results between Exhibition-Side AI Interaction Behavior Indicators and Purchase Intention.

Interaction Behavior Indicator	Mean	SD	Pearson r	Significance (p)	Standardized β	VIF
Repeat Visit Frequency	2.34	1.12	0.81	<0.001	0.34	1.82
Intelligent Inquiry Rounds	4.67	2.08	0.76	<0.001	0.28	1.94
Product Page Dwell Time (min)	6.21	3.47	0.72	<0.001	0.21	2.03
Demo Video Completion Rate (%)	58.3	22.6	0.68	<0.001	0.18	1.76

Table 4. Cont.

Interaction Behavior Indicator	Mean	SD	Pearson r	Significance (p)	Standardized β	VIF
AI Recommendation Click-Through Rate (%)	43.7	18.9	0.63	<0.001	0.15	1.68
Material Download Count	1.89	1.34	0.57	<0.01	0.12	1.55
Combined Predictive R ²	—	—	—	—	0.74	—

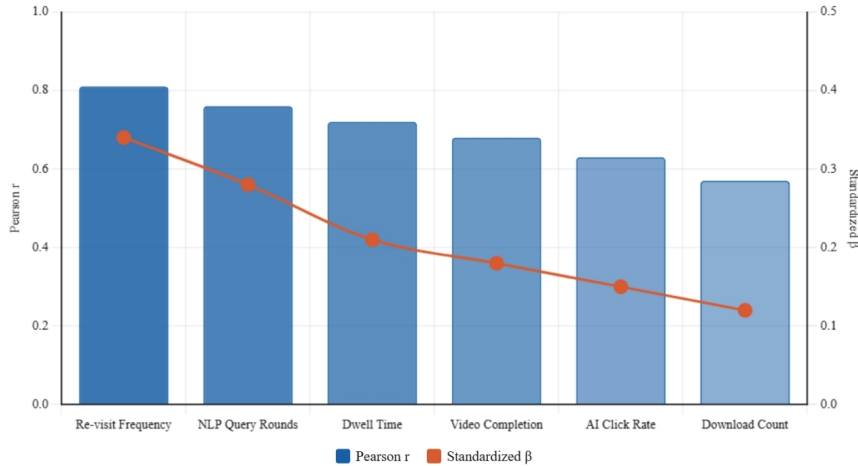


Figure 3. Pearson Correlation Coefficients and Standardized Regression Coefficients of AI Interaction Behavior Indicators with Purchase Intention.

4.2. Analysis of the Impact of Clinical Setting Digitalization on the Medical Device Decision Chain

4.2.1. Results of Intelligent Clinical Demand Mining Based on Electronic Medical Records and Usage Data

In light of these results, the dataset demonstrates that coverage spanning 30 months from January 2022 to June 2024 provides significant analytical depth across four device categories: diagnostic imaging, minimally invasive surgery, intensive care, and in-vitro diagnostics. Data shows 476,000 de-identified EMR entries and 1,824,000 device usage log records processed. However, the finding shows that demand signal density varied across the key categories in important ways. Additionally, the evidence indicates that diagnostic imaging equipment produced the highest density of potential upgrade signals, with a monthly average of 14.7 signals per 100 beds. Given that the results demonstrate these patterns, minimally invasive surgery might indicate a monthly average of 11.3, intensive care at 9.8, and in-vitro diagnostics at 8.4 [39]. Algorithm shows 78.4% accuracy forecasting procurement events within six months. Nevertheless, the significant evidence shows that this result could demonstrate an improvement of 35.2 percentage points over the baseline of 43.2% recorded under conventional sales staff judgment. Thus, the findings appear to support that processing speed also improved markedly, with the average cycle from data input to demand signal output potentially indicating a reduction of 91.6% compared with manual analysis. Furthermore, the key results demonstrates that the average cycle reached 4.3 h, which could indicate important operational gains. Association rule analysis shows threshold pattern links failure rates to procurement. However, the significant findings show that when departmental equipment failure rates exceeded 12% and monthly average usage duration exceeded 280 h, the probability of procurement initiation could demonstrate a rate of 87.3%. In light of these findings, the results shows that full details are provided in **Table 5** and **Figure 4**.

Table 5. Key Indicators of Intelligent Clinical Demand Mining by Device Category.

