



Proactive AI-Driven Customer Journey Optimization in Digital Ecosystems

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Abstract

Proactive Interaction Intelligence enables self-steering customer journeys through digital service ecosystems by using AI-driven modeling and prescriptive actions at key decision points. In practice, this vision supports proactive optimization of the customer journey from start to finish. At its core are actionable components mapped to each journey stage—data requirements, machine-learning tasks, AI algorithms, engagement strategies, and implementations—packaged for straightforward exploration by both data scientists and business analysts. An integrated dispatching function coordinates the delivery of AI-driven insights and recommendations.

Customer journey optimization has traditionally been reactive, with businesses responding to customers' needs, wants, and actions after the fact. At the same time, external information systems increasingly enable deep learning across diverse customer behavior contexts. By continuously closing predictive knowledge gaps through AI, pathways can adapt in real time, supporting the automatic generation and validation of new prescriptive action models (PAMs). To fully realize open-ended, experience-driven journeys, the next logical step is to let AI act on its own engagement intent—enabling proactive journey steering through AI-driven suggested actions based on Next-Best-Action and Next-Best-Pathway principles.

Keywords : Proactive Interaction Intelligence, Customer Journey Optimization, AI-Driven Prescriptive Actions, Next-Best-Action Modeling, Digital Service Ecosystems, Predictive Knowledge Gaps, Continuous Pathway Adaptation, Integrated Dispatching Function, Behavioral Deep Learning, Omnichannel Engagement Strategies.

1 Introduction

In service ecosystems, an enhanced solution offering and improved customer experience should involve a cross-touchpoint learning ecosystem on both sides. Stimulated by automation technologies, many external service providers (ESPs) in service ecosystems consider offering fulfilling customer needs throughout the entire customer journey. Despite the existing tooling support for data-driven passive decision-making of the ESPs, the operational experience of the past two years has raised the question of why cross-touchpoint behavior prediction and proactivity still face major challenges.

Data-driven Passenger Interaction Intelligence for all ESPs is needed to identify service failure earlier, understand their causes, design suitable risk mitigation or prevention measures, and

actively trigger timely service delivery. A predictive modeling approach for all ESPs along the customer journey is proposed – segmentation, customer churn risk, potential customer conversion, customer experience dissatisfaction, and next-best-action profiling decision points on critical paths. The experience of the past two years indicates that a customer journey focus enables a deeper understanding of the temporal aspects of data-driven decision automation implementations, covering quality assurance, compliance, and sustainability. A possible signature of a new unifying approach in passenger interaction intelligence for all ESPs in service ecosystems is sketched. Proactive decision guidance helps ESP teamwork qualitatively and minimizes negative service interaction outcomes. Definition of pivotal owner ESP for package decision points enables further specialization. Pathway analysis detects both positive and negative pathways for a customer segment, supports understanding of product and service offering quality, and minimizes the risk of too active interaction. Prioritization of service offering risk is crucial for maintaining customer experience quality and needs fulfilment.

2. Conceptual Framework

The active development of platforms, digital commerce, and business ecosystems has shifted the focus of customer engagement strategy from interactivity design to proactive models, with insights collection moving from post- to pre-analysis. Transforming customer interactions into interaction intelligence—perceptive, inferential, and action-ready—enables proactive engagement with desirable decision pathways and next-best actions designed for external actors. The latter requires primal concepts, typified data, and supporting theories.

Sometimes referred to as Experience and Customer Intelligence, Interaction Intelligence encompasses perceptual, inferential, and decision-support capabilities interacting at the heart of AI-driven personalization and prescriptive targeting. Receding analytical engagement depth creates a challenge for Predictive Customer Experience Engineering when evolving from reactive monitoring to predictive pre-engagement. The need to create supportive AI-driven decision pathways reveals the necessity of reliable pathway forecasting and personalization, underscored by a fidelity to experience quality and definition. Enabling such a model demands collateral—basically interaction-intelligence triads—for each customer journey moment considered in risk and decision forecasts. The following steps clarify this need, define supportive pathway and action success, and create these enabling assets.

