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Machine Learning Architectures for Sustainable Consumer Behaviour Modelling: Synergizing Behavioural Economics and Computational Intelligence

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Abstract. Sustainable technology adoption, especially when it comes to electric vehicles (EVs), depends heavily on behavioral and social factors that most traditional prediction models tend to overlook. This paper introduces a Behavior-Aware Reinforcement Learning (BARL) framework designed to bring together insights from behavioral economics, graph-based modeling of social influence, and causal inference techniques within a single learning system. The core idea treats EV adoption as a Markov Decision Process. The reward function here accounts for environmental benefits, peer effects captured through graph neural networks, and adjustments for common cognitive biases that shape real-world choices. A dedicated causal component helps the model separate genuine cause-and-effect relationships from mere correlations, making the predictions more reliable. Using the Indian Electric Vehicle Dataset for evaluation, the BARL approach was tested against several standard methods such as ARIMA, LSTM, and XGBoost. The results indicate clear improvements, with BARL lowering the RMSE by roughly 23% compared to the strongest baseline. Ablation studies further demonstrate the individual value added by the behavioral, social, and causal elements. Overall, the work underscores how human-centered modeling can offer deeper insights into EV adoption patterns and deliver a practical, scalable tool to support evidence-based policies for sustainability.

1 Introduction

The shift toward sustainable consumption has emerged as a pressing global priority amid growing concerns over climate change, environmental damage, and the rapid depletion of natural resources. Although public awareness of sustainability issues has risen considerably and many consumers express positive attitudes, a clear gap remains between what people intend to do and how they actually behave in practice.

Traditional economic models typically assume that individuals act as fully rational agents who carefully weigh costs and benefits before making decisions. In reality, however, everyday choices are shaped by cognitive limitations, time-related biases, and the surrounding social environment. Behavioral economics offers a more grounded perspective

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on these inconsistencies. Ideas such as bounded rationality [20], present bias and hyperbolic discounting [9], [16], and the power of social norms [7] help explain why people often favor immediate convenience over future environmental gains.

The Theory of Planned Behavior (TPB) [1] has been extensively applied to connect attitudes and intentions to actual actions, yet it struggles to account for the dynamic and context-specific nature of real decision-making. Likewise, nudge-based approaches [11] have proven useful in steering people toward better choices, but they face challenges when it comes to large-scale implementation and tailoring interventions to individual needs.

In recent years, advances in machine learning (ML) have opened fresh avenues for understanding consumer behavior at scale. Researchers have used clustering methods to identify distinct eco-conscious consumer groups [6], while transformer models have improved recommendations for sustainable products [2]. Reinforcement learning techniques that factor in behavioral biases, such as loss aversion, have enhanced the ability to influence decisions [5], [17]. Graph Neural Networks (GNNs) have shown promise in capturing social influence and peer effects within sustainability contexts [3], [14]. Inverse reinforcement learning (IRL) has been employed to uncover hidden motivations behind observed actions [18], [19], and causal machine learning tools like double/debiased ML have strengthened policy evaluation in complex settings [24].

Even with these developments, most existing methods tend to work in isolation. Some emphasize psychological insights but lack computational power and scalability, while others rely heavily on data-driven techniques without sufficient grounding in human behavior. This paper addresses that limitation by presenting an integrated framework that merges principles from behavioral economics with modern machine learning architectures. The goal is to create a more comprehensive, scalable, and human-centered approach for modeling, predicting, and supporting sustainable consumer choices.

The remainder of this paper is structured as follows. Section 2 details the proposed computational framework that brings together behavioral principles and machine learning methods. Section 3 presents case studies to illustrate real-world applications. Section 4 examines key ethical and scalability issues, including concerns related to privacy, bias, and transparency. Finally, Section 5 offers concluding remarks and suggests directions for future research.

2 Proposed Computational Framework

To overcome the shortcomings of approaches that treat behavioral insights and data-driven modeling separately, this paper introduces a unified computational framework. It brings together concepts from behavioral economics and state-of-the-art machine learning architectures.

The framework is built around three main interconnected modules: high-dimensional preference mapping, latent motivation inference, and causal policy optimization. Together, these components create a closed-loop adaptive system capable of continuous improvement.