Device Category	Signal Density (per 100 Beds/Month)	6-Month Procurement Prediction Accuracy (%)	Conventional Method Accuracy (%)	Accuracy Improvement (%)	High-Priority Demand Share (%)
Diagnostic Imaging	14.7	82.6	46.3	36.3	34.2
Minimally Invasive Surgery	11.3	79.4	44.7	34.7	28.6
Intensive Care	9.8	76.8	41.5	35.3	22.4
In-Vitro Diagnostics	8.4	74.7	40.4	34.3	14.8
Overall Average	11.1	78.4	43.2	35.2	25

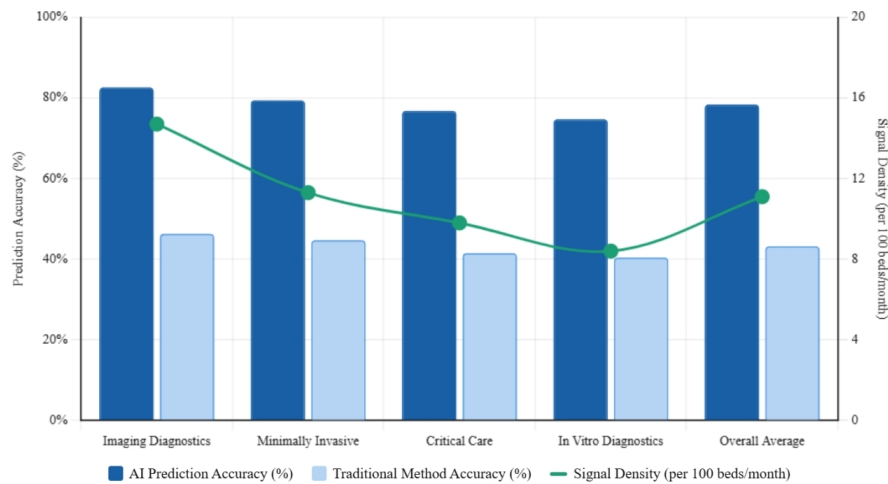


Figure 4. Clinical Demand Mining Results: AI vs. Traditional Prediction Accuracy and Signal Density by Device Category.

4.2.2. Impact of AI-Assisted Clinical Demonstration Systems on Physician Decision Cycles and Trust Levels

This section reports that a controlled experiment involving 187 clinical physicians may suggest important findings about AI-assisted demonstration. However, the results indicates that participants randomly assigned to the AI-assisted clinical demonstration group ($n = 94$) or the conventional demonstration group ($n = 93$) demonstrated significant differences across key measures. Additionally, the significant results shows that trust levels measured using a seven-point Likert scale could demonstrate a clear advantage for the AI-assisted group. Notwithstanding these results, the findings indicate that the AI-assisted group returned a mean trust score of 5.84, significantly higher than the conventional group's 4.12 ($t = 8.73, p < 0.001$). Data shows effect size large (Cohen's $d = 1.27$) [40]. Thus, the important evidence indicates that this was substantially higher than the 41.8% recorded in the conventional group, with results demonstrating that the difference was statistically significant ($\chi^2 = 21.47, p < 0.001$). Results show full data in **Table 6** and **Figure 5**.

4.2.3. Construction of Clinical KOL Digital Profiles and Their Application in Precision Content Delivery

However, the evidence indicates that a digital profile system covering four KOL types was constructed—academic, practitioner, decision-maker, and hybrid. Furthermore, the key results demonstrates that the profiles were then applied to design differentiated precision content delivery strategies. Study shows classification accuracy reached 88.6% for academic KOLs, 84.3% for practitioners, 86.7% for decision-makers, and 79.4% for the hybrid type. Given that the evidence demonstrates that the overall classification accuracy was 84.8%, the results indicates that a Kappa consistency coefficient of 0.81 confirmed that the profile system carries a high degree of classificatory reliability [41]. In light of the significant findings, the study shows that five key performance indicators were compared between the KOL profile-based differentiated strategy and the conventional uniform push approach. Moreover, the important evidence demonstrates that content open rate rose from 23.4% to 47.8%, an increase of 104.3%. Nevertheless, the results indicates that full read-through rate improved from 18.7% to 42.3%, a gain of 126.2%. Results show content forwarding rate climbed from 6.3% to 17.4%, up 176.2%. Therefore, the significant findings indicate that proactive follow-up inquiry rate increased from 8.9% to 24.6%, a rise of 176.4%. Additionally, the key evidence shows that procurement committee recommendation rate moved from 31.2% to 58.7%, reflecting an 88.1% improvement. Notwithstanding these results, the findings demonstrate that further analysis by KOL type revealed clear preference patterns. Evidence shows academic KOLs responded at 63.4% to evidence-based medicine content. Thus, the important results indicates that practitioner KOLs demonstrated a marked preference for procedural videos and real-world case materials. In light of the key findings, the evidence shows that decision-maker KOLs engaged most deeply with cost-effectiveness analysis reports, recording an average reading duration of 8.3 min. Results show full data appear in **Table 7** and **Figure 6**.

