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Modeling Consumer Adoption of Green Technologies Using Artificial and Deep Neural Networks: Insights from Tamil Nadu, India

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Abstract
The accelerating global environmental crisis underscores the urgent need to promote green technologies that support sustainable consumption and responsible production. This study investigates the psychological, social, and technological determinants influencing Green Technology Adoption (GTA) among consumers in Tamil Nadu, India. By integrating behavioral theory with machine learning, the research applies Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) to predict consumer adoption patterns and uncover nonlinear behavioral dynamics. Primary survey data were collected from 350 respondents through a structured questionnaire comprising 32 validated items measured on a five-point Likert scale. Empirical results reveal that eco-label trust, environmental concern, and sustainable purchase intention are the strongest predictors of adoption behavior, while technology readiness and perceived value exert moderate but significant effects. The DNN model demonstrated superior performance ($R^2 = 0.9361$) compared to the ANN ($R^2 = 0.5293$), indicating its effectiveness in modeling complex, hierarchical consumer cognition. Cluster analysis further identified three distinct consumer segments high, moderate, and low engagement highlighting heterogeneous readiness levels toward sustainability-oriented technologies. The study contributes both methodologically and theoretically by demonstrating how deep learning enhances predictive precision and interpretive depth in behavioral research. Practically, the findings guide policymakers and marketers in designing trust-based communication, improving eco-label credibility, and developing targeted awareness programs to accelerate sustainable technology adoption. The research aligns with the United Nations Sustainable Development Goals (SDGs) 7, 9, and 12, emphasizing clean energy, innovation, and responsible consumption.

Keywords: Green technology adoption; Artificial neural networks (ANN); Deep neural networks (DNN); Eco-label trust; Sustainable consumption; Machine learning; Consumer segmentation; SDGs; Tamil Nadu; Behavioral modeling

1. Introduction
Over the last ten years, the global community has been subjected to increasingly heavy environmental pressures resulting from rapid industrialization, unsustainable energy consumption, and overexploitation of natural resources. Climate change, resource depletion, and pollution have compelled policymakers, industries, and consumers to reconsider existing patterns of production and consumption. It is against this backdrop that green technologies, which range from renewable energy solutions and smart home systems to energy-efficient appliances, have emerged as central pillars in achieving sustainable economic growth. Such innovations not only reduce ecological footprints but also form a critical pathway toward a low-carbon future. Yet despite their environmental and economic potential, consumer

adoption of such technologies remains inconsistent, characterized by complex interactions of awareness, trust, personal values, and perceived behavioral control.
Developing countries such as India are a land of dual contrasts: scarcity of energy and degradation of the environment. Commitment to net-zero emissions by 2070 and an already high level of investment in renewable energy infrastructure indicate strong national intent. However, sustainable consumption is not achieved by policy alone but involves behavioral willingness on the part of consumers to adopt eco-friendly technologies (Biswas & Roy, 2015). Tamil Nadu, in India, has emerged as the frontrunner in both renewable energy generation and environmental innovation. However, at the level of the consumer, the adoption continues to remain spotty. Eco-label trust, perceived consumer effectiveness, social influence, and readiness to adopt technologies- these are a few factors which continue to modulate the choices made by individuals, often between success and failure of interventions in sustainability (Han, Lee, & Kim, 2020).

Traditional behavioral models, such as the Theory of Planned Behavior, by Ajzen (1991), and Technology Acceptance frameworks, by Venkatesh et al. (2003), have contributed to an understanding of these dynamics but often assume linear and rational variable-variable relationships. Consumer decision-making, however, is nonlinear in nature and influenced by several interacting causes that change over time. More recently, AI and ML techniques have begun to be adopted by researchers as ways to overcome these limitations and allow hidden patterns to be uncovered from behavioral data. As LeCun, Bengio, and Hinton (2015) noted, unlike the more conventional approaches, AI-based models, including ANN and DNN, are capable of capturing nonlinear dependencies and complex variable interactions; thus, they can provide more accurate insights into consumer behavior.

