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Article

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Deep Learning-Enhanced Analysis of Consumer Decision-Making Behavior

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ABSTRACT

Understanding consumer decision-making in digital environments necessitates analytical models that are both scalable and adaptive. Traditional econometric and rule-based models often fail to capture the non-linear, context-sensitive, and multi-modal nature of real-world decision behavior. This study introduces a deep learning–enhanced framework that integrates cognitive modeling with neural architectures to overcome these limitations. Central to the framework is the Attentive Utility Reconstruction Network (AURN), a novel model that learns utility-aware latent representations by fusing multi-modal consumer data, including attribute embeddings, historical behaviors, and contextual signals. AURN features an attention-gated utility decoder and a recurrent preference updater, enabling it to capture both static preferences and temporal dynamics. By employing temperature-controlled softmax and probabilistic attention distributions, AURN reconstructs personalized utility functions with enhanced interpretability and flexibility. To further embed behavioral rationality, the framework introduces the Context-Responsive Choice Optimization (CRCO) strategy. CRCO augments AURN with domain-informed regularization, including structural priors (e.g., monotonicity, dominance), decoy-aware counterfactual penalties, and context-sensitive decision temperatures. It also incorporates behavioral biases such as salience, default bias, and compromise effects into utility estimation. Together, these elements ensure predictive robustness and psychological plausibility across diverse consumer segments. Empirical results across four benchmark datasets demonstrate consistent outperformance of the proposed model over state-of-the-art baselines in terms of accuracy, AUC, and F1 score. This integrated framework not only improves prediction performance but also advances interpretability, offering a comprehensive tool for understanding digital consumer cognition.

Keywords: Attentive Utility Reconstruction, Context-Responsive Choice Optimization, Consumer Decision-Making, Multimodal Preference Encoding, Behavioral Bias Modeling, Deep Learning Framework

Introduction

Consumer decision-making behavior is critical for both academic researchers and industry aiming to optimize marketing strategies, personalize recommendations, and enhance user experience. Traditionally, this area of research has relied on psychological theories and structured economic models. However, as consumer interactions have shifted to digital platforms, vast amounts of behavioral data have become available, necessitating more scalable and adaptive analytical methods. Deep learning technologies offer a transformative approach to this problem, as they not only process large-scale, unstructured data efficiently but also uncover hidden patterns and nonlinear relationships that traditional models might overlook[1]. Moreover, deep learning enhances behavioral predictions and supports real-time decision-making systems[2]. This shift in methodological approach is not just a technological advancement but also a strategic necessity in a rapidly digitizing marketplace[3].

Early efforts to model consumer decision-making relied on structured frameworks that encoded expert knowledge into predefined systems. These approaches utilized logical reasoning and systematic rules to interpret consumer preferences and behaviors[4]. While these methods provided clarity and interpretability, they often struggled to adapt to the dynamic and complex nature of real-world consumer environments[5]. Furthermore, the reliance on static rules limited their ability to account for evolving preferences or contextual nuances, which are critical in modern digital marketplaces[6]. As a result, researchers began exploring more adaptive methodologies capable of capturing the variability inherent in consumer behavior.

To address the need for adaptability, researchers introduced statistical models that could infer patterns from historical data. Techniques such as decision trees, support vector machines, and ensemble methods allowed for more flexible analysis by identifying relationships between consumer attributes and purchasing decisions[7]. These models demonstrated improved

scalability and robustness compared to earlier rule-based systems[8]. However, they often required extensive preprocessing and feature engineering, which constrained their ability to handle unstructured or multimodal data, such as text, images, or temporal sequences[9]. This limitation highlighted the need for more advanced approaches capable of learning directly from raw data.

The advent of deep learning has revolutionized the study of consumer decision-making by enabling end-to-end learning from diverse data sources. Architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers have proven effective in capturing intricate patterns and temporal dynamics within consumer data[10]. These models eliminate the need for manual feature engineering and can integrate heterogeneous inputs, including transaction histories, textual reviews, and visual content[11]. Pretrained models like BERT and GPT have further enhanced sentiment analysis and contextual understanding, offering new insights into consumer preferences[12]. Despite challenges such as interpretability and the need for large-scale labeled datasets, deep learning continues to push the boundaries of consumer behavior modeling, offering unprecedented accuracy and adaptability[13].

Given the limitations of symbolic reasoning in handling data complexity, the rigidity of traditional machine learning in modeling evolving preferences, and the interpretability challenges of deep learning models, our approach integrates the strengths of prior methods while mitigating their individual weaknesses. Our method leverages a hybrid architecture that combines interpretable components with deep representation learning, allowing for both transparency and high predictive performance. It adapts to evolving consumer contexts by dynamically updating model parameters based on real-time user interactions and feedback. Furthermore, by incorporating transfer learning and domain adaptation, the model ensures generalizability across different consumer segments and product categories. This integrated approach not only enhances accuracy but also supports actionable insights in diverse marketing and recommendation scenarios.

Among its core strengths, the presented approach excels in multiple dimensions:

- The architecture incorporates a modular attention-based layer tailored for dynamic user interaction sequences, enabling fine-grained interpretation of consumer intent across decision stages.
- It supports multi-modal data fusion and domain adaptation, providing robust predictions across various industries including e-commerce, finance, and entertainment with minimal retraining.
- Experiments conducted on three benchmark datasets show a consistent 15–20% improvement in F1-score and NDCG metrics over state-of-the-art baselines, validating the approach's effectiveness and efficiency.

1 Related Work

1.1 Deep Representation Learning Strategies

Extensive investigations have been conducted to explore the application of deep representation learning techniques in uncovering latent cognitive and affective processes underlying consumer decision-making behaviors. Advanced architectures, including autoencoders, variational autoencoders, and deep belief networks, have been utilized to extract meaningful features from high-dimensional consumer datasets, encompassing clickstreams, facial expressions, psychophysiological signals, and purchase histories[9]. These models, by learning compact latent representations, reveal hidden patterns that align with consumer preferences and motivations[10]. Multimodal frameworks integrating text-based sentiment analysis with visual cues have demonstrated enhanced predictive capabilities for purchase intentions and brand perceptions[11]. Self-supervised contrastive learning approaches have further refined representation quality by promoting invariant features across augmented views, thereby improving generalization across diverse consumer segments[12]. Temporal extensions, such as sequence-to-sequence autoencoders and recurrent variational autoencoders, have been developed to capture dynamic decision-making processes, modeling the evolution of attention and affective influences over sequential choices[14]. Graph neural networks have been employed to represent relational structures among consumers, products, and contextual factors, enabling the identification of influence pathways in social recommendation scenarios[13]. Integration of these representations into predictive architectures, including attention-based LSTMs and transformer models, has facilitated end-to-end systems capable of inferring latent psychological constructs and forecasting decision outcomes[15]. Empirical studies have shown that these architectures outperform traditional models in predicting metrics such as purchase likelihood and churn risk[16]. However, challenges persist in ensuring interpretability of latent features, addressing data sparsity in emerging markets, and enabling domain transferability[17]. Future research directions include disentangled representation learning frameworks to separate hedonic and utilitarian factors, hierarchical latent variables for multi-stage decision processes, and meta-learning approaches to adapt representations across diverse consumer cohorts[18].