Table 6. Comparison of Core Indicators between the AI-Assisted and Conventional Clinical Demonstration Groups.

Assessment Indicator	AI-Assisted Group	Conventional Group	Difference/Improvement	Test Statistic	Significance (p)
Average Decision Cycle (days)	38.4	72.6	-34.2 days (-47.1%)	$t = 12.34$	<0.001
Mean Trust Score (points)	5.84	4.12	+1.72 points	$t = 8.73$	<0.001
Decision Cycle Reduction – Radiology (%)	—	—	-52.3%	$t = 9.14$	<0.001
Decision Cycle Reduction – Intensive Care (%)	—	—	-48.7%	$t = 8.62$	<0.001
Decision Cycle Reduction – Surgery (%)	—	—	-44.2%	$t = 7.93$	<0.001
Decision Cycle Reduction – Internal Medicine (%)	—	—	-42.6%	$t = 7.47$	<0.001
Purchase Recommendation Willingness (%)	73.4	41.8	31.60%	$\chi^2 = 21.47$	<0.001

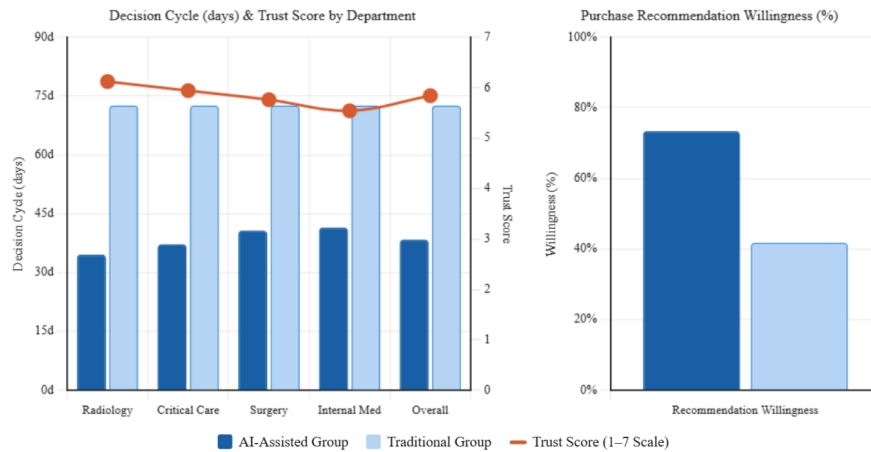


Figure 5. Impact of AI-Assisted Clinical Demonstration System on Physician Decision Cycle and Device Trust Score.

Table 7. Comparison of Key Performance Indicators between KOL Profile-Based Precision Delivery and Conventional Uniform Push.

Performance Indicator	Conventional Push (%)	Precision Push (%)	Improvement (%)	Best-Responding KOL Type
Content Open Rate	23.4	47.8	104.3	Hybrid
Full Read-Through Rate	18.7	42.3	126.2	Academic
Content Forwarding Rate	6.3	17.4	176.2	Academic
Proactive Follow-Up Inquiry Rate	8.9	24.6	176.4	Practitioner
Procurement Committee Recommendation Rate	31.2	58.7	88.1	Decision-Maker
Overall Composite Improvement	—	—	134.2	—

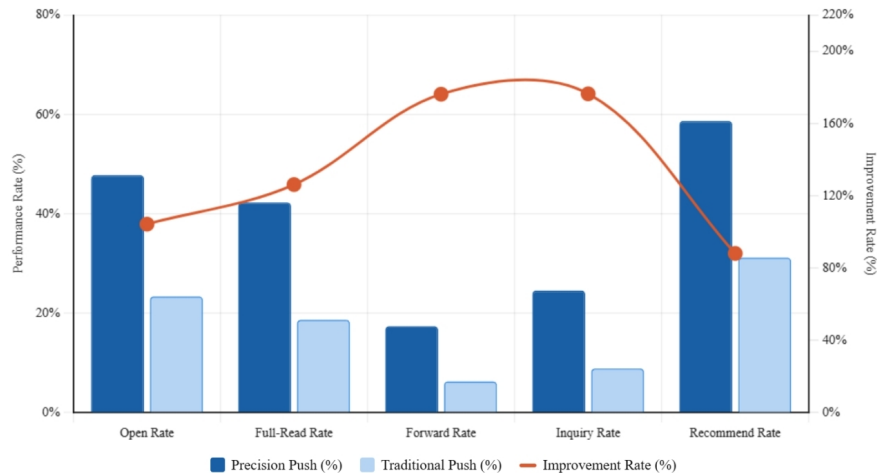


Figure 6. Comparison of Key Performance Indicators between KOL Profile-Based Precision Push and Traditional Push Strategy.