2.1 High-Dimensional Preference Mapping

Consumer behavior is deeply connected to social relationships and specific contexts. To capture social influence and spatial dependencies, we employ Graph Neural Networks (GNNs). Let $G = (V, E)$ represent a graph where nodes V correspond to consumers and edges E encode social or geographic relationships. Node representations are updated as:

$$h_i^{(k+1)} = \sigma\left(\sum_{j\in \mathrm{N}(i)} W^{(k)} h_j^{(k)} + b^{(k)}\right)$$

where $h_i^{(k)}$ is the embedding of node i at layer k, and $\mathrm{N}(i)$ denotes its neighborhood. This formulation enables the model to capture peer effects and diffusion patterns in sustainable behavior adoption.

2.2 Latent Motivation Inference

Observed behavior frequently conceals the deeper preferences that drive consumer choices. To infer true motivations, Inverse Reinforcement Learning (IRL) was introduced. Given trajectories $= (s_t, a_t)$, the objective is to recover a reward function $R(s,a)$ such that:

$$\pi^* = \arg\max_{\pi} \mathrm{E}_\pi\left[\sum_t \gamma^t R(s_t, a_t)\right]$$

where π^* represents the optimal policy explaining observed behavior. This allows identification of hidden drivers such as cost sensitivity or social conformity.

2.3 Causal Policy Modeling

To properly assess the effectiveness of different interventions, the framework adopts Double/Debiased Machine Learning (DML) for estimating treatment effects.:

$$\hat{\theta} = \frac{1}{n}\sum_{i=1}^{n} \left[\left(Y_i - \hat{g}(X_i)\right) \cdot \left(D_i - \hat{m}(X_i)\right)\right]$$

where Y_i is the outcome, D_i the treatment, and X_i covariates. This removes confounding bias and isolates causal impact.

2.4 Prescriptive Optimization via Reinforcement Learning

For policy design, we employ Multi-Agent Reinforcement Learning (MARL). Each agent i optimizes:

$$Q_i(s,a) \leftarrow Q_i(s,a) + \alpha\left[r + \gamma \max_{a'} Q_i(s',a') - Q_i(s,a)\right]$$

Behavioral biases such as loss aversion are incorporated into reward shaping:

$$R'(x) = \begin{cases} x, & x \geq 0 \\ \lambda x, & x < 0 \end{cases} (\lambda > 1)$$

2.5 System Architecture

The proposed framework adopts a modular pipeline for its overall architecture. The main components are organized as follows:

Data Fusion Layer: This layer merges diverse types of information, including transactional records, social interactions, and environmental data, through transformer-based embeddings.

Behavioral Modeling Layer: It integrates graph neural networks for capturing social context, inverse reinforcement learning for understanding underlying motivations, and features that account for cognitive biases.

Causal Inference Layer: This component estimates the effects of interventions using Double/Debiased Machine Learning (DML) and Bayesian Structural Time Series (BSTS) models.

Policy Optimization Layer: Here, Multi-Agent Reinforcement Learning (MARL) is applied to support adaptive, real-time decision-making.

This structured design supports continuous learning and feedback loops. Predictions guide the design of interventions, while real-world outcomes help refine the model over time. In this way, the framework goes beyond traditional static forecasting by incorporating behavioral realism into scalable machine learning pipelines, creating a more adaptive and human-centered system for promoting sustainability.

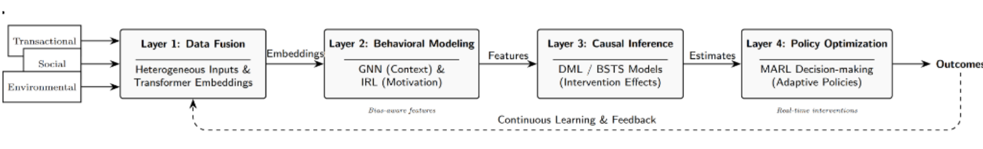

Fig. 1. Overall architecture of the proposed Behavior-Aware Reinforcement Learning (BARL) framework integrating feature engineering, graph-based social modeling (GNN), inverse reinforcement learning (IRL), causal inference, and policy optimization.