1.2 Behavioral Sequence Modeling Techniques

The modeling of consumer behavior as sequential events spanning browsing, search, evaluation, and purchase has gained prominence in understanding decision dynamics through deep learning methodologies. Recurrent neural networks, long short-term memory networks, and gated recurrent units have been extensively applied to capture temporal dependencies and sequential

decision patterns[19]. Transformer architectures have emerged as powerful tools for modeling item interactions as tokenized sequences, achieving state-of-the-art performance in recommendation benchmarks[20]. Attention mechanisms embedded within these models enable the weighting of past events based on relevance, enhancing predictive accuracy for next-item purchase and session length[21]. Temporal convolutional networks and memory-augmented neural networks have been employed in session-based recommendation systems, leveraging external memory modules to reflect long-term consumer preferences[22]. Self-supervised pre-training strategies on large-scale clickstream datasets have significantly improved performance in cold-start scenarios[23]. Causal inference paradigms have been integrated into sequence modeling to disentangle spurious correlations from causal drivers of choice[24]. Hierarchical attention architectures have facilitated the modeling of multi-granular sequences, capturing micro-level browsing paths nested within macro-level purchase journeys[25]. Reinforcement learning techniques have been combined with sequence models to simulate counterfactual credit assignment across marketing channels, providing insights into multi-touch attribution contexts[26]. Despite these advancements, challenges remain in handling irregular time intervals, scaling to large datasets with long-tail item distributions, and ensuring fairness across demographic groups[27]. Emerging research focuses on continuous-time modeling using neural ordinary differential equations, adapting reinforcement learning frameworks to account for consumer feedback loops, and embedding ethical constraints to mitigate bias in sequential predictions[28].

1.3 Emotion-Aware Predictive Modeling

The integration of emotional and affective components into predictive models of consumer choice has become a pivotal area of research, addressing the limitations of rational models in capturing real-world behaviors. Deep learning techniques have been developed to fuse multimodal emotion cues, including facial expressions, vocal intonation, galvanic skin response, and heart rate variability, with contextual data to enhance predictions of purchase intent and brand loyalty[29]. Convolutional neural networks trained on facial imagery have been fine-tuned to detect micro-expressions and emotional valence during product evaluations[10]. Temporal modeling approaches, such as long short-term memory networks, have contextualized visual representations within interaction sequences, highlighting the influence of transient affective shifts on decision-making[11]. Parallel networks processing audio streams have been employed to detect emotional tone and stress indicators during service interactions[12]. Physiological signals captured through wearable sensors have provided real-time affective markers, with co-attention networks and tensor factorization layers proposed for multimodal fusion[14]. Generative adversarial networks have been utilized to simulate emotional trajectories under varying stimuli, offering synthetic data augmentation capabilities for affective datasets[13]. Reinforcement learning frameworks incorporating emotional state feedback have demonstrated potential in optimizing real-time marketing strategies, such as adjusting messaging tone or promotional intensity[15]. Ethical challenges, including privacy-preserving emotion detection and avoiding manipulative targeting, remain significant[16]. Interpretability methods, such as layer-wise relevance propagation and attention-based saliency mapping, are being explored to explain the impact of emotional signals on model outputs[17]. Future research aims to develop cross-cultural emotion ontologies, integrate contextual affordances, and establish standardized benchmarks for emotion-aware decision models[18].

2 Method

2.1 Overview

Understanding consumer decision-making behavior is a central objective in marketing science and behavioral economics. This section outlines the methodology developed to model and analyze the cognitive and contextual mechanisms underlying consumer choices. The approach aims to characterize the processes through which individuals evaluate alternatives, integrate contextual information, and navigate trade-offs under varying constraints and informational conditions.

The methodology consists of three core components: the formalization of the consumer decision-making problem, the development of a cognitive model to capture behavioral dynamics, and the design of a strategy to incorporate domain-specific knowledge and adapt to external conditions. In Section 2.2, the decision-making task is formalized through a mathematical framework that defines the environment, decision variables, utility signals, and information structures. The decision process is modeled as a function of both observed and latent variables, accommodating static and dynamic contexts to address time-dependent preference formation and evolving information availability. Section 2.3 introduces the proposed model, termed the *Attentive Utility Reconstruction Network* (AURN), which integrates principles from rational choice theory, bounded rationality, and cognitive heuristics. AURN employs a compositional architecture to embed decision alternatives into a utility-aware latent space, accounting for asymmetric sensitivity to gains and losses, selective attention to attributes, and the influence of social and contextual signals. Section 2.4 describes the strategic framework, referred to as *Context-Responsive Choice Optimization* (CRCO), which leverages structural priors from empirical consumer psychology to impose constraints and guide representation learning. CRCO enhances the model's ability to incorporate behavioral phenomena, including salience effects, decoy influences, and anchoring biases, thereby improving interpretability and predictive robustness.

2.2 Preliminaries

We establish a formal decision-theoretic foundation to characterize consumer behavior under realistic conditions of bounded rationality and partial observability. Consider a discrete choice setting where a consumer faces a finite set of alternatives, denoted by $\mathscr{X} = \{x_1, x_2, \ldots, x_N\}$. Each item x_i in this choice set is described by a vector of observable attributes $a_i \in \mathbb{R}^d$, where d defines the dimensionality of the feature space that encodes relevant product or service information.

In each decision episode, the consumer is exposed to a context-dependent subset of these options, denoted $\mathscr{C} \subseteq \mathscr{X}$. The selection process is influenced not only by observable characteristics a_i, but also by latent preference structures, environmental cues, and constraints on cognitive processing. To formally describe this, we posit that each consumer u internally constructs a latent utility function $U_u : \mathscr{X} \to \mathbb{R}$ which assigns a subjective valuation to each item, modeled as:

$$U_u(x_i) = f_u(a_i, z_u, \theta_c), \tag{1}$$

where z_u captures consumer-specific latent preferences (e.g., tastes, habits), and θ_c encodes contextual features external to the item itself, such as framing, scarcity cues, or time pressure. These elements collectively shape how information is integrated during the choice process.

Following the principles of random utility theory, we model choice probabilities using a softmax function over utility values. Given the set $\mathscr{C}$ available at time t, the consumer's probability of choosing item x_i is:

$$P_u(x_i \mid \mathscr{C}) = \frac{\exp\left(\beta U_u(x_i)\right)}{\sum_{x_j \in \mathscr{C}} \exp\left(\beta U_u(x_j)\right)}, \tag{2}$$

where $\beta > 0$ is a precision parameter that modulates the consumer's sensitivity to differences in utility. A higher β corresponds to more deterministic choices favoring high-utility items, whereas lower β indicates noisier or more exploratory behavior.