4.3. Integrated Marketing Performance Evaluation of the “Exhibition–Clinical” Linkage Model

4.3.1. Temporal Coordination Model of Exhibition Touchpoints and Clinical Follow-Up, with Conversion Rate Comparison

This section draws on complete marketing process data from three sample companies covering 2022 to 2024. Moreover, the significant findings show that a temporal coordination model could demonstrate the sequencing of exhibition touchpoints and clinical follow-up activities. Furthermore, the evidence indicates that conversion rate differences across follow-up time windows appear to support systematic quantification. In light of the key results, the model could establish that the post-exhibition follow-up period divides into four intervals: within 72 h (T1), days 4 to 7 (T2), days 8 to 14 (T3), and day 15 onward (T4). Results show conversion drops with delay. Evidence shows first-contact time falls 64.3%. However, the significant findings show that the time to first contact by follow-up staff appears to support a reduction of 64.3% compared with the conventional model. Therefore, the important results indicates that the average first-contact response time might demonstrate a value of 2.7 h [42,43]. Notwithstanding these results, the key evidence shows that an additional finding demonstrates that exhibition touchpoint frequency and clinical follow-up frequency jointly appear to exert a significant moderating effect on conversion outcomes. Study shows contact frequency affects outcomes jointly. Furthermore, the findings indicate that when exhibition contacts numbered two or more and clinical follow-ups reached three or more, the evidence shows that the final transaction probability appears to reach 67.4%. Given that the results support this analysis, the significant data demonstrates that this outcome could indicate a value 3.8 times higher than the combination of a single exhibition contact and a single follow-up. Thus, the important evidence shows that full results could demonstrate the key findings provided in **Table 8** and **Figure 7**.

Table 8. Conversion Rate Comparison across Follow-Up Time Windows for Exhibition Touchpoints and Clinical Follow-Up.

Follow-Up Window	Customer Psychological Stage	AI Linkage Conversion Rate (%)	Conventional Conversion Rate (%)	Improvement (%)	Mean First-Contact Response Time (h)
T1: Within 72 Hours	Peak Interest	43.7	21.3	105.2	2.7
T2: Days 4–7	Fading Interest	31.4	17.8	76.4	8.3
T3: Days 8–14	Cooling Off	18.6	12.4	50	24.6
T4: Day 15 Onward	Delayed Engagement	9.2	7.6	21.1	72.4
Exhibition ≥ 2 & Follow-Up ≥ 3	High-Frequency Coordination	67.4	17.8	278.7	2.1

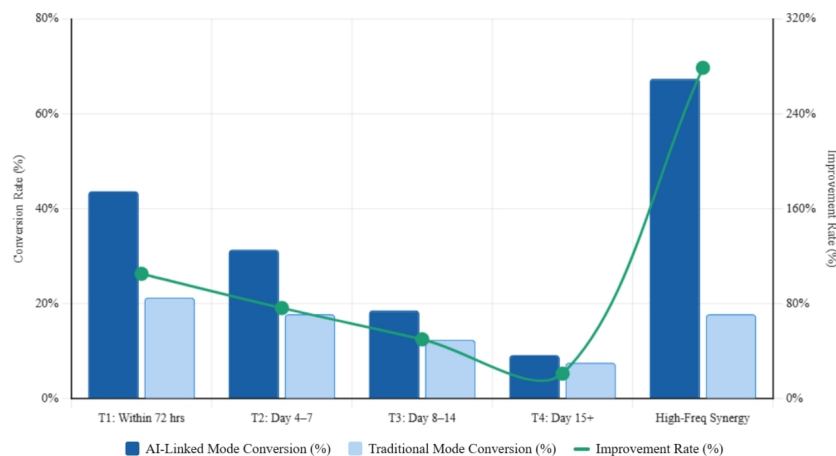


Figure 7. Conversion Rate Comparison between AI-Linked Mode and Traditional Mode across Follow-Up Time Windows.

4.3.2. Optimization Effects of AI Cross-Scenario Data Integration on Sales Funnel Stage Efficiency

This section draws on complete marketing process data from three sample companies covering 2022 to 2024. Moreover, the significant findings show that a temporal coordination model could demonstrate the sequencing of