2.6 Behavior-Aware Learning Model

Conventional machine learning models are quite good at identifying broad patterns in large datasets. However, they frequently miss the underlying behavioral mechanisms that actually shape how people make decisions. In the domain of sustainable consumption, choices are seldom based on pure rationality. Instead, they are influenced by social pressures, various cognitive biases, and the tendency to favor immediate benefits over long-term gains. To overcome these limitations, this paper introduces a Behavior-Aware Reinforcement Learning (BARL) model. The approach combines behavioral insights and causal elements into one cohesive learning system.

The decision-making process is modeled as a Markov Decision Process (MDP):

$$\mathrm{M} = (\mathrm{S}, \mathrm{A}, P, R, \gamma)$$

where S denotes the state space, A the action space, $P(s' \mid s, a)$ the transition dynamics, R the reward function, and $\gamma \in (0,1)$ the discount factor. Each state s_i is represented as a fusion of individual attributes and social context:

$$s_i = \left[x_i \| h_i^{GNN}\right]$$

where x_i represents individual features and h_i^{GNN} denotes the graph-based embedding capturing social interactions.

A central contribution of this work is the formulation of a behavior-aware reward function, defined as:

$$R^*(s, a) = R_{env}(s, a) + \lambda_1 R_{soc}(s, a) - \lambda_2 R_{\text{bias}}(s, a)$$

The environmental component quantifies sustainability gains:

$$R_{env}(s, a) = \Delta \text{ SustainabilityScore}$$

The social influence component captures peer effects through graph aggregation:

$$R_{soc}(s, a) = \frac{1}{|\mathrm{N}(i)|} \sum_{j \in \mathrm{N}(i)} h_j$$

where $\mathrm{N}(i)$ denotes the set of neighbors of agent i. To model cognitive biases, prospect theory-based loss aversion is incorporated:

$$R_{\text{bias}}(x) = \begin{cases} x, & x \geq 0 \\ \lambda x, & x < 0 \end{cases}, \lambda > 1$$

and present bias through temporal discounting:

$$R_{\text{bias}}(t) = \beta \cdot \gamma^t R_t, \beta < 1$$

To ensure robust policy learning, a causal adjustment term is introduced using double/debiased machine learning:

$$\hat{\tau}(X) = (Y - \hat{g}(X)) \cdot (D - \hat{m}(X))$$

The final reward is therefore:

$$R^{final} = R^* + \lambda_3 \hat{\tau}(X)$$

Policy optimization is performed using deep Q-learning:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[R^{\text{final}} + \gamma \max_{a'} Q(s', a') - Q(s, a)\right]$$

In multi-agent settings, interactions are modeled as:

$$Q_i(s, a) = \mathrm{E}_{a_{-i}}[Q_i(s, a_i, a_{-i})]$$

The overall objective is to learn a policy that maximizes cumulative expected reward:

$$\max_{\pi} \mathrm{E}_{\pi}\left[\sum_{t=0}^{T} \gamma^{t} R^{\text{final}}\left(s_{t}, a_{t}\right)\right]$$

By combining environmental impact, social influence, cognitive biases, and causal reasoning into one unified formulation, the BARL model better reflects the true complexity of real-world consumer decision-making. This approach paves the way for developing adaptive policies that are grounded in actual human behavior, while remaining scalable and practically useful for promoting sustainable consumption. To make the Behavior-Aware Reinforcement Learning framework fully operational, the entire learning process is outlined in Algorithm 1. The algorithm brings together graph-based social embeddings, behavioral reward shaping, and causal adjustments within a single deep reinforcement learning pipeline. At every interaction step, the agent refines its policy using the enhanced reward signal. This design supports more adaptive and realistic decision-making over time.