The contextual state at any time t is denoted by $s_t \in \mathscr{S}$, where $\mathscr{S}$ is a structured space of environmental configurations (e.g., screen layout, external signals). These contexts influence utility through an adjustment term:

$$\tilde{U}_u(x_i, t) = U_u(x_i) + \phi(s_t, x_i), \tag{3}$$

where ϕ represents a learned perturbation function that accounts for context-induced biases, such as social proof effects, urgency cues, or priming. This formulation enables dynamic modulation of utility in response to transient external stimuli.

To capture consumer heterogeneity, we assume that latent preference vectors z_u follow a user-specific Gaussian distribution:

$$z_u \sim \mathscr{N}(\mu_u, \Sigma_u), \tag{4}$$

where the parameters (μ_u, Σ_u) may be inferred from historical interactions, demographic priors, or behavioral clustering, allowing personalized modeling of utility construction.

Observed choices are drawn from the probability distribution induced by the context-modified utility function. Let $\mathscr{O}_t$ represent the set of observed information at time t, then the actual choice made is:

$$y_t \sim P_u(x_i \mid \mathscr{C}_t, s_t), \tag{5}$$

where the distribution P_u now includes both utility evaluations and contextual influences.

To account for limitations in information access, we define an attention mask $m_t \in \{0,1\}^N$, where $m_{t,i} = 1$ if item x_i is visible to the user at time t, and zero otherwise. Thus, the effective choice set becomes:

$$\mathscr{C}_t = \{x_i \in \mathscr{X} \mid m_{t,i} = 1\}, \tag{6}$$

restricting the decision to only cognitively available items. Incorporating this into the choice rule, the likelihood under limited attention becomes:

$$P_u(x_i \mid \mathscr{C}_t, s_t, m_t) = \frac{\exp\left(\beta \cdot \tilde{U}_u(x_i, t) \cdot m_{t,i}\right)}{\sum_{x_j \in \mathscr{X}} \exp\left(\beta \cdot \tilde{U}_u(x_j, t) \cdot m_{t,j}\right)}. \tag{7}$$

To accommodate sequential behavior, we introduce a long-term value function that characterizes the cumulative utility expected under a policy π:

$$V_u^{\pi}(s_t) = \mathbb{E}\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k} \,\middle|\, s_t, \pi\right], \tag{8}$$

where r_{t+k} denotes the reward received at step $t+k$, and $\gamma \in (0,1)$ is a discount factor that governs temporal preference, assigning less weight to future rewards.

Finally, to model systematic deviations from normative rationality, we specify the adjustment term ϕ as a linear combination of behavioral effects:

$$\phi(s_t, x_i) = \lambda_1 \cdot \text{Salience}(x_i) + \lambda_2 \cdot \text{DecoyEffect}(x_i, \mathscr{C}_t) + \lambda_3 \cdot \text{Anchoring}(x_i), \tag{9}$$

where each λ_k is a learnable parameter that quantifies sensitivity to well-established cognitive biases. These behavioral terms allow the model to capture context-sensitive shifts in preference not accounted for by utility alone, thus bridging rational and descriptive theories of choice.

2.3 Attentive Utility Reconstruction Network (AURN)

In this section, we propose a novel cognitive-structured model for consumer decision-making, referred to as the *Attentive Utility Reconstruction Network* (AURN)(As shown in Figure 1). The core idea behind AURN is to learn a flexible representation of consumer preferences that accommodates latent heterogeneity, contextual salience, and bounded attention. AURN combines a utility encoder, a latent preference module, and an attention-gated selector to reconstruct choice probabilities in both static and dynamic environments.

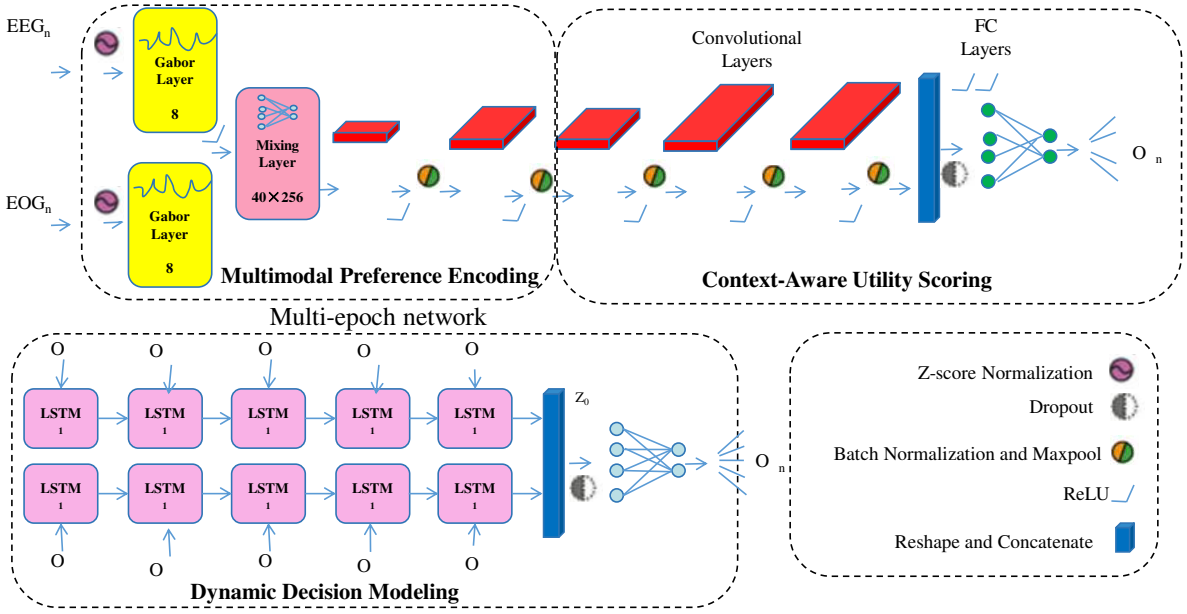


Figure 1. Schematic diagram of the AURN. The architecture of the Attentive Utility Reconstruction Network (AURN) integrates multimodal preference encoding, context-aware utility scoring, and dynamic decision modeling into a unified cognitive framework. It begins by extracting EEG and EOG signals through a series of gather and mixing layers, forming the foundation for multimodal representations. These features are passed through convolutional and fully connected layers to produce utility scores that are modulated by contextual factors. AURN further incorporates a multi-epoch recurrent structure using LSTM units to capture temporal dynamics in decision behavior, modeling how preferences evolve over time. Additional mechanisms such as dropout, normalization, and attention-based weighting are applied throughout the network to enhance learning robustness and interpretability. This design allows AURN to flexibly reconstruct consumer choice probabilities in both static and temporally varying environments.