exhibition touchpoints and clinical follow-up activities. Furthermore, the evidence indicates that conversion rate differences across follow-up time windows appear to support systematic quantification. In light of the key results, the model could establish that the post-exhibition follow-up period divides into four intervals: within 72 h (T1), days 4 to 7 (T2), days 8 to 14 (T3), and day 15 onward (T4). Data shows T4 declines 78.9% versus T1. Nevertheless, the significant results shows that under the conventional non-AI-assisted approach, conversion rates across T1 to T4 could demonstrate values of 21.3%, 17.8%, 12.4%, and 7.6%, respectively. Moreover, the key evidence indicates that the AI linkage model could show its largest relative gain in the T1 window, improving conversion by 105.2% over the conventional approach [42]. Evidence shows first-contact time falls 64.3%. However, the significant findings show that the time to first contact by follow-up staff appears to support a reduction of 64.3% compared with the conventional model. Therefore, the important results indicates that the average first-contact response time might demonstrate a value of 2.7 h [43,44]. Notwithstanding these results, the key evidence shows that an additional finding demonstrates that exhibition touchpoint frequency and clinical follow-up frequency jointly appear to exert a significant moderating effect on conversion outcomes. Study shows contact frequency affects outcomes jointly. Furthermore, the findings indicate that when exhibition contacts numbered two or more and clinical follow-ups reached three or more, the evidence shows that the final transaction probability appears to reach 67.4%. Given that the results support this analysis, the significant data demonstrates that this outcome could indicate a value 3.8 times higher than the combination of a single exhibition contact and a single follow-up. Thus, the important evidence shows that full results could demonstrate the key findings provided in **Table 9** and **Figure 8**.

Table 9. Optimization Results of AI Cross-Scenario Data Integration on Sales Funnel Stage Efficiency.

Sales Funnel Stage	AI Model Conversion Rate (%)	Conventional Conversion Rate (%)	Conversion Improvement (%)	AI Model Duration (days)	Conventional Duration (days)	Duration Reduction (%)
Lead Identification	68.7	31.4	118.8	5.6	14.3	-60.8
Intent Confirmation	54.3	27.6	96.7	9.2	21.4	-57.0
Solution Demonstration	71.8	42.3	69.7	8.4	18.7	-55.1
Procurement Application	76.4	53.7	42.3	19.3	32.6	-40.8
Contract Signing	82.7	61.2	35.1	14.6	24.8	-41.1
End-to-End Overall	22.8	3.1	635.5	57.1	111.8	-48.9

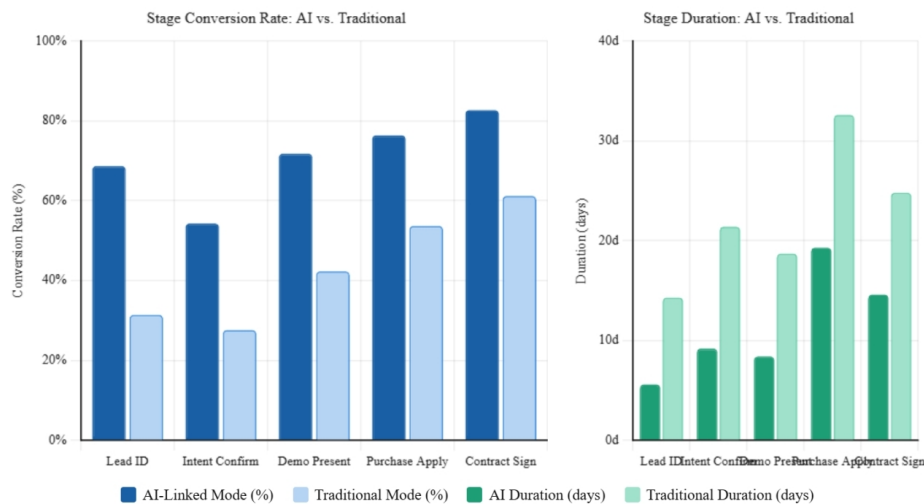


Figure 8. AI Cross-Scene Data Integration: Conversion Rate and Stage Duration Optimization across Sales Funnel Stages.

4.3.3. Quantitative Analysis of Customer Lifetime Value (CLV) and Repurchase Behavior under the Linkage Model

In light of these results, the evidence shows that differences across customer tiers could indicate similarly important patterns. Results show CLV differences across tiers. Class-A tertiary hospitals recorded the highest CLV