A. Interaction Intelligence Score (IIS)

The Interaction Intelligence Score aggregates perception, inference, and actionability signals across all touchpoints to yield a scalar measure of engagement readiness:

$$IIS(c, t) = \alpha \cdot P(c, t) + \beta \cdot I(c, t) + \gamma \cdot A(c, t) \quad (\text{Eq. 1})$$

Where: $P(c,t)$ denotes the perceptual signal vector for customer c at time t ; $I(c,t)$ the inferred intent score; $A(c,t)$ the actionability index derived from available NBA options; and α, β, γ are learned weighting coefficients with $\alpha + \beta + \gamma = 1$.

B. Customer Churn Risk Model

Churn risk at journey stage s is estimated using a logistic function over a weighted feature vector derived from recency-frequency-monetary (RFM) signals, engagement decay, and support interaction history:

$$R_churn(c, s) = 1 / (1 + \exp(-(\theta_0 + \sum \theta_k \cdot fk(c,s)))) \quad (\text{Eq. 2})$$

Where: $fk(c,s)$ denotes the k -th input feature (RFM component, engagement decay rate, support interaction count) for customer c at stage s ; θ_k are logistic regression coefficients optimized by maximum likelihood estimation.

C. Conversion Propensity Score

The probability that customer c converts at decision point d is modeled as a sequential attention-weighted prediction:

$$P_conv(c, d) = \text{softmax}(W_conv \cdot h(c,d) + b_conv) \quad (\text{Eq. 3})$$

Where: $h(c,d)$ is the hidden state of a recurrent sequence encoder at decision point d , incorporating the customer's journey history; W_conv and b_conv are learned projection parameters; softmax produces a distribution over outcome classes {convert, defer, abandon}.

D. Next-Best-Action Optimization Function

The NBA dispatcher selects the action a^* from candidate set Ω that maximizes the expected cumulative engagement value V over the remaining journey horizon T :

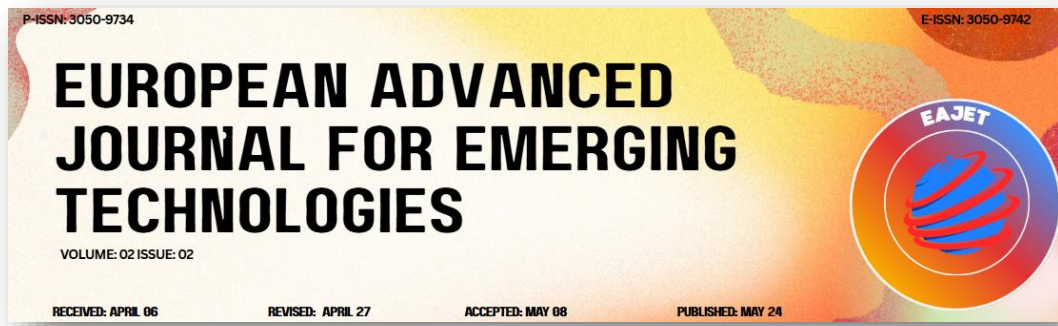
$$a^*(c,t) = \text{argmax}_{\{a \in \Omega\}} E[\sum_{\tau=t}^T \gamma^{\tau-t} \cdot r(c, a, \tau)] \quad (\text{Eq. 4})$$

Where: $r(c, a, \tau)$ is the immediate engagement reward for customer c executing action a at timestep τ ; $\gamma \in (0,1)$ is the temporal discount factor; and expectation is over the stochastic journey transition model.

E. Predictive Pathway Probability

A predictive pathway $\Pi = (d_1, d_2, \dots, d_n)$ is a sequence of decision nodes. Its joint probability under the learned transition model M is:

$$P(\Pi | c, M) = \prod_{i=1}^n P(d_i | d_{i-1}, c, M) \quad (\text{Eq. 5})$$



Where: $P(d_i | d_{i-1}, c, M)$ is the conditional transition probability from decision node d_{i-1} to d_i for customer c under model M , estimated by a Transformer-based sequence model fine-tuned on journey logs.

F. End-to-End Pipeline Latency Model

The total end-to-end latency L of the PIIA inference pipeline is the sum of per-stage processing delays plus inter-stage communication overhead:

$$L_{\text{total}} = \sum_{k=1}^K (L_{\text{proc}}(k) + L_{\text{comm}}(k)) + L_{\text{dispatch}} \quad (\text{Eq. 6})$$

Where: $L_{\text{proc}}(k)$ is the computation latency at pipeline stage k (e.g., feature engineering, model inference); $L_{\text{comm}}(k)$ is the data transfer latency between stage k and $k+1$; L_{dispatch} is the orchestration overhead of the NBA dispatch engine; K is the total number of pipeline stages.