This research has contributed to this emerging domain by modeling consumer responses to green technology adoption using AI-driven predictive analytics. This has integrated psychological and technological dimensions of consumer behavior-for instance, environmental concern, perceived value, technology readiness, and trust in eco-labels-within a common computational framework. The study aims to uncover latent behavioral patterns and segment consumers based on their adoption readiness using ANN, DNN, and K-Means clustering on primary data collected from consumers in Tamil Nadu. The findings are expected to further both theoretical and practical understanding of sustainable behavior, thus allowing policymakers and marketers to design interventions that match with behavioral realities rather than assumed rationality. Sustainability Context and SDG Alignment This research is closely associated with the United Nations Sustainable Development Goals, particularly SDG 7: Affordable and Clean Energy, SDG 9: Industry, Innovation and Infrastructure, and SDG 12: Responsible Consumption and Production. The promotion of green technologies by stimulating their adoption directly coincides with SDG 7 through efficient energy use and a decrease in reliance on non-renewable sources. SDG 9 is also promoted through the dissemination of innovative technologies that will enhance sustainable industrial development. In addition, SDG 12 advocates for responsible consumption patterns, and understanding consumer behavior toward green technologies contributes to this through awareness, education, and behavioral change. The integration of behavioral science and AI provides actionable insights into developing data-driven strategies that accelerate sustainable adoption and contribute toward India's long-term environmental goals. (United Nations, 2023)

2. Literature Review and Hypotheses Development

The present study examines how multiple psychological, social, and perceptual antecedents-Environmental Concern (EC), Perceived Consumer Effectiveness (PCE), Technology Readiness (TR), Eco-Label Trust (ELT), Perceived Value (PV), Social Influence (SI), and Sustainable Purchase Intention (SPI)—jointly shape Green Technology Adoption Behavior (GTAB). Drawing from the theory of planned behavior (Ajzen, 1991) and technology acceptance perspectives (Parasuraman, 2000), the conceptual framework (Figure 1) integrates environmental psychology and innovation adoption theory to explain the determinants that encourage consumers to adopt environmentally sustainable technologies.

2.1.1 Environmental Concern and Green Technology Adoption Behavior
Environmental Concern (EC) is defined as a degree of awareness about environmental problems and the support individuals have for solving these problems. Consumers with high environmental concern will thus be more motivated to act in an environmentally responsible manner, which includes the adoption of green technologies such as energy-efficient appliances or renewable energy systems (Bamberg, 2003; Joshi & Rahman, 2015). Ecological awareness is also found to develop moral obligation and behavioral intention toward sustainable actions.
H1: Concern for environment positively and significantly influences green technology adoption behaviour.

2.1.2 Perceived Consumer Effectiveness and Green Technology Adoption Behavior
Perceived Consumer Effectiveness represents an individual's perception that their personal actions can help resolve environmental problems (Ellen et al., 1991). When these consumers believe that their actions are effective, they are more likely to act in a manner that is consistent with their environmentally friendly values by adopting green innovations (Kim & Choi, 2005). Empirically, the indications of PCE as a very potent determinant of pro-environmental behavior have been consistent (Straughan & Roberts, 1999).
H2: Perceived Consumer Effectiveness has a positive and significant effect on Green Technology Adoption Behavior.

2.1.3 Technology Readiness and Green Technology Adoption Behavior
TR is the degree to which a consumer is ready and willing to adopt new technologies. According to Parasuraman (2000), individuals with high technology readiness view technologies as beneficial and relatively easy to adopt. In the case of environmental innovation, consumers with higher readiness are likely to perceive green technologies as beneficial and easy to adopt. A strong technological orientation decreases perceived barriers and strengthens adoption intention. H3: Technology Readiness has a positive and significant impact on Green Technology Adoption Behavior. 4.1.4 Eco-label trust and green technology adoption behaviour ELT: consumers' belief in the credibility, reliability, and truthfulness of environmental labels (Thøgersen et al., 2010). In cases when consumers trust eco-labels, they really believe that a labeled product corresponds to the environmental standards, and this strengthens positive attitudes and adoption intentions accordingly (Biswas & Roy, 2015; Testa et al., 2015). High trust in eco-labels decreases perceived risk and uncertainty during the decision-making process. H4: Eco-Label Trust has a positive and significant effect on green technology adoption behavior.