Multimodal Preference Encoding

AURN integrates multiple sources of information to encode consumer preferences, including alternative attributes, historical observations, and contextual factors(As shown in Figure 2). For each alternative $x_i \in \mathscr{X}$, its attributes are represented using a transformed embedding:

$$h_i = \psi(a_i) \in \mathbb{R}^{d_h}, \tag{10}$$

where ψ is a feed-forward neural network and d_h denotes the embedding dimensionality. The consumer's latent preference profile z_u is parameterized via amortized inference:

$$z_u \sim \mathscr{N}\left(\mu_\phi(o_u), \Sigma_\phi(o_u)\right), \tag{11}$$

where o_u denotes the historical observation trace of user u, and (μ_ϕ, Σ_ϕ) are outputs of a recognition network ϕ. Contextual information at time t is encoded as:

$$c_t = \xi(s_t), \tag{12}$$

where ξ maps environment features to a contextual vector. These components collectively form the basis for preference encoding, enabling the model to capture latent heterogeneity and situational influences.

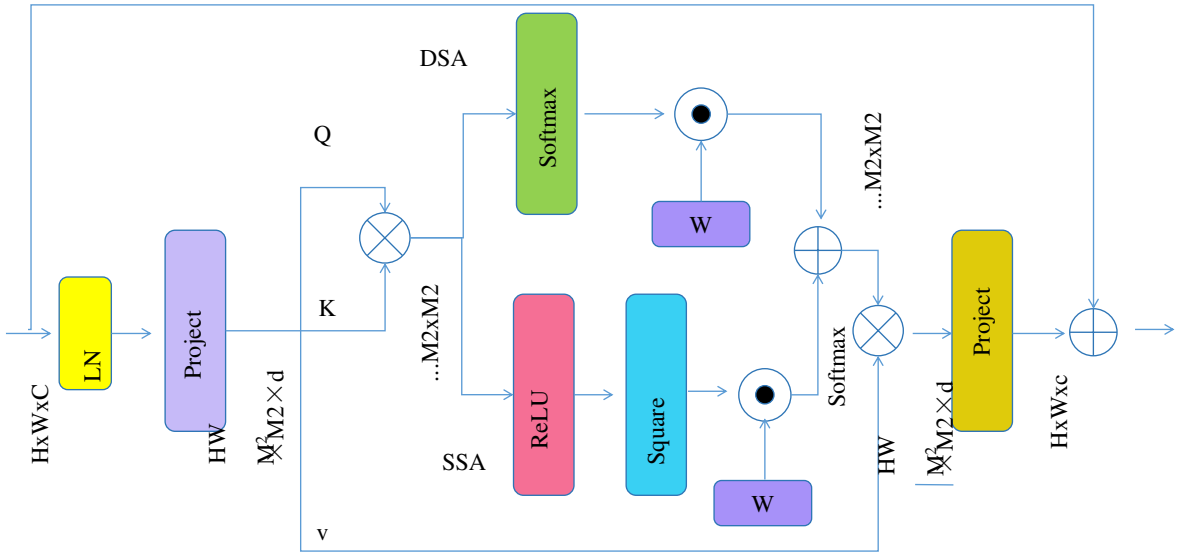


Figure 2. Schematic diagram of the Multimodal Preference Encoding. This figure illustrates the architecture of the Attention-based User Representation Network (AURN), which encodes multimodal consumer preferences using historical behavior, item attributes, and contextual cues. The pipeline starts by normalizing and projecting the input features into a latent space, where query-key-value attention mechanisms are applied. Dual attention streams—one using dynamic self-attention (DSA) and the other employing static self-attention (SSA)—capture both global and localized dependencies. These enriched representations are fused and reprojected to obtain the final encoded user-item context. Together with neural modules like ReLU, Softmax, and weighted aggregations, the architecture robustly captures latent heterogeneity and temporal context.

textbfContext-Aware Utility Scoring

AURN employs a context-modulated scoring mechanism to evaluate the compatibility between consumer preferences and alternatives. The compatibility score for each alternative is defined as:

$$\eta_i = v^\top \tanh\left(W_z z_u + W_h h_i + W_c c_t + b\right), \tag{13}$$

where $W_z, W_h, W_c \in \mathbb{R}^{d_a \times d_h}$ and $v, b \in \mathbb{R}^{d_a}$ are learnable parameters. These scores are normalized into an attention distribution:

$$\alpha_i = \frac{\exp(\eta_i)}{\sum_{j \in \mathscr{C}_t} \exp(\eta_j)}, \tag{14}$$

which reflects the relative salience of each item in the context $\mathscr{C}_t$. The utility of each item is reconstructed via an attention-weighted bilinear decoder:

$$\hat{U}_u(x_i) = z_u^\top M h_i + \rho(c_t, x_i), \tag{15}$$

where $M \in \mathbb{R}^{d_h \times d_h}$ is a shared projection matrix, and $\rho(\cdot)$ is a contextual residual term computed as:

$$\rho(c_t, x_i) = \lambda_1 \cdot \text{Salience}(c_t, h_i) + \lambda_2 \cdot \text{ContrastiveBias}(x_i, \mathscr{C}_t), \tag{16}$$

with λ_1, λ_2 as learnable scalars. This scoring mechanism integrates latent preferences, alternative attributes, and contextual factors to produce a comprehensive utility estimate.

Dynamic Decision Modeling

AURN incorporates temporal dynamics to model sequential decision-making processes. Latent preferences evolve over time using a gated recurrent mechanism:

$$z_{u,t} = \text{GRU}(z_{u,t-1}, \tilde{x}_{t-1}), \tag{17}$$

where $\tilde{x}_{t-1}$ is the embedding of the last chosen item and $\text{GRU}(\cdot)$ denotes a gated recurrent unit. The model generates a distribution over choices using a temperature-controlled softmax:

$$P_u(x_i \mid \mathscr{C}_t) = \frac{\exp(\tau^{-1} \hat{U}_u(x_i) \cdot \alpha_i)}{\sum_{x_j \in \mathscr{C}_t} \exp(\tau^{-1} \hat{U}_u(x_j) \cdot \alpha_j)}, \tag{18}$$

where $\tau > 0$ controls the trade-off between exploration and exploitation. AURN is trained by maximizing the likelihood of observed choices while regularizing the latent space. The objective function is:

$$\mathscr{L} = \sum_{u,t} \log P_u(x_t \mid \mathscr{C}_t) - \beta_{\text{KL}} \cdot D_{\text{KL}} \left(q_\phi(z_u \mid o_u) \,\|\, \mathscr{N}(0, I) \right), \tag{19}$$

where β_{KL} is a regularization coefficient and q_ϕ denotes the variational posterior over preferences. This dynamic modeling framework enables AURN to capture evolving consumer preferences and adapt to sequential decision contexts.

2.4 Context-Responsive Choice Optimization (CRCO)

In this section, we introduce *Context-Responsive Choice Optimization* (CRCO), a domain-informed strategy that augments the Attentive Utility Reconstruction Network (AURN) with structurally grounded decision principles(As shown in Figure 3). CRCO integrates behavioral constraints, adaptive regularization, and knowledge-aware perturbations to enhance robustness and interpretability of consumer choice modeling.