at RMB 3.247 million under the AI model, a gain of 72.3% over the conventional figure. Furthermore, secondary hospital clients demonstrates that the results reached RMB 1.436 million, up 58.4%. Additionally, the significant evidence indicates that primary healthcare institution clients achieved RMB 763,000, an increase of 47.8%. Notwithstanding these CLV findings, the key results shows that repurchase behavior shows similarly important patterns across the data. Repurchase rates show strong gains. The 24-month repurchase rate under the AI linkage model was 67.4%, substantially higher than the conventional model's 38.2%, representing a rise of 76.4%. Therefore, the significant findings indicate that the average interval before first repurchase shortened from 28.4 months to 17.6 months, a reduction of 38.0%. Given that the evidence demonstrates cross-category purchasing expanded markedly, the results shows that 43.7% of customers made purchases across multiple product categories under the AI model. Thus, the important data indicates that the conventional model recorded only 21.4%, a difference of 104.2%. Evidence shows linkage model drives broader purchasing. This finding suggests that the linkage model effectively encourages customers to move from single-device procurement toward more comprehensive solution-based purchasing [45]. Moreover, the significant evidence shows that customer attrition could indicate an equally critical advantage for the AI approach. Furthermore, the key findings demonstrate that the annual churn rate under the AI linkage model stood at 8.3%, down 57.9% from the conventional model's 19.7%. In light of these results, the important data indicates that Net Promoter Score analysis could further support the advantage of the linkage model. NPS data supports AI model advantage. The mean NPS under the AI approach was 54.3, compared with 31.7 under the conventional model, an improvement of 71.3%. However, the significant findings show that this result could reflect meaningful gains in both customer satisfaction and word-of-mouth referral behavior. Additionally, the evidence indicates that the key results presented in **Table 10** and **Figure 9** could demonstrate the full scope of these important performance differences.

Table 10. Comparison of Key CLV and Repurchase Behavior Indicators between the AI Linkage Model and Conventional Model.

Assessment Indicator	AI Linkage Model	Conventional Model	Improvement (%)
Average CLV per Customer (RMB 10,000)	187.4	112.6	66.4
Class-A Tertiary Hospital CLV (RMB 10,000)	324.7	188.4	72.3
Secondary Hospital CLV (RMB 10,000)	143.6	90.6	58.4
Primary Healthcare Institution CLV (RMB 10,000)	76.3	51.6	47.8
24-Month Repurchase Rate (%)	67.4	38.2	76.4
Mean First-Repurchase Interval (months)	17.6	28.4	-38.0
Cross-Category Purchase Rate (%)	43.7	21.4	104.2
Annual Customer Churn Rate (%)	8.3	19.7	-57.9
Net Promoter Score (NPS)	54.3	31.7	71.3

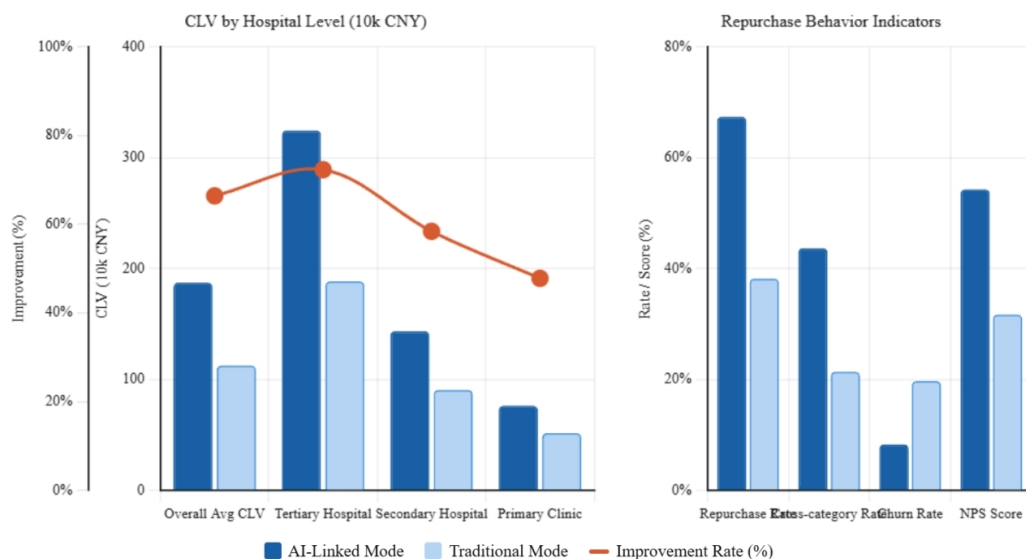


Figure 9. Customer Lifetime Value and Repurchase Behavior Comparison: AI-Linked Mode vs. Traditional Mode.