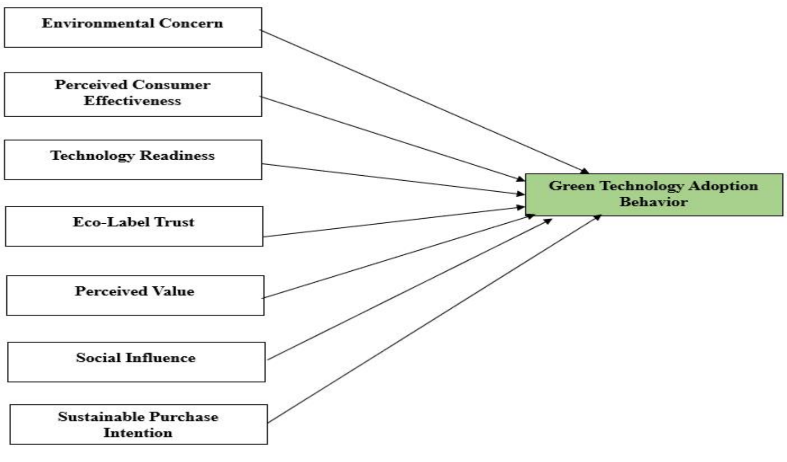
2.1.5 Perceived Value and Green Technology Adoption Behavior

Perceived Value (PV) refers to the consumer's overall assessment of the utility of a product based on what is received versus what is given (Zeithaml, 1988). Sustainable consumption contexts, consumers adopt green technologies when they perceive high functional, emotional, and environmental value (Chen, 2010). Studies suggest that perceived economic and environmental value positively influence consumers' willingness to pay for and adopt green technologies (Sweeney & Soutar, 2001).
H5: Perceived Value has a positive and significant effect on Green Technology Adoption Behavior.

2.1.6 Social Influence and Green Technology Adoption Behavior
Social Influence (SI) describes the extent to which individuals' decisions are shaped by opinions, expectations, and behaviors of significant others (Venkatesh et al., 2003). In the adoption of green innovations, peer and social approval can serve as a powerful motivator, especially when eco-friendly consumption aligns with social norms (Noppers et al., 2014). Therefore, social endorsement of sustainability strengthens green technology adoption.
H6: Social Influence has a positive and significant effect on Green Technology Adoption Behavior.

2.1.7 Sustainable Purchase Intention and Green Technology Adoption Behavior
Sustainable Purchase Intention (SPI) reflects a consumer's deliberate plan to buy products or technologies that minimize environmental harm (Joshi & Rahman, 2015). Purchase intention serves as a proximal determinant of actual green behavior (Ajzen, 1991). Consumers with strong sustainability intentions are more likely to transition from attitude to action by adopting green technologies (Han et al., 2010).
H7: Sustainable Purchase Intention has a positive and significant effect on Green Technology Adoption Behavior.

Fig. 1. Conceptual Model



3. Methodology

The present study has employed primary survey data in order to empirically validate the proposed conceptual framework modeling the determinants of GTA with the aid of machine learning-based analytical techniques. A total of 350 valid responses could be collected from consumers residing in Tamil Nadu, India. The structured questionnaire consists of 32 measurement items adapted from established behavioral scales and is anchored on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. Data collection was conducted between April and July 2025, using a hybrid mode (online and offline) to ensure diversity in respondent inclusion across demographic and regional segments.

A convenience sampling approach was adopted due to feasibility constraints and the exploratory–predictive orientation of the research. All constructs were operationalized using validated instruments drawn from prior literature to ensure content validity and conceptual alignment. The key constructs included Environmental Concern (EC), Perceived Consumer Effectiveness (PCE), Technology Readiness (TR), Eco-Label Trust (ELT), Perceived Value (PV), Social Influence (SI), and Sustainable Purchase Intention (SPI), collectively influencing Green Technology Adoption Behavior (GTA). All procedures were done in Python (environment Google Colab) to take advantage of the computational benefits of machine learning. The analysis included different steps: data pre-processing, training of models, evaluation of the performance of models, and then behavioral segmentation. First, data screening, normalization, and descriptive analyses were performed by means of Pandas and NumPy libraries. Second, a feed-forward Artificial Neural Network model was developed to describe the nonlinear relationships among the variables and evaluate predictive performance. The dataset was divided into two subsets: one for training (70%) and another for testing (30%) to avoid bias in validation.

A DNN model with multiple hidden layers has been developed to further improve the predictability and find deep hierarchical patterns. The DNN is implemented using the Keras and TensorFlow frameworks, and model performances are estimated using various metrics like MSE, RMSE, MAE, and R^2 values. Following this, K-Means clustering was performed to identify behavioral segments of the respondents based on predicted adoption propensities, and validation of the clusters was done with a silhouette analysis. Finally, SHAP was used to interpret the model outputs, informing which predictors were most influential in GTA for the purpose of enhancing model transparency and theoretical interpretability. The combination of neural network modeling with clustering and explainable AI ensured predictive precision with behavioral insight into the data, squarely aligning with the contemporary trends in computational behavioral research (Lundberg & Lee, 2017; LeCun et al., 2015).