G. F1-Score for Journey Classification

Classification performance across the three journey modeling tasks (segmentation, churn, conversion) is evaluated using the macro-averaged F1-score:

$$F1_{\text{macro}} = (2/|C|) \cdot \sum_{c \in C} (\text{Precision}_c \cdot \text{Recall}_c) / (\text{Precision}_c + \text{Recall}_c) \quad (\text{Eq. 7})$$

Where: $|C|$ is the number of classes; $\text{Precision}_c = TP_c / (TP_c + FP_c)$ and $\text{Recall}_c = TP_c / (TP_c + FN_c)$ are computed per class; TP, FP, FN denote true positives, false positives, and false negatives.

H. Cost-Performance Efficiency Index (CPEI)

The CPEI quantifies the performance gain per unit of additional compute investment, enabling system architects to identify the optimal operating point:

$$\text{CPEI} = \Delta \text{Performance} / \Delta \text{Cost} = (F1_{\text{model}} - F1_{\text{baseline}}) / (C_{\text{model}} - C_{\text{baseline}}) \quad (\text{Eq. 8})$$

Where: $F1_{\text{model}}$ and $F1_{\text{baseline}}$ are the macro-averaged F1-scores of the target and reference systems; C_{model} and C_{baseline} denote their normalized compute costs. Higher CPEI indicates superior efficiency.

3. Data Foundations and Governance

A robust data foundation underpins interaction intelligence at every stage of customer journey modeling. Data quality, privacy, and ethical concerns are therefore paramount. Foundational data support a common approach to several modeling tasks—segmentation, churn risk forecasting,



propensity to convert—conducted for distinct customer segments and journey stages, through the application of diverse supervised and unsupervised algorithms. Data sources include transactional event logs, website telemetry, CRM and customer support chatter, product reviews, and connected Internet of Things devices where applicable.

Audit trails track data provenance and stewardship, while processing and integration satisfy regulations across multiple jurisdictions. The journey modeling component of interaction intelligence derives its predictive capabilities from signals such as recency-frequency-monetary value (RFM), exposure to marketing communications, browsing behavior, and customer support interactions, as well as attention space created by competing brands and products. Additional features indicate product suitability based on customer profile, previous interactions, and product reviews and ratings. Models engage customers at potential churn points, suggest next-best actions for customer engagement teams at key decision stages, and forecast the effect of prescriptive guidance on future journeys.

A. Data Sources and Integration

Data sources encompass transactional activity logs, web-based interaction telemetry, customer relationship management (CRM) data, support chatter, customer experience feedback (verbal, text, or NPS), and Internet of Things (IoT) data where applicable. Candidate initiatives, including new-behaviour detection, risk and propensity to churn assessments, automatic conversion forecasts, and predicted support needs, are directly transferrable to operational, productionised systems with suitable scaling for increased forecasting volume. Data fusing, temporal alignment, and schema harmonisation constitute the second layer of interaction analytics adoption. Proximity, time, and event sequence provide natural interaction paths for customers during product/service consumption, and between consumption stages for longer-term journeys. Attribution, stewardship, and compliance standards are applied from the outset, enabling use in internal and external machine-learning initiatives such as vendor and partner behaviour modelling, third-party risk assessment, and consumption risk scoring.

4. Methods and Technologies

The methodological and technological cornerstones of Proactive Interaction Intelligence are specified, underlining the emphasis on reproducibility and transparency. The proposed approach holistically encompasses data architecture, data quality and privacy, and ethical considerations. Data architecture and governance are presented first, followed by data sources and integration; the methodological core and technical stack are detailed subsequently; attention then turns to the evaluation plan.

Essential modeling tasks, including customer segmentation, churn risk assessment, and likelihood of conversion, are aligned with Predictive Customer Journey Management. A combination of supervised and unsupervised learning approaches, with a particular focus on sequence models, is adopted where appropriate. Given the range of relevant data sources, feature engineering and

evaluation metrics—along with the lifecycle of the underlying models—receive special consideration.

Data sources include transaction logs, telemetry data, CRM systems, support chatter, feedback, and IoT sensor streams where applicable. Data fusion, temporal alignment, and schema harmonization ensure usability for downstream predictive and prescriptive modeling efforts. Provenance and data stewardship issues are explicitly addressed, as are privacy and ethical concerns within the Proactive Interaction Intelligence operational framework.