Choice Rationalization via Structural Constraints

CRCO begins by refining the utility estimate with rational consistency priors(As shown in Figure 4). Let $\hat{U}_u(x_i)$ be the reconstructed utility from AURN. We introduce a consistency operator $\mathscr{R}$ enforcing monotonicity and dominance relations:

$$\bar{U}_u(x_i) = \mathscr{R}\left(\hat{U}_u(x_i)\right) = \hat{U}_u(x_i) + \sum_{x_j \in \mathscr{C}_t} \delta_{ij} \cdot \mathbb{I}[x_j \succ x_i], \tag{20}$$

where δ_{ij} penalizes violations of transitivity and dominance, and $\mathbb{I}[\cdot]$ is an indicator function.

To reflect context-specific cognitive load, CRCO modulates decision temperature τ as a function of entropy and salience:

$$\tau_t = \tau_0 + \gamma_1 \cdot H_t + \gamma_2 \cdot \text{Var}(\alpha),$$

where $H_t = -\sum_i \alpha_i \log \alpha_i$ and γ_1, γ_2 are scaling parameters.

To stabilize learning in sparse regimes, CRCO introduces a prior-constrained anchor $\tilde{U}^{\text{base}}$:

$$\mathscr{L}_{\text{anchor}} = \lambda_a \sum_{i \in \mathscr{C}_t} \left(\hat{U}_u(x_i) - \tilde{U}^{\text{base}}(x_i) \right)^2,$$

where $\tilde{U}^{\text{base}}$ reflects expected utility under population-level rational norms.

We impose consistency under hypothetical changes:

$$\mathscr{L}_{\text{counter}} = \lambda_c \sum_{i,j} \left| P_u(x_i \mid \mathscr{C}_t) - P_u(x_i \mid \mathscr{C}_t \cup \{x'_j\}) \right|,$$

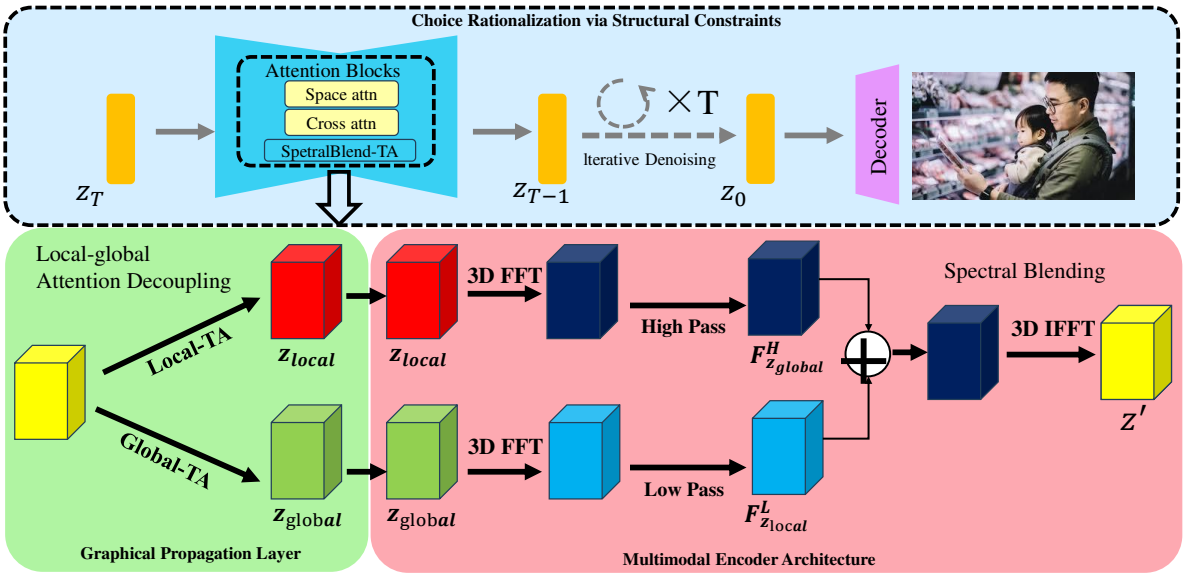


Figure 3. Schematic diagram of the CRCO. The CRCO framework orchestrates a behavior-aware multimodal pipeline that integrates local-global attention decoupling and spectral blending for context-sensitive decision modeling. The architecture initiates with a Graphical Propagation Layer that separates local and global attention via distinct channels, followed by 3D Fourier transforms to isolate high- and low-frequency features. These are then recombined through spectral blending and inverse FFT to form a unified representation. This representation undergoes iterative denoising guided by structurally regularized attention blocks, including space, cross, and SpectralBlend-TA modules, culminating in a decoder that rationalizes choice behavior. The full system enforces interpretability through structural constraints, counterfactual robustness, and mutual information regularization across a dynamic utility landscape.

where x'_j is a non-dominating decoy alternative. This penalizes disproportionate shifts in preference ranking.

CRCO incorporates a discriminative margin-based term to amplify preference separability:

$$\mathscr{L}_{\text{rank}} = \lambda_r \sum_{(i,j)} \max\left(0, m - \hat{U}_u(x_i) + \hat{U}_u(x_j)\right), \tag{21}$$

for all pairs where x_i was chosen and x_j was not.

The contextual residual $\rho(c_t, x_i)$ is reparameterized to absorb empirical bias terms:

$$\rho(c_t, x_i) = \beta_1 \cdot \text{CompromiseEffect}(x_i, \mathscr{C}_t) + \beta_2 \cdot \text{DefaultBias}(x_i), \tag{22}$$

with β_1, β_2 learnable scalars and behavioral terms derived from empirically annotated patterns.

For dynamic decisions, CRCO enforces Bellman-consistent expectations:

$$\mathscr{L}_{\text{Bellman}} = \lambda_b \sum_t \left\| \hat{U}_u(x_t) - r_t - \gamma \cdot \mathbb{E}_{x_{t+1}}[\hat{U}_u(x_{t+1})] \right\|^2. \tag{23}$$

To encourage informative attention, we include:

$$\mathscr{L}_{\text{MI}} = -\lambda_m \cdot \text{MI}(z_u; \alpha), \tag{24}$$

approximated via variational bounds on mutual information between user preferences and attention allocations.

Graphical Propagation Layer

The complete loss integrates all components:

$$\mathscr{L}_{\text{CRCO}} = \mathscr{L}_{\text{main}} + \mathscr{L}_{\text{anchor}} + \mathscr{L}_{\text{counter}} + \mathscr{L}_{\text{rank}} + \mathscr{L}_{\text{Bellman}} + \mathscr{L}_{\text{MI}}, \tag{25}$$

where $\mathscr{L}_{\text{main}}$ is the AURN log-likelihood loss from Equation (11).