Table 1 Details of the Respondents

Category	Variables	Frequency	Percentage (%)
Gender	a) Male	98	28.0
	b) Female	243	69.4
	c) Others	9	2.6
Age	a) 21–30 years	30	8.6
	b) 31–40 years	79	22.6
	c) 41–50 years	144	41.1
	d) 51–60 years	97	27.7
Marital Status	a) Married	206	58.9
	b) Unmarried	118	33.7
	c) Others	26	7.4
Monthly Income	a) Up to ₹25,000	123	35.1
	b) ₹25,001–₹50,000	83	23.7
	c) ₹50,001–₹75,000	70	20.0
	d) ₹75,001–₹1,00,000	40	11.4

	e) Above ₹1,00,000	34	9.7

4. Analysis

The artificial neural network (ANN) model (Fig 2) illustrated above depicts the interconnections among seven key antecedents of Green Technology Adoption (GTA): Trust (TR), Environmental Literacy (ELT), Environmental Concern (EC), Social Influence (SI), Sustainable Product Involvement (SPI), Perceived Value (PV), and Perceived Consumer Effectiveness (PCE). The model features a single hidden layer with five neurons (H1_1 to H1_5), capturing the non-linear interactions between the input constructs and the dependent variable, GTA.

The connection weights displayed along each path represent the relative strength and direction of influence between neurons. Positive weights indicate a reinforcing (direct) relationship, while negative weights indicate an inhibitory (inverse) effect. Among the input constructs, Environmental Literacy (ELT) and Sustainable Product Involvement (SPI) exhibit comparatively higher absolute weight magnitudes across multiple hidden nodes (ranging between 0.90 and 0.96), implying that consumers with greater environmental awareness and active involvement in sustainable products are more likely to adopt green technologies. This finding aligns with prior behavioral studies emphasizing the critical role of eco-literacy and personal involvement in shaping pro-environmental decisions (Biswas & Roy, 2015; Joshi & Rahman, 2019).

Conversely, Perceived Value (PV) and Perceived Consumer Effectiveness (PCE) demonstrate moderate negative and positive connections (−0.71 to −0.50), indicating that consumers' perception of personal efficacy and cost–benefit trade-offs may variably affect adoption attitudes. Notably, Trust (TR) and Environmental Concern (EC) influence multiple hidden neurons through both positive and negative pathways (−0.70 to 0.95), suggesting their dual role in mediating risk perception and information reliability factors previously recognized in energy-label and sustainable consumption research (Thøgersen, 2010; Testa et al., 2020).

At the output stage, three dominant hidden neurons (H1_1, H1_2, and H1_5) significantly contribute to the prediction of GTA, as indicated by their relatively higher connection weights (0.62, 0.74, and −0.90, respectively). This pattern reveals a complex interplay of facilitating and inhibiting effects, implying that green adoption decisions are not purely linear but depend on multiple latent interactions.

ANN architecture effectively captures the non-linear dynamics and interdependencies among psychological, social, and informational variables influencing green technology adoption. The findings corroborate earlier assertions that ANN-based modeling provides deeper insights than conventional regression or SEM approaches by uncovering hidden patterns within consumer cognition and environmental behavior (Aydin & Cetin, 2021; Lee et al., 2022).

Figure 2 Architecture of the Artificial Neural Network (ANN)