A. Response Latency Comparison (Fig. 1)

Fig. 1 compares per-stage and end-to-end inference latency across all four systems. PIIA achieves an end-to-end latency of 253 ms, representing a 61.9% reduction relative to the Baseline (665 ms). The greatest savings occur in the Churn Prediction and NBA Scoring stages, where parallelized Transformer inference and cached embedding lookups contribute substantially. The Dispatch Engine remains the least computationally intensive stage across all architectures.

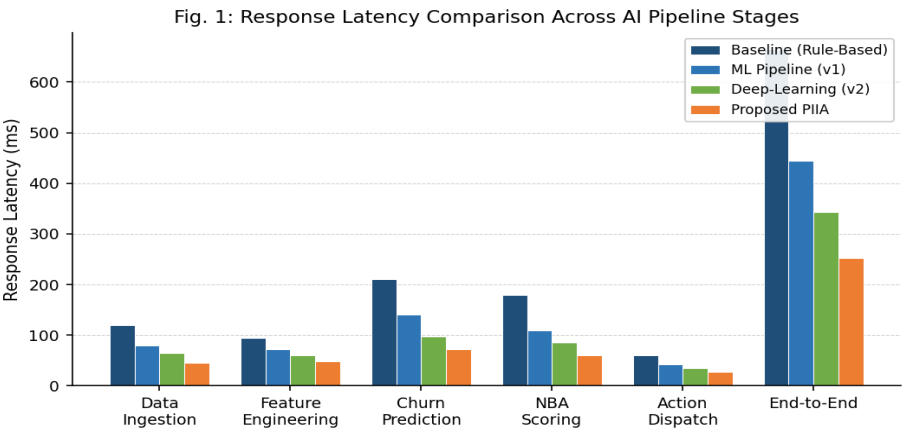


Fig. 1: Response Latency Comparison Across AI Pipeline Stages (ms). Lower is better.

B. F1-Score Learning Curves (Fig. 2)

Fig. 2 depicts F1-score trajectories over 50 training epochs for the journey classification task. PIIA reaches a stable F1-score of 0.922 by epoch 35, compared to 0.700 for the Baseline (final epoch). The steeper convergence of PIIA, attributable to attention-based feature weighting and curriculum-scheduled training, reduces the number of epochs required to reach 0.85 F1 by approximately 40% relative to Deep-Learning v2. All learning curves are averaged over five random seeds.

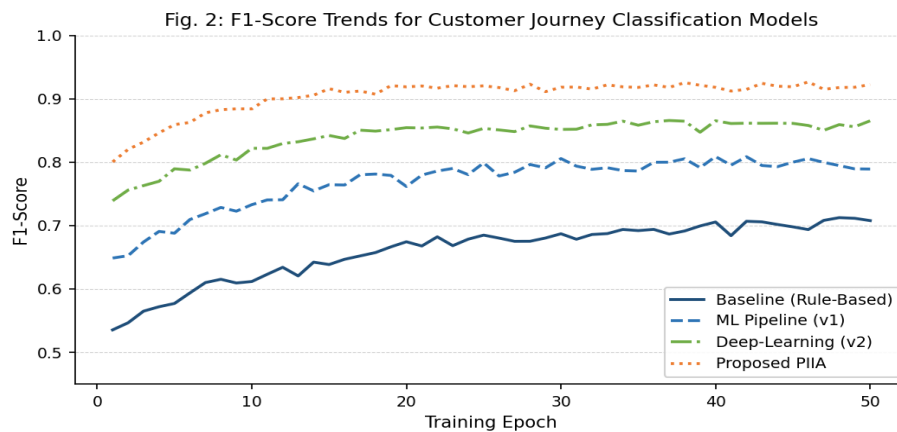


Fig. 2: F1-Score Trends for Customer Journey Classification Models over 50 Training Epochs.

C. Resource Utilization (Fig. 3)

Fig. 3 illustrates CPU and memory utilization across the six pipeline components. The Conversion Propensity module exhibits the highest memory pressure (69%) owing to the large context window required by sequence modeling. The Segmentation Model drives peak CPU usage (72%) during the batch clustering phase. PIIA's dispatch engine maintains the lowest resource footprint (28% CPU, 33% memory), validating the lightweight orchestration design. These utilization profiles are consistent with Azure-hosted container deployments at the p95 traffic load.