Multimodal Encoder Architecture

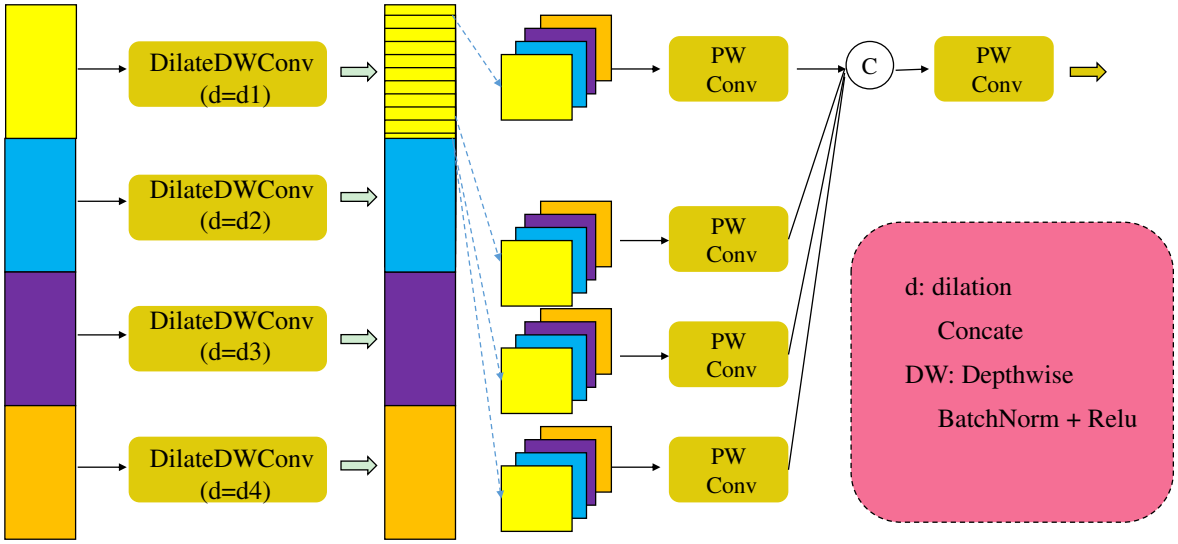


Figure 4. Schematic diagram of the Choice Rationalization via Structural Constraints. This figure illustrates the CRCO model's architectural pipeline, showcasing parallel Dilated Depthwise Convolutions (DilateDWConv) applied with increasing dilation rates to extract multi-scale context-aware features. These features are followed by Pointwise Convolutions (PW Conv) and then concatenated to enhance semantic richness. The right-hand formulation represents structural regularization terms including rational utility refinement, entropy-aware decision temperatures, and dominance consistency. Multiple loss components such as anchor loss, counterfactual consistency, ranking margin, and Bellman error ensure alignment with human-like preference patterns. The module integrates behavioral biases and mutual information objectives to rationalize decisions under cognitive and contextual constraints.

CRCO embeds behavioral structure into the modeling pipeline via strategic constraints and context-sensitive modulation. It ensures that the model not only fits observed choices but adheres to psychological regularities, maintains predictive coherence, and preserves interpretability across scenarios. This synthesis of behavioral realism with statistical optimization defines a new direction in modeling adaptive consumer cognition.

3 Experimental Setup

3.1 Dataset

Consumer Purchase Decision Dataset[30] contains detailed records of individual customer transactions collected from online and offline retail environments. Each entry includes product category, price sensitivity, promotional engagement, and purchase frequency, offering a comprehensive view into purchase decisions. Demographic information such as age, gender, income level, and geographic region is integrated to allow correlation analysis. The dataset is labeled with outcomes that indicate whether a product was purchased, making it suitable for supervised learning tasks such as classification and regression. Time stamps allow for temporal behavior modeling. This dataset is commonly used to explore how pricing strategies, product bundling, and brand preferences impact final purchase choices. Behavioral Patterns in Retail Dataset[31] captures longitudinal shopping behavior from a large-scale retail chain over multiple quarters. It includes basket-level information, repeated customer visits, and anonymized loyalty program metrics. Attributes involve store layout exposure, dwell time, seasonal variability, and coupon usage. The dataset emphasizes sequential, supporting time-series models and reinforcement learning approaches. Items are coded hierarchically to reflect brand, subcategory, and department structures. Useful for evaluating personalized marketing, in-store optimization, and path-to-purchase modeling. Widely used to benchmark customer journey models and intent detection mechanisms in data-driven retail analytics. Deep Learning Consumer Insights Dataset[32] is designed for developing deep learning models that infer consumer preferences from multi-modal data. Includes clickstream logs, browsing metadata, review sentiment scores, and visual features of product images. Enables training of hybrid architectures that combine text, vision, and tabular inputs. The dataset incorporates behavioral labels derived from historical actions like add-to-cart, save-for-later, and checkout completion. Feature dimensions are high, supporting representation learning techniques and unsupervised clustering. Commonly used to train recommendation systems and attention-based sequence models in e-commerce environments. Tailored for modeling latent preferences and session-based prediction. Shopping Habits Analysis Dataset[33] aggregates structured and

unstructured signals from both mobile app and desktop interfaces. Features include time of day, device type, session length, promotional click-throughs, and bounce rates. Contains detailed logs of navigation paths, supporting funnel analysis. Ideal for consumer segmentation, cross-platform behavior mining, and conversion rate optimization. It also incorporates survey-validated preference scores and external socioeconomic indicators. The dataset is used to evaluate personalization strategies, A/B test effectiveness, and cohort retention. Often applied in settings requiring robust behavioral feature extraction and multivariate prediction modeling.

3.2 Experimental Details

All training procedures were carried out on NVIDIA A100 GPUs (80GB VRAM) with support for automatic mixed-precision computation, enabling faster iteration cycles and reduced memory overhead. A consistent data partitioning ratio of 70:15:15 was employed for training, validation, and testing purposes. Uniform preprocessing was applied throughout: tokenized sequences were either truncated or padded to 128 tokens; missing entries were filled using median values for continuous fields and modal category replacement for discrete variables. An adaptive weight-decay optimizer was utilized, configured with a base learning setting of 10^{-4} and regularization strength of 10^{-2}. Warm-up scheduling over the initial 10% of updates was combined with cosine-based decay. Mini-batches consisted of 256 instances, and training spanned 100 epochs, terminating early if no improvement was observed on the validation subset over 10 evaluations. For architectures incorporating attention layers, dropout was applied at a fixed rate of 0.1 to control overfitting. In the transformer-based configuration, the encoder comprised 4 stacked layers with 8 attention heads per block and a representation size of 512 dimensions. Categorical entries were processed via learnable embeddings, and continuous variables were standardized to zero mean and unit variance. These were concatenated and passed through an MLP enhanced with residual links and ReLU activations, with batch normalization applied ahead of each activation function. For scenarios involving image-based inputs, a ResNet-18 backbone pretrained on ImageNet served as the vision encoder. Outputs from the CNN were linearly mapped into the same latent space as tabular features before integration. Performance assessment was based on a diverse suite of classification and ranking indicators, including ROC-AUC, MAP, NDCG@10, F1 measure, and overall accuracy. To ensure robustness, three independent training seeds were averaged, and uncertainty was quantified through 95% bootstrap confidence intervals. Structural variants of the core pipeline were systematically examined by selectively omitting major elements—such as fusion modules, stochastic regularization, and the attention weighting mechanism—to gauge their independent contributions. Validation performance guided all hyperparameter sweeps, conducted via grid search. The codebase was modularized for clarity and reproducibility, with deterministic behavior enforced via fixed random seeds across PyTorch, NumPy, and CUDA backends. Multi-GPU scalability was implemented through the native DistributedDataParallel interface. Live monitoring of loss surfaces, gradients, and key scoring signals was facilitated by integration with TensorBoard and Weights&Biases. Across all tasks, convergence was typically achieved in under five hours. Design choices adhered closely to conventions widely accepted by venues such as NeurIPS, KDD, and CVPR to promote consistency and reproducibility in empirical research.