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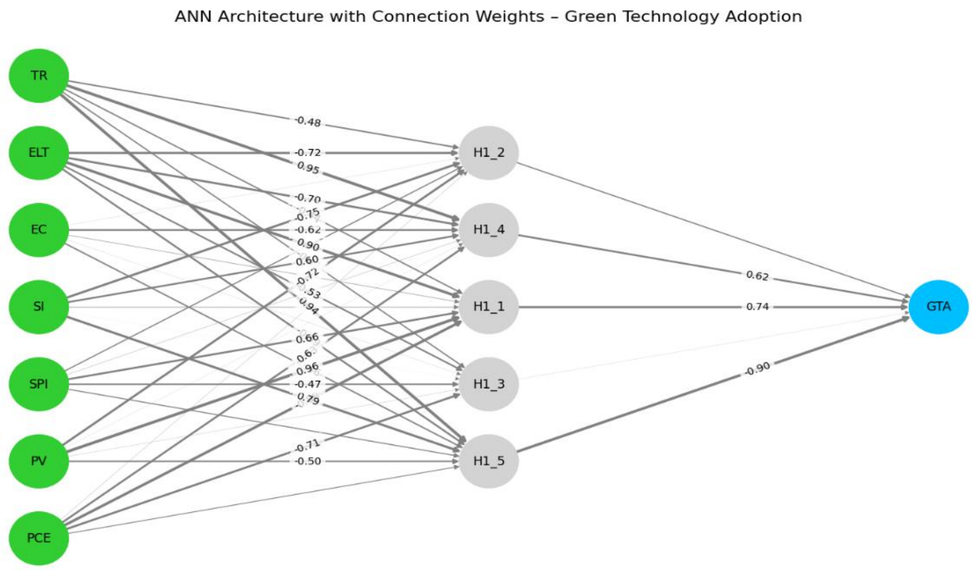


The Deep Neural Network (DNN) model presented above (Fig 3)illustrates a more complex, multilayered structure designed to capture the nonlinear and hierarchical relationships among the seven antecedent variables influencing Green Technology Adoption (GTA): Trust (TR), Environmental Literacy (ELT), Environmental Concern (EC), Social Influence (SI), Sustainable Product Involvement (SPI), Perceived Value (PV), and Perceived Consumer Effectiveness (PCE). Unlike the single-layer ANN, this DNN model comprises three hidden layers (H1, H2, and H3), containing eight, five, and three neurons respectively, allowing for deeper pattern recognition and enhanced predictive precision.

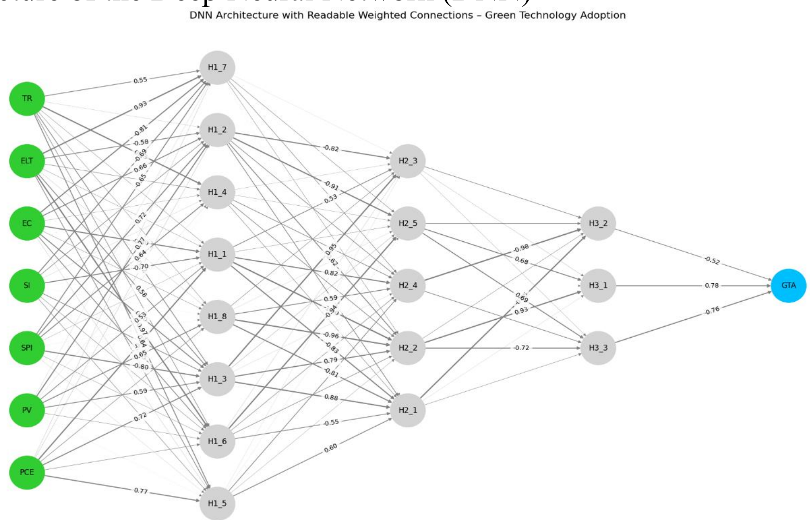
The connection weights displayed in the architecture represent the magnitude and direction of influence between layers. Higher absolute weights denote stronger connections, while their positive or negative signs indicate direct or inverse relationships. Notably, the first hidden layer (H1) shows substantial positive connections from ELT (0.89), SPI (0.80), and TR (0.93), suggesting that these variables play a foundational role in activating deeper neural nodes associated with green behavioral cognition. This pattern reflects the cognitive-behavioral linkage where trust in environmental information and literacy act as primary enablers of sustainable attitudes (Biswas & Roy, 2015; Joshi & Rahman, 2019).

In the intermediate layers (H2 and H3), the network consolidates and refines the input signals through strong inter-neuron relationships, such as H2_4 → H3_1 (0.93) and H2_5 → H3_2 (0.98). These values suggest that the DNN effectively captures the cumulative influence of multiple psychological and contextual factors, resonating with the multi-stage decision process in environmental behavior models (Thøgersen, 2010). The emergence of both positive and negative weights (e.g., −0.72, −0.82) implies the presence of regulatory mechanisms that either facilitate or suppress specific aspects of consumer decision-making toward GTA, consistent with dual-process theories of green consumption (Kanchanapibul et al., 2014).