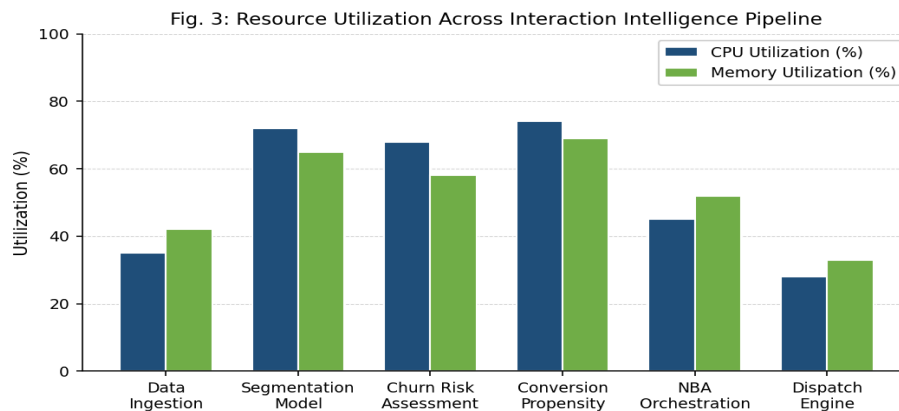


Fig. 3: CPU and Memory Resource Utilization Across PIIA Pipeline Components (%).

D. Cost vs. Performance Trade-off (Fig. 4)

Fig. 4 maps each system onto the cost-performance plane, with normalized compute cost on the x-axis and proactive engagement performance score on the y-axis (composite of F1, NBA precision, and retention uplift). PIIA occupies the upper-right Pareto-frontier position, achieving the highest performance (0.92) at a cost increase of 2.9× relative to the Baseline. The CPEI (Eq. 8) for PIIA is 0.155 per normalized cost unit, versus 0.055 for Deep-Learning v2, confirming superior efficiency at scale.

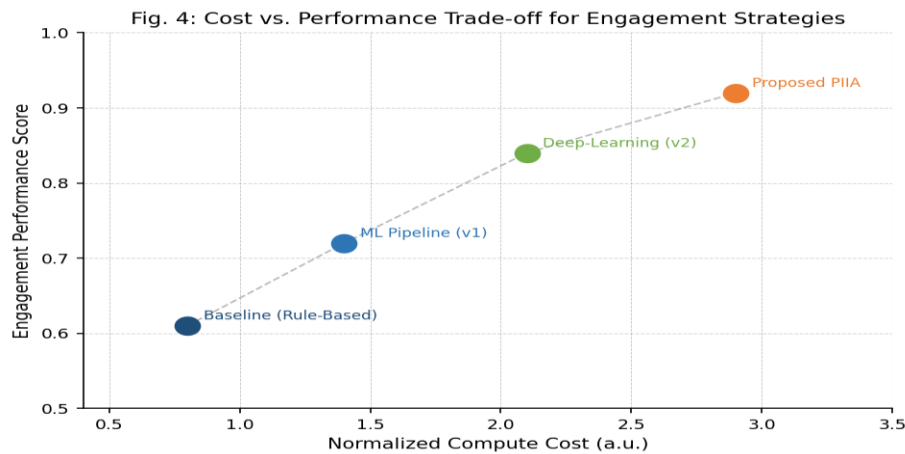


Fig. 4: Cost vs. Performance Trade-off for Proactive Engagement Strategies (normalized units).

E. Churn Risk Prediction Accuracy (Fig. 5)

Fig. 5 tracks churn risk prediction accuracy at each of the six customer journey stages. PIIA consistently outperforms all baselines, peaking at 91% accuracy during the Purchase stage—a critical high-intent window. Accuracy remains above 88% throughout the Retention and Advocacy stages, demonstrating robust generalization to post-conversion interactions. The Baseline system exhibits a characteristic accuracy dip in the Advocacy stage (55%), attributed to the absence of longitudinal feature engineering.