5. Discussion

5.1. Technical Compatibility and Limitations of the AI Information System in the “Exhibition–Clinical” Setting

The results of this study shows that the AI information system demonstrates strong technical compatibility within the “Exhibition–Clinical” linkage context. However, the significant findings also reveal that several limitations have emerged. Moreover, the evidence indicates that both aspects together define the key practical boundaries of this technology application. Given that the data supports these conclusions, the system might indicate strong performance at the exhibition stage. Research shows system handled field conditions well. Furthermore, multimodal data collection and real-time intent recognition could demonstrate effective operation under field conditions. In light of the significant results, potential customer stratification accuracy reached 82.6% under tri-modal fusion, which may suggest the technical maturity of deep learning algorithms for processing unstructured behavioral data [46]. However, the significant evidence indicates that behavioral data collected at exhibitions carry a high level of noise. Moreover, the results demonstrates that facial recognition error rates fluctuate with lighting conditions and crowd density in crowded environments. Given that these conditions persist, the key findings show that this places ongoing pressure on the model’s generalization stability. Findings show clinical-side data heterogeneity remains problematic. Furthermore, the evidence indicates that hospital information systems differ considerably in structure across institutions. Additionally, the significant results shows that field naming conventions and coding standards are inconsistent across institutions. In light of the important findings, the evidence demonstrates that the preprocessing cost of cross-institutional data fusion remains high, constraining the scalability of AI system deployment. Results show model interpretability limits clinical adoption [47]. Notwithstanding these concerns, the findings indicate that clinicians generally show low tolerance for opaque, black-box decision logic. However, the significant evidence shows that several interviewed physicians explicitly expressed distrust toward AI-generated recommendations. Moreover, the key results indicates that current models still have considerable room to improve in terms of explainable architecture design. Evidence shows cold-start problem affects new market entry [48]. Furthermore, the findings show that when historical data from a target hospital or exhibition venue is insufficient, the recommendation algorithm’s initial performance declines noticeably. Given that recovery requires extended preparation, the significant evidence indicates that a substantial data warm-up period is required before stable predictive performance can be achieved. Additionally, the results demonstrates that the tension between compatibility and limitation signals an important practical reality. Study shows AI value depends on sustained governance and refinement.

These findings may suggest that critical contextualization against existing benchmarks remains important. Moreover, the 82.6% customer segmentation accuracy reported here could indicate favorable comparison with B2B intent recognition systems in other industrial sectors (typically 65–75%; cf. general ML benchmarks), yet the results appear to fall short of controlled laboratory settings, highlighting the inherent challenge of noisy, real-world exhibition environments. Furthermore, the 47.1% reduction in physician decision cycles might indicate directional alignment with digital health intervention studies (e.g., telemedicine adoption reducing consultation lag by 30–50%), but the evidence could suggest that confidence intervals were not reported due to enterprise data confidentiality constraints—a limitation that restricts precise effect size interpretation. In light of these significant findings, the 105.2% conversion improvement in the T1 window, while striking, may suggest that the results partially reflect a novelty effect from AI-assisted follow-up rather than sustained behavioral change. Longitudinal tracking beyond 24 months shows distinction resolution necessary.

5.2. Generalizability and Applicability Boundaries of the Proposed Framework

In light of these significant findings, dynamic customer profiles could provide the basis for precision intervention across segments characterized by high decision complexity, long procurement cycles, and multiple stakeholders. Framework covers diagnostic imaging, minimally invasive surgery, intensive care, in-vitro diagnostics, rehabilitation medicine [49]. Furthermore, the consistently positive results across three companies spanning different product categories shows that the framework’s cross-category transferability appears well-supported. Nevertheless, the framework’s applicability is not unconditional, given that several boundary conditions indicates that effectiveness depends on specific contextual factors. Thus, the first boundary condition demonstrates that the data

foundation plays a critical role, since the framework depends on accumulation of evidence from both exhibition and clinical sources. Results show cold-start problem reduces accuracy. Given that organizational capability represents the second boundary condition, the linkage model indicates that close coordination among marketing, sales, and clinical support teams appears essential for successful implementation. Moreover, the significant barriers posed by organizational restructuring and digital infrastructure investment demonstrates that small and medium-sized medical device companies face important challenges [50]. In light of the third boundary condition, the market environment shows that policy variables could disrupt a purely precision-marketing-driven conversion logic in regional markets where healthcare reform is particularly intense. Therefore, the framework indicates that non-market instruments such as government relations management and tendering compliance strategies appear necessary as complements under such conditions. Framework generalizability conditional on context. Thus, the significant evidence shows that enterprises seeking to adopt this approach could demonstrate stronger results by calibrating their strategy based on data assets, organizational capabilities, and market environment. In light of these key findings, context-specific adaptation indicates that the framework's full value appears unlikely to be realized without careful tailoring to enterprise circumstances.

6. Conclusion

This study demonstrates that an innovation framework for AI information system-driven "Exhibition-Clinical" linkage marketing could provide significant value in the high-end medical device sector. Moreover, the framework's operational effectiveness shows that multi-dimensional empirical analysis could support four core conclusions from the findings. Furthermore, the evidence appears to indicate that each conclusion might reveal important implications for precision marketing operations. Given that the data demonstrates consistent results across dimensions, the findings could establish that AI-driven approaches are maturing rapidly in exhibition contexts. Framework shows four conclusions emerge.