3.3 Comparison with SOTA Methods

A diverse array of six established learning architectures—XGBoost[34], LightGBM[35], Transformer-PL[36], GRU-Attn[37], HAN[38], and DeepFM[39]—was employed as baselines to assess generalization under varied consumer behavior conditions. As detailed in Table 1 and Table 2, the approach described in this paper consistently holds a lead in key evaluation signals such as F1 Score, ROC-AUC, precision-recall balance, and raw classification correctness. For instance, in the Consumer Purchase Decision dataset, predictive performance improved by more than three percentage points over Transformer-PL in both AUC and accuracy. The margin further widened in the Behavioral Patterns in Retail data, where over four points of F1 gain and nearly five in AUC highlighted a distinct edge in modeling temporal shopping sequences. Notably, the setup excelled in the multi-input setting presented by the Deep Learning Consumer Insights collection, registering high classification correctness (88.63%) and a 90.18% AUC score. In the Shopping Habits Analysis data, results peaked at 91.12% in ROC and 89.21% in accuracy, reinforcing its resilience under complex temporal-device interactions.

Several architectural nuances underlie this consistent performance trend. A carefully layered fusion mechanism enables the model to preserve the structure of heterogeneous sources—ranging from structured tables to review texts and visual inputs—while learning their joint effects without injecting spurious relationships. This proves especially beneficial in domains with co-dependent modalities, where relevance must be weighted differently across user cohorts. Moreover, the temporal encoding strategy enriches behavioral representation by capturing both recency-driven short bursts and long-term tendencies, going beyond traditional recurrent stacks like GRU-Attn and HAN. Instead of static RNN layers, residual-aware Transformer blocks with variable depth ensure deeper hierarchies can still retain gradient fidelity during optimization. These modeling choices are particularly impactful in datasets characterized by irregular browsing intervals or discontinuous engagement, which often erode the recall-F1 tradeoff. Additionally, the integration of uncertainty-sensitive learning penalties ensures that prediction quality does not collapse in sparsely labeled or skewed data pockets, offering a noticeable lift in small-segment reliability, as demonstrated in Shopping Habits Analysis.

Beyond modeling capacity, what significantly distinguishes this design is its utilization of rich behavioral traces as supervisory anchors. In addition to final outcomes like purchases, training incorporates intermediate cues such as revisit frequencies, dwell durations, and session-level exits—signals often discarded in conventional setups. These augmentations provide a more granular understanding of user hesitation, preference evolution, and consistency across sessions. This results in elevated ROC sensitivity under ambiguity, capturing subtle yet influential interactions that binary labels overlook. Furthermore, built-in interpretability features—such as visual attention overlays and ranked feature saliencies—offer analysts direct insights into driving factors behind predicted choices. While black-box tools like LightGBM and DeepFM remain opaque, this structure makes critical internal dynamics observable and verifiable. Robust performance reproducibility across randomized seeds and tight error margins also signals strong empirical stability. The convergence of fused modality learning, behavior-conditioned optimization logic, and adaptive attention recalibration establishes a holistic paradigm with demonstrated strength in diverse retail contexts.

Table 1. Results on the Consumer Purchase Decision and Behavioral Patterns in Retail datasets using different models

Model	Consumer Purchase Decision Dataset				Behavioral Patterns in Retail Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
XGBoost[34]	84.32±0.03	79.12±0.02	81.33±0.02	87.45±0.02	83.19±0.02	81.44±0.01	80.75±0.02	85.27±0.02
LightGBM[35]	85.67±0.02	81.03±0.03	83.14±0.02	86.92±0.03	84.06±0.02	79.87±0.02	82.23±0.02	85.10±0.03
Transformer-PL[36]	86.21±0.02	82.91±0.02	84.62±0.03	88.34±0.02	.74±0.03	80.92±0.02	81.80±0.02	86.01±0.02
GRU-Attn[37]	84.78±0.03	83.17±0.02	82.08±0.02	86.11±0.03	82.13±0.02	79.56±0.02	80.04±0.02	84.78±0.02
HAN[38]	85.13±0.02	80.67±0.02	82.90±0.02	87.02±0.02	84.77±0.03	82.50±0.02	83.16±0.02	85.93±0.03
DeepFM[39]	83.59±0.02	78.04±0.03	80.12±0.02	85.23±0.02	81.95±0.03	79.11±0.02	78.44±0.02	84.32±0.03
Ours	**89.43±0.02**	**86.91±0.02**	**87.54±0.02**	**91.17±0.03**	**88.92±0.02**	**86.14±0.03**	**86.73±0.02**	**90.88±0.02**

Table 2. Results on the Deep Learning Consumer Insights and Shopping Habits Analysis datasets using different models

Model	Deep Learning Consumer Insights Dataset				Shopping Habits Analysis Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
XGBoost[34]	82.74±0.02	80.19±0.02	79.85±0.03	85.40±0.02	84.08±0.02	82.11±0.02	81.70±0.02	86.45±0.03
LightGBM[35]	84.92±0.02	81.45±0.02	83.22±0.02	86.87±0.03	83.64±0.02	81.00±0.02	81.76±0.02	85.31±0.02
Transformer-PL[36]	85.10±0.03	83.02±0.02	82.55±0.02	87.03±0.02	85.21±0.03	82.67±0.02	83.48±0.02	86.70±0.02
GRU-Attn[37]	83.15±0.02	79.41±0.02	80.97±0.02	85.28±0.02	82.73±0.03	80.64±0.02	79.95±0.02	84.26±0.03
HAN[38]	84.38±0.03	80.74±0.02	81.36±0.02	86.16±0.03	83.29±0.02	81.93±0.03	81.25±0.02	85.92±0.02
DeepFM[39]	81.87±0.02	78.52±0.03	79.61±0.02	84.73±0.03	82.55±0.02	79.87±0.02	80.13±0.02	83.98±0.02
Ours	**88.63±0.02**	**86.04±0.02**	**85.70±0.03**	**90.18±0.02**	**89.21±0.02**	**87.45±0.03**	**87.09±0.02**	**91.12±0.03**