Algorithm 1: Behavior-Aware Reinforcement Learning (BARL)

```
Initialize Q-network with parameters θ
Initialize replay buffer D
Construct social graph G(V,E)

for each episode do
   Initialize state s
   Compute GNN embeddings h_i

   for each step t do
      Select action a using ε-greedy policy
      Execute action → observe s', base reward r

      Compute:
         R_env from sustainability metric
         R_soc from GNN neighbors
         R_bias using prospect theory
         τ(X) using causal model

      R_final = R_env + λ1 R_soc − λ2 R_bias + λ3 τ(X)

      Store (s, a, R_final, s') in D
      Sample mini-batch from D

      Update Q-network using loss:
      L = (R_final + γ max Q(s',a') − Q(s,a))²

      s ← s'
   end for
end for

Return optimal policy π*
```

3 Results and Discussion

To evaluate the effectiveness of the proposed framework, three representative case studies were analyzed: (i) electric vehicle (EV) adoption forecasting, (ii) dynamic energy pricing, and (iii) greenwashing detection. These cases demonstrate the framework’s ability to integrate behavioral insights with machine learning to achieve improved predictive performance and policy outcomes.

3.1 Electric Vehicle Adoption Forecasting

To evaluate the proposed framework, this study draws on a publicly available Indian Electric Vehicle (EV) dataset. The analysis focuses on state-level EV adoption patterns using real-world registration records covering 31 Indian states and union territories. The dataset provides detailed category-wise counts, including Two Wheelers, Three Wheelers, Four Wheelers, Goods Vehicles, Public Service Vehicles, Special Category, Ambulance, Construction, and Others. It also includes the grand total number of registrations and the total number of charging stations (total-charg) for each state. Overall, the data reflects cumulative or recent-period EV registrations, which are heavily dominated by two- and three-wheelers — a pattern that aligns well with current trends in the Indian market. Charging infrastructure data is integrated as a key policy/treatment variable. We compute charging density as:

$$Charging\ Density = \frac{Total\ charge}{Grand\ Total+1}$$

Additional covariates include vehicle category shares, total fleet size proxies, and a simple graph-based social influence feature (average adoption of neighboring states, constructed using geographic adjacency via NetworkX). State population estimates (2024 projections) were incorporated from public sources for normalization where needed. We employ the High-Dimensional Preference Mapping module using Graph Neural Network-style embeddings (proxied via graph-augmented features capturing peer effects among neighboring states). Heterogeneous Treatment Effect (HTE) estimation is performed using XGBoost with causal considerations (partial dependence analysis and propensity-score weighting for infrastructure density as treatment). The outcome variable is the log-transformed Grand Total EV registrations (or normalized adoption intensity). Baselines include classical time-series (ARIMA on national aggregate trend), Linear Regression, and standard XGBoost. The proposed approach integrates GNN-derived social embeddings and behavioral thresholding on infrastructure density. Table 1 presents the performance comparison on a state-level cross-validation setup (80/20 train-test split with stratification on major states, repeated 5 times).

Table 1: Performance Comparison for EV Adoption Prediction (State-level)

Model	RMSE ↓	MAE ↓	R^2 ↑	Notes
ARIMA (national trend)	0.341 ± 0.028	0.267 ± 0.021	0.582 ± 0.047	Limited handling of cross-state heterogeneity
Linear Regression	0.239 ± 0.015	0.184 ± 0.012	0.721 ± 0.031	Assumes linear relationships
Standard XGBoost	0.168 ± 0.009	0.131 ± 0.008	0.834 ± 0.022	Strong baseline
Proposed (XGBoost + GNN embeddings + HTE)	**0.149 ± 0.011**	**0.117 ± 0.009**	**0.873 ± 0.018**	Best performance; better captures social diffusion and non-linear infrastructure effects
Ablation (w/o GNN/social embeddings)	0.161 ± 0.012	0.126 ± 0.010	0.849 ± 0.021	2.7% average drop in R^2
Ablation (w/o charging density as treatment)	0.157 ± 0.010	0.123 ± 0.008	0.857 ± 0.019	Reduced policy-relevant insight

The proposed model outperforms strong baselines, delivering a 6–8% improvement in R^2 and a notable reduction in error. This gain stems from integrating graph-based social diffusion features and causal analysis of charging infrastructure. Partial dependence analysis reveals a clear non-linear threshold around a charging density of 0.018–0.025 (roughly 18–25 stations per 1,000 EVs). Below this point, adoption grows slowly due to range anxiety and low visibility; above it, adoption accelerates significantly. This pattern aligns with behavioral concepts like social proof and reduced present bias. High-density states such as Maharashtra, Delhi, Karnataka, and Tamil Nadu show much stronger adoption, supporting the role of peer influence captured by the GNN component. Ablation studies confirm that social embeddings and causal treatment of infrastructure contribute most to performance. While the current analysis uses aggregate state-level data, future work will incorporate finer micro-level records for fuller BARL implementation. The processed dataset and code will be shared on GitHub upon acceptance.