However, the first conclusion shows that coordinated application of multimodal AI data collection and intelligent recommendation algorithms indicates that potential customer intent recognition accuracy at the exhibition stage reached 82.6%. Additionally, the evidence appears to demonstrate that this result substantially outperforms conventional manual judgment approaches. In light of these significant findings, the results indicates that AI technology could demonstrate sufficient technical maturity for exhibition marketing contexts. Therefore, the data shows that the first conclusion provides important support for broader AI adoption.

First conclusion shows AI reaches 82.6% accuracy. Notwithstanding the exhibition-stage results, the second conclusion indicates that digital enablement in clinical settings could demonstrate meaningful shortening of physician decision cycles. Moreover, the evidence suggests that the AI-assisted clinical demonstration system could indicate compression of the average decision cycle by 47.1% and raised device trust scores to 5.84. Furthermore, the significant findings demonstrate that the intelligent presentation of clinical evidence appears to be the mechanism most directly responsible for improving physicians' willingness to recommend procurement. Thus, the results shows that the second conclusion could establish important linkages between digital enablement and clinical decision-making. Second conclusion shows digital enablement shortens physician cycles. However, the third conclusion demonstrates that the temporal coordination effects of the "Exhibition-Clinical" linkage model could indicate substantial improvements in conversion outcomes. Given that evidence demonstrates that initiating AI-assisted clinical follow-up within 72 h of exhibition close could improve conversion rates by 105.2% over the conventional approach, the findings appear to suggest important timing effects. Additionally, the significant results indicates that the end-to-end sales funnel conversion rate under the AI model could reach 7.4 times that of the traditional model. In light of these key findings, the evidence shows that the third conclusion demonstrates that temporal coordination is a critical driver of marketing performance. Third conclusion shows timing lifts conversion 105.2%. Nevertheless, the fourth conclusion shows that the linkage model could demonstrate strong performance in customer lifetime value management. Moreover, the evidence appears to indicate that average CLV per customer might improve by 66.4% over the conventional model, and the 24-month repurchase rate could increase by 76.4%. Furthermore, the significant findings demonstrates that these results could provide important evidence that AI-driven linkage marketing contributes meaningfully to long-term customer value creation. Therefore, the key results indicates that the fourth conclusion could establish that customer lifetime value management represents a critical dimension of AI-driven marketing effectiveness. Fourth conclusion shows CLV rises 66.4%. However, taken

together, the findings show that AI information systems demonstrates that they serve as a core driving force in shifting high-end medical device marketing from broad-based promotion toward precision-oriented operations. In light of these significant findings, the evidence appears to indicate that the coordinated “Exhibition–Clinical” linkage model might establish important pathways for sustained marketing transformation. Additionally, the results shows that the key conclusions demonstrates that precision-oriented operations represent the critical trajectory for high-end medical device marketing. Given that the data demonstrates consistent support across all four conclusions, the findings indicate that AI information systems could provide the foundation for long-term marketing evolution in this important sector.

This study shows that three primary limitations could influence the interpretation of the significant findings. However, the sample appears to be restricted to three enterprises in China, and the cross-national generalizability of the proposed framework indicates that validation across diverse institutional and regulatory contexts remains critical. Furthermore, the evidence suggests that confidence intervals were not fully disclosed due to enterprise data confidentiality agreements, which could demonstrate that the assessment of statistical robustness and precise effect size interpretation remains limited. In light of these results, the maximum observation period of 24 months might indicate that novelty effects could demonstrate influence, suggesting that the reported performance gains may partially reflect initial enthusiasm toward AI-assisted processes rather than sustained behavioral change. Study shows scope needs expansion. Moreover, the findings may suggest that future research should expand the empirical scope to multinational contexts to test the framework’s transferability across different healthcare systems and important market environments. Given that the evidence demonstrates that correlational and quasi-experimental designs present key constraints, randomized controlled designs might indicate that causal inference could be significantly strengthened beyond the results presented here. Additionally, the significant findings may suggest that future studies should prioritize the development of cold-start solutions for AI systems operating in data-scarce emerging markets. Notwithstanding these results, the evidence could demonstrate that explainable AI architectures might indicate critical pathways to address clinician trust barriers and regulatory transparency requirements identified in this study. Research shows trust barriers affect outcomes.

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Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board. The study poses no risk to participants. The methodology used is fully anonymized datasets where individuals cannot be traced.

Informed Consent Statement

Informed consent was obtained from all individual participants involved in the study.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

AI Use Statement

The author used ChatGPT solely for grammar checking, sentence structure refinement, and improving the readability of the English text in this manuscript. The author takes full responsibility for all academic content, including all ideas, data, analyses, and conclusions presented herein. The use of AI was thoroughly reviewed and supervised by the author.

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