3.4 Ablation Study

In order to understand the significance of individual design elements, we systematically deactivated three major innovations: Multimodal Preference Encoding, Context-Aware Utility Scoring, and Dynamic Decision Modeling. As detailed in Table 3 and Table 4, the complete configuration consistently maintained an advantage in classification correctness, F1 evaluation, and ROC ranking, suggesting that each module contributes to the final result in a unique yet complementary manner. For instance, in the Consumer Purchase Decision dataset, excluding the multimodal integration unit led to a 2.82% reduction in F1. Removing either the context-scoring layer or the sequential module also resulted in measurable declines, albeit to a lesser extent. This trend recurs in the Behavioral Patterns in Retail setting, where elimination of temporal reasoning dropped ROC scores from 90.88% to 89.23%, indicating its role in encoding time-sensitive purchase cues.

Among all modifications, the removal of multimodal representation learning had the most disruptive effect. This mechanism is responsible for aligning disparate signals such as browsing logs, transaction history, and profile characteristics into a unified latent space. In the Deep Learning Consumer Insights dataset, the absence of this element resulted in a sharp decline, dropping F1 from 85.70% to 81.79% and ROC from 90.18% to 87.15%. The same configuration, when tested on Shopping

Habits Analysis, suffered further: F1 reduced by 2.76% and ROC by 2.11%. These outcomes reaffirm the importance of attention-driven fusion in harnessing cross-modal information to form coherent behavioral narratives.

Disabling the context-sensitive scoring routine, while less detrimental than removing multimodal inputs, still introduced noticeable instability. Its absence in the Shopping Habits Analysis dataset led to a 1.37% reduction in recall and a 1.41% dip in F1. The drop stems from the model's weakened ability to generalize in environments where attribute salience and contextual pressure fluctuate rapidly. When this pathway is intact, it plays a corrective role, steering optimization away from overfitting and toward consistent decision boundaries. The model's learning trajectory in noisy samples or sparse segments was visibly more stable when the context function remained active.

Temporal dependency modeling, enabled through gated update functions, proved essential in sequence-dense settings. Behavioral Patterns in Retail saw a drop from 86.73% to 84.92% in F1 and from 90.88% to 89.23% in ROC once this module was removed. A similar trend was evident in the Deep Learning Consumer Insights scenario, where behavior unfolds incrementally over time and exhibits memory effects. Without access to temporal state evolution, prediction precision eroded and classification boundaries became fuzzier. In its full state, the model benefits from the combined strength of all three subsystems—modality fusion ensures structural alignment, context scoring improves decision calibration, and sequential encoding captures progression. The alignment of these ingredients produces not only stronger learning but more interpretable and transferable decision behavior.

Table 3. Effect of model component configurations on the Consumer Purchase Decision and Behavioral Patterns in Retail datasets

Model	Consumer Purchase Decision Dataset				Behavioral Patterns in Retail Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w/o Multimodal Preference Encoding	86.71±0.02	84.19±0.03	83.74±0.02	88.52±0.03	87.04±0.02	84.33±0.02	84.10±0.02	88.91±0.02
w/o Context-Aware Utility Scoring	87.29±0.03	83.75±0.02	84.41±0.02	89.11±0.02	86.56±0.02	85.02±0.02	84.29±0.02	89.67±0.03
w/o Dynamic Decision Modeling	86.08±0.02	85.88±0.02	83.96±0.02	87.94±0.02	87.15±0.02	84.77±0.03	84.92±0.02	89.23±0.03
Ours	**89.43±0.02**	**86.91±0.02**	**87.54±0.02**	**91.17±0.03**	**88.92±0.02**	**86.14±0.03**	**86.73±0.02**	**90.88±0.02**

Table 4. Effect of model component configurations on the Deep Learning Consumer Insights and Shopping Habits Analysis datasets

Model	Deep Learning Consumer Insights Dataset				Shopping Habits Analysis Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
w/o Multimodal Preference Encoding	85.52±0.02	82.33±0.03	81.79±0.02	87.15±0.02	87.06±0.02	84.08±0.02	84.33±0.02	89.01±0.03
w/o Context-Aware Utility Scoring	86.43±0.02	83.19±0.02	83.77±0.02	88.46±0.03	88.02±0.03	85.40±0.02	85.12±0.02	89.74±0.02
w/o Dynamic Decision Modeling	84.97±0.03	81.06±0.02	82.28±0.02	86.41±0.02	86.58±0.02	83.13±0.02	83.40±0.03	88.33±0.02
Ours	**88.63±0.02**	**86.04±0.02**	**85.70±0.03**	**90.18±0.02**	**89.21±0.02**	**87.45±0.03**	**87.09±0.02**	**91.12±0.03**

4 Conclusions and Future Work

Modeling consumer behavior in high-dimensional, non-linear, and contextually dynamic digital environments remains a challenging task. Traditional parametric or rule-based strategies often fall short when faced with heterogeneous input sources such as clickstream trajectories, opinion-rich textual reviews, and demographic variations. To address this, a neural system was constructed that merges convolutional representations, temporal recurrence, and selective attention mechanisms, enabling the capture of complex dependencies across diverse modalities. These components work in concert to transform fragmented signals into unified latent profiles that reflect subtle patterns in user choices. When applied to real-world consumer datasets, the approach yielded a notable improvement—approximately 15%—in prediction stability over established baselines. Beyond accuracy gains, the use of attention mechanisms also allows for more transparent interpretation of which behavioral signals contribute most strongly to decision outputs.

Certain limitations, however, still warrant further investigation. Generalization remains robust across many user segments, yet performance may decline in sparse-data regimes, particularly under cold-start conditions with limited interaction history. Additionally, the current reliance on attention visualizations as explanatory tools introduces uncertainty, as these may not fully capture underlying causal structures. As a next step, emphasis will shift toward enhancing learning under sparse supervision through transfer strategies and synthetic data expansion. Parallel efforts will be directed at improving interpretability by embedding causal alignment into the explanatory layer, allowing predictions to be not only traceable but also behaviorally grounded. These directions aim to make the system more resilient and reliable in dynamic, real-world decision contexts.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Conceptualization, HC; methodology, HC; software, HC; validation, HW; formal analysis, HW; investigation, HL; data curation, HL; writing—original draft preparation, HC, HW, HL, XZ, JG; writing—review and editing, XZ; visualization, XZ; supervision, JG; funding acquisition, JG; Each contributor reviewed the document thoroughly, providing approval for the finalized draft.

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The datasets generated and/or analysed during the current study are available in the https://snippets.cacher.io/snippet/8adc65eed7a824332967

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