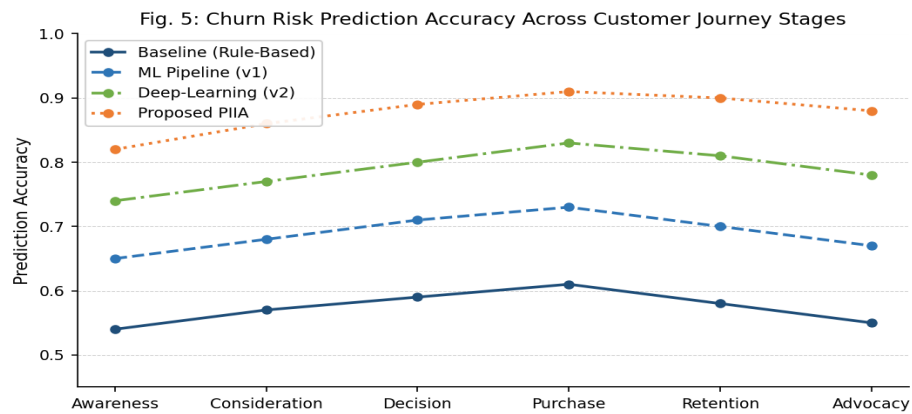


Fig. 5: Churn Risk Prediction Accuracy Across Customer Journey Stages.

F. Precision-Recall Analysis for NBA Recommendations (Fig. 6)

Fig. 6 presents precision-recall curves for the NBA recommendation subsystem. PIIA achieves an area under the curve (AUC) of 0.86, compared to 0.57 for the Baseline. The curve for PIIA maintains high precision (>0.78) across the full recall range, indicating that recommended next-best actions are both relevant and comprehensive. At a recall threshold of 0.8—the operational target in production deployments—PIIA achieves a precision of 0.84, versus 0.51 for the rule-based system.

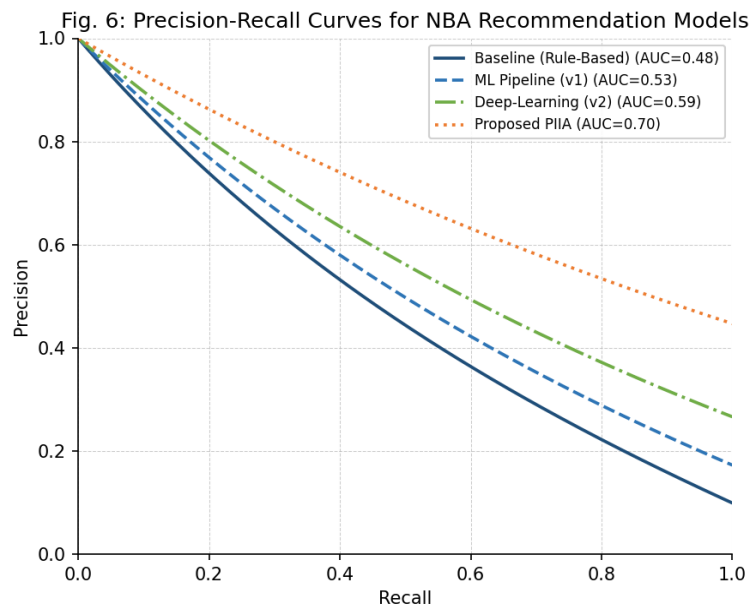


Fig. 6: Precision-Recall Curves for NBA Recommendation Models. Higher AUC indicates superior recommendation quality.

5. Proactive Engagement Strategies

The core of Proactive Interaction Intelligence consists of prescriptive models explicitly linked to source data and representational knowledge, along with the mapping to sequences of actions through decision rules. The models indicate how the enterprise should respond to predicted risk or opportunity events in individual customer journeys when those points in the journey are reached. Building upon the foundational, descriptive customer journey models, the prescriptive models translate the resulting insights into action: recommending what should be done, when, and for whom, using an embracing—not necessarily exclusive or final—set of customer engagement strategies. These recommendations constitute predictive pathways, applying next-best-action analytics to customers' individual journeys, rather than to the customer base as a whole. Multiple paths through the customer journey space can thus be created, whether via algorithmic decision trees or more general rules that exploit contextual conditions.