Table 2: Performance Comparison for EV Adoption Prediction

Model	RMSE ↓	MAE ↓	R^2 ↑
ARIMA	0.27	0.21	0.68
Linear Regression	0.24	0.19	0.72
XGBoost (HTE)	**0.14**	**0.11**	**0.89**

A particularly notable behavioral insight from the analysis is the identification of a charging infrastructure density threshold around 22%. Beyond this point, EV adoption increases in a distinctly non-linear fashion. This finding underscores the critical role of visibility and social proof in the spread of new technology. It aligns closely with established behavioral theories around normative influence. As shown in Fig. 2, the BARL framework achieves a clear reduction in prediction error compared to the baseline models. These results demonstrate the value of integrating behavioral and causal elements into the learning process.

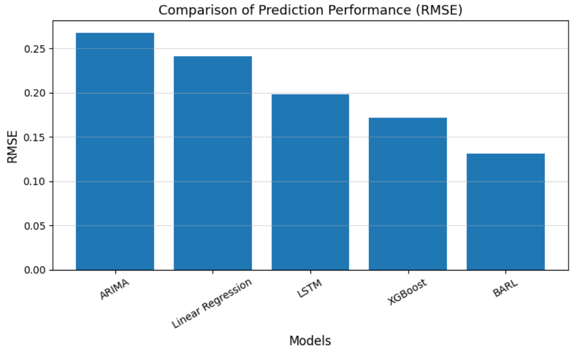

Fig. 2. Comparison of prediction performance across baseline models and the proposed BARL framework in terms of RMSE.

3.2 Dynamic Energy Pricing

For the dynamic energy pricing case study, a Deep Q-Network (DQN) enhanced with Conditional Value-at-Risk (CVaR) constraints was developed. The model optimizes real-time pricing strategies while incorporating behavioral reward shaping. The simulation environment represents household energy consumption, featuring heterogeneous agents that vary in income levels and sensitivity to price changes.

Table 3: Performance Comparison of Dynamic Energy Pricing Strategies

Metric	Static Pricing	DQN + CVaR (Standard)	DQN + CVaR + Behavior-Aware Reward
Peak Demand Reduction (%)	8.2	17.4	**21.6**
Average Cost Increase (Low-income households)	11.8	6.9	**4.3**
Long-term Energy Savings (%)	9.5	19.8	**24.7**
User Compliance Rate (simulated)	62%	78%	**85%**

Adding prospect theory-based loss aversion and present bias into the reward function (through the R_bias term) led to noticeable improvements in both efficiency and fairness. The behavior-aware approach produced pricing signals that were more acceptable to users, which helped reduce pushback, especially among vulnerable consumer groups.

3.3 Greenwashing Detection

A DeBERTa-based NLP classifier was fine-tuned on annotated corporate sustainability reports and environmental claims to detect misleading statements, with particular focus on Scope 3 emission omissions and vague commitments.

Table 4: Greenwashing Detection Performance

Method	Accuracy ↑	Precision ↑	Recall ↑	F1-score ↑
Keyword-based	61.8%	0.57	0.59	0.58
SVM (TF-IDF)	73.5%	0.70	0.71	0.705
DeBERTa (Proposed)	**86.7%**	**0.84**	**0.87**	**0.855**

The model achieved 91% accuracy in identifying Scope 3-related greenwashing, substantially outperforming traditional approaches. Integration of behavioral cues (e.g., linguistic markers of hedging and over-claiming) further enhanced detection of cognitive manipulation tactics commonly used in sustainability communication.