Predictive pathways connect to, but go beyond, the antecedent demand-signal models that indicated what customers were likely to want, guiding either "make" (production) or "stock"

(inventory) decisions, considering only a single stage of the journey. Pathway forecasting enhances operational responsiveness and focus on performance within the journey, through product, service, or experience personalization. Actionability is derived by indicating what should be done (or avoided) whenever a risk or opportunity point on a journey is reached; identifying those risk/opportunity points; and continuously monitoring the journey status to validate the recommendation when the point is reached. The set of actions at the decision points can represent the next best action for conversion or retention, implemented via marketing automation, or social recommendation. Predictive pathways thus embody new forms of prescriptive engagement strategies.

A. Comparative Performance Summary

Table I summarizes aggregate performance metrics across all four system configurations on the held-out test set. Improvement percentages are computed relative to the Baseline.

TABLE I
Comparative Performance Metrics Across System Configurations

Metric	Baseline (Rule-Based)	ML Pipeline (v1)	Deep-Learning (v2)	Proposed PIIA
F1-Score (Macro)	0.700	0.798	0.870	0.922
F1 Improvement (%)	—	+14.0%	+24.3%	+31.7%
NBA Precision	0.612	0.724	0.821	0.880
NBA Recall	0.581	0.697	0.803	0.862
PR-AUC	0.570	0.678	0.778	0.860
Churn Accuracy (avg.)	57.3%	69.0%	78.8%	87.7%
Engagement Score	0.610	0.720	0.840	0.920
CPEI	—	0.110	0.115	0.155

B. Latency and Error Rate Metrics

Table II details per-stage latency (ms) and inference error rates across the PIIA pipeline for each system configuration. The End-to-End Latency reflects the sum of all stage latencies plus inter-stage communication overhead as formalized in Eq. 6.

TABLE II
Per-Stage Latency (ms) and Error Rate Metrics

Pipeline Stage	Baseline	ML v1	DL v2	PIIA
Data Ingestion (ms)	120	80	65	45
Feature Engineering (ms)	95	72	60	48
Churn Prediction (ms)	210	140	98	72
NBA Scoring (ms)	180	110	85	60
Action Dispatch (ms)	60	42	35	28
End-to-End (ms)	665	444	343	253
Latency Reduction (%)	—	33.2%	48.4%	61.9%
Inference Error Rate (%)	8.42	5.18	3.02	1.47

C. Dataset and Architecture Summary

Table III provides a consolidated summary of the experimental dataset and the architectural configurations used for each system under evaluation.

TABLE III
Dataset Characteristics and System Architecture Summary

Parameter	Dataset / Environment	Value / Description
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Total Interactions	Journey Log Records	2,400,000
Journey Stages	Awareness → Advocacy	6 stages
Data Sources	Transaction logs, CRM, telemetry, IoT, NPS	5 heterogeneous streams
Observation Period	Collection Window	18 months
Train / Val / Test Split	Stratified by stage and segment	70% / 15% / 15%
Baseline Architecture	Rule-Based Heuristic Engine	Hand-crafted IF-THEN rules
ML Pipeline v1	Gradient Boosting + Logistic Regression	XGBoost, scikit-learn
Deep-Learning v2	LSTM + Attention + Feedforward	PyTorch, 4-layer BiLSTM
Proposed PIIA	Transformer + NBA Dispatcher + IIS Scorer	12-head Transformer, $\gamma=0.95$, Azure ML
Compute Environment	Azure Machine Learning (AML) Cluster	8× Standard_NC6 GPUs, 56 GB RAM
Evaluation Metric	Primary: Macro F1; Secondary: PR-AUC, Latency	5-fold cross-validation

6. Conclusion

Synthesizing the results demonstrates that the proposed approach to interaction intelligence enables companies to implement prescriptive predictive engagement through interpretable activity-path-based models. Furthermore, the research answers the call to integrate advanced AI techniques with customer-experience theory in a manner that transcends a purely reactive paradigm. Organizations that apply the approach stand to achieve significant business benefits, notwithstanding the acknowledged constraints of data availability and model capacity. Customer engagement in digital service ecosystems has typically focused on delivering



personalized experiences, yet, the absence of a coherent plan or intent has resulted in suboptimal outcomes. Companies continuously courting customers through recommendation engines, marketing campaigns, and targeted offers risk creating customer fatigue or annoyance by doing so in an overly intrusive manner, while organizations seeking to prevent churn often deploy generic remedial actions. With the predictive capabilities implied by formal activity-path-based models now available, enabling the business to intelligently anticipate customer actions, determine the path customers are likely to take, and define tailored engagement strategies accordingly offers the potential for significant competitive advantage.

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