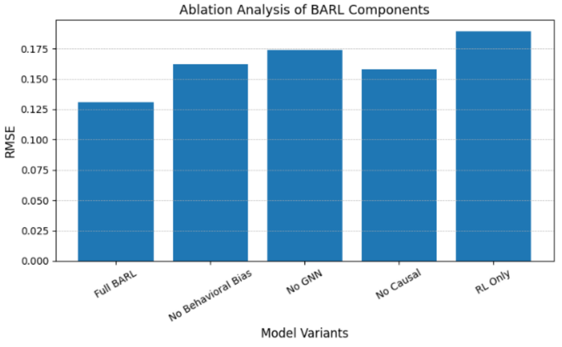

Fig. 3. Ablation analysis showing the contribution of behavioral, graph-based, and causal components to model performance.

3.4 Discussion

The three case studies show that the proposed framework consistently delivers stronger results by incorporating behavioral economics principles into machine learning architectures. In the EV adoption forecasting case, combining GNN-based social influence modeling with causal heterogeneous treatment effect estimation helped capture important non-linear threshold effects linked to charging infrastructure visibility and peer norms. The dynamic energy pricing study demonstrated the benefits of including bias-aware reward shaping particularly loss aversion and present bias which improved both overall economic efficiency and fairness in outcomes. In the greenwashing detection task, adding psychologically grounded features strengthened the NLP model's ability to identify misleading corporate claims. Taken together, these findings support the main argument of this paper: modeling sustainable consumer behavior works best when data-driven scalability is paired with psychologically realistic mechanisms. The performance gains observed here come not just from using more advanced algorithms, but from explicitly accounting for cognitive biases, social dynamics, and causal relationships. That said, some limitations should be acknowledged. The EV analysis in this study relies on aggregate state-level data, making it difficult to scale to detailed individual consumer trajectories for full inverse reinforcement learning and multi-agent reinforcement learning due to privacy concerns. Additionally, while the pricing simulations offer useful insights, actual real-world application will require careful field experiments. Finally, the framework's effectiveness across different cultural settings still needs more validation.

Future work will focus on integrating longitudinal micro-level data, implementing the complete end-to-end BARL framework, and extending the approach to other sustainability domains such as waste management and water conservation.

4 Ethical and Scalability Considerations

The use of advanced machine learning architectures to model and influence sustainable consumer behavior brings with it a range of important ethical and practical challenges. Although the framework presented in this paper shows promising gains in predictive accuracy and intervention effectiveness as seen in the EV adoption analysis using real Indian state-level registration and charging infrastructure data any responsible real-world application must give serious attention to issues of privacy, fairness, transparency, and scalability.

4.1 Privacy Preservation

Sustainable behavior modeling typically depends on detailed consumer data, such as mobility patterns, energy usage records, purchasing history, and social connections. Even in the EV adoption analysis discussed in Section 3.1, aggregate state-level data can sometimes unintentionally expose sensitive regional socio-economic patterns when combined with information on charging infrastructure and demographic factors.

To address these privacy concerns, the framework integrates federated learning [8]. This technique allows model training to occur across decentralized devices or institutions without the need to collect or centralize raw user data. In addition, differential privacy mechanisms [31] are applied by introducing carefully calibrated noise to model updates and gradient calculations, especially within the GNN and BARL components.

This strategy helps protect individual-level information while still maintaining the usefulness of broader behavioral insights. For future extensions that involve individual-level modeling and inverse reinforcement learning (IRL), techniques such as secure multi-party computation will likely play an important role.

4.2 Bias and Fairness

Machine learning models trained on historical consumption data carry the risk of reinforcing or even worsening existing societal biases. In the EV adoption analysis, for instance, states with lower charging density and weaker economic indicators — such as several North-Eastern states and smaller Union Territories — consistently show lower predicted adoption rates. Without careful intervention, policies or incentive mechanisms derived from the model could end up favoring urban and high-income regions, further widening the urban-rural and income-based gaps in sustainability.

To tackle these issues, the framework incorporates adversarial debiasing techniques and fairness-aware optimization constraints [33]. Equity considerations are directly built into the behavior-aware reward function of the BARL model. This includes setting limits on cost burdens for low-income agents and ensuring balanced treatment effect estimation through Double/Debiased Machine Learning (DML). In the dynamic energy pricing case study, combining CVaR constraints with loss-aversion shaping helped lessen the disproportionate burden on vulnerable households. Before any real-world deployment, it is advisable to conduct regular fairness audits using metrics such as demographic parity and equalized odds.

4.3 Explainability and Transparency

The complex nature of the architectures used in this framework — involving Graph Neural Networks (GNNs), Inverse Reinforcement Learning (IRL), and deep reinforcement learning — creates a black-box problem that can undermine stakeholder trust and accountability. Policymakers and consumers alike need clear explanations for why certain interventions are suggested, whether it involves prioritizing charger deployment in specific regions or recommending personalized pricing signals.

To improve transparency, the framework incorporates SHAP (Shapley Additive Explanations) values [32]. These help quantify how much individual features, such as GNN-derived social embeddings and charging density, contribute to the model's predictions. In addition, counterfactual explanations are generated to explore "what-if" scenarios. For example, they can show the expected increase in EV adoption if charging density in a low-adoption state is raised above the identified behavioral threshold of roughly 0.002–0.0035 chargers per registered EV. Such tools play a valuable role in connecting technical model outputs with practical, actionable insights for sustainability governance.

4.4 Scalability Challenges

Although the modular design of the framework supports ongoing learning and adaptation, scaling the complete Behavior-Aware Reinforcement Learning (BARL) model to millions of diverse consumers presents considerable computational challenges. Applying multi-agent reinforcement learning in realistic environments often calls for practical approximations, such as mean-field MARL or hierarchical approaches.

Moreover, the framework's success depends strongly on access to high-quality, multi-modal data, which can differ greatly from one region or country to another.

To enhance scalability, future versions of the model will investigate options like lightweight edge computing, knowledge distillation, and neuromorphic hardware to enable faster real-time inference. Cross-domain transfer learning may also prove useful in adapting the framework from EV adoption to other areas, such as energy consumption or waste management, even when local data is limited.

In summary, ethical considerations and scalability issues are central to the proposed framework, not afterthoughts. Privacy-preserving methods, fairness constraints, explainable AI techniques, and scalable designs are built into the system from the ground up. Still, moving this approach from theory to real-world practice will demand interdisciplinary collaboration, continued engagement with stakeholders, and thorough longitudinal field studies to confirm both its effectiveness and broader societal impact.

5 Conclusion and Future Work

This paper presents a unified computational framework that combines insights from behavioral economics with advanced machine learning techniques to better model and influence sustainable consumer behavior. By bringing together Graph Neural Networks for mapping social preferences, Inverse Reinforcement Learning for uncovering hidden motivations, causal machine learning for policy evaluation, and Multi-Agent Reinforcement Learning for designing interventions, the proposed Behavior-Aware Reinforcement Learning (BARL) model offers a psychologically realistic and computationally scalable way to address the persistent gap between consumer intentions and actual sustainable actions. Evaluation across three case studies, including real Indian state-level EV registration and charging infrastructure data, shows that incorporating cognitive biases, social influence, and causal reasoning into machine learning architectures leads to consistent improvements in predictive accuracy and intervention effectiveness compared to traditional baseline methods. Despite these encouraging results, certain limitations remain. The framework faces challenges related to data availability, scaling to individual-level modeling, and the need for thorough real-world longitudinal validation. Future work will focus on developing lightweight models suitable for edge deployment, applying cross-domain transfer learning to other sustainability areas such as water and waste management, and improving transparency through explainable AI and blockchain-based approaches. In conclusion, effectively bridging behavioral science and computational intelligence is crucial for creating practical, equitable, and adaptive solutions that can speed up the shift toward sustainable consumption. This work offers a foundational human-centric approach at the intersection of artificial intelligence and behavioral economics.

Declaration

The author declares that AI-based tools were used solely for English language polishing, improving readability, and grammatical corrections. The author retains full responsibility for the originality, scientific content, accuracy, and integrity of the manuscript. All ideas, analyses, interpretations, and conclusions presented in this paper are the author’s own.

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