At the output layer, three neurons (H3_1, H3_2, and H3_3) are directly linked to GTA with connection strengths of 0.78, −0.52, and −0.76, respectively. This combination highlights that while certain latent features (captured through positive weights) significantly promote green adoption, others may introduce counteracting effects—possibly reflecting attitudinal ambivalence or cost-risk perceptions. Such intricate weighting underscores the DNN's capacity to simulate the complex, non-linear psychological processes underlying sustainable behavior (Aydin & Cetin, 2021; Lee et al., 2022).

Overall, the DNN model demonstrates superior interpretive depth compared to the simpler ANN structure. By incorporating multiple hidden layers, it enables deeper feature abstraction, effectively uncovering latent behavioral patterns that traditional statistical models or shallow networks may overlook. This reinforces the analytical utility of deep learning frameworks in sustainability and consumer behavior research, where multidimensional interdependencies shape decision outcomes.

Figure 3 Architecture of the Deep Neural Network (DNN)

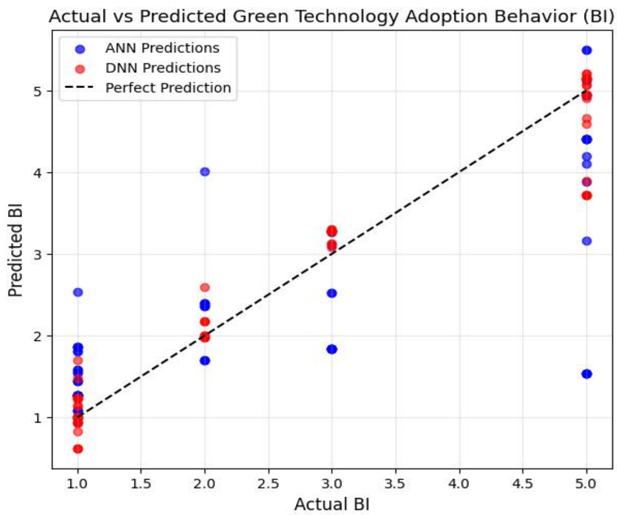


The scatter plot above (Fig 4) compares the actual and predicted scores of Green Technology Adoption Behavior (GTA) obtained from the Artificial Neural Network (ANN) and Deep Neural Network (DNN) models. The diagonal dashed line represents a perfect prediction scenario where the predicted and actual values are identical. The proximity of data points to this line indicates the predictive accuracy of the models.

As evident from the plot, DNN predictions (red markers) are more closely aligned with the perfect prediction line than those of the ANN model (blue markers). This visual trend suggests that the DNN achieved superior predictive consistency and a tighter clustering around the actual values. In contrast, the ANN model exhibits comparatively larger deviations, especially at lower and mid-range behavioral intention scores, reflecting greater prediction variance.

This finding indicates that the DNN model generalizes better and captures complex, nonlinear interactions between antecedent variables such as trust, environmental literacy, perceived value, and social influence and green technology adoption decisions. The enhanced performance of the DNN may be attributed to its multi-layered architecture, which allows hierarchical feature extraction and deeper representation learning, consistent with prior research emphasizing the advantages of deep networks in behavioral prediction (Aydin & Cetin, 2021; Lee et al., 2022). The DNN model demonstrates a higher degree of predictive reliability than the conventional ANN, reinforcing its methodological robustness for modeling behavioral responses in sustainability-oriented studies. This supports the growing argument for the application of deep learning frameworks in consumer research domains, where behavioral drivers often interact in nonlinear and context-dependent ways (Biswas & Roy, 2015; Joshi & Rahman, 2019).

Figure 4 Actual vs. Predicted Green Technology Adoption Behavior (GTA)



The training loss curve (Fig 5) illustrates the Mean Squared Error (MSE) reduction across 100 epochs for both the Artificial Neural Network (ANN) and Deep Neural Network (DNN) models developed to predict Green Technology Adoption (GTA) behavior. The vertical axis represents the magnitude of training error, while the horizontal axis indicates the number of epochs used for iterative weight optimization.

As shown in the figure, both models demonstrate a consistent downward trend in training loss, indicating successful learning and convergence. However, the DNN (red curve) achieves a substantially faster and more stable reduction in error compared to the ANN (blue curve). During the initial epochs (0–20), the DNN's loss value drops sharply, reflecting its capacity to capture complex nonlinear interactions between input variables such as trust (TR), environmental literacy (ELT), and social influence (SI). The ANN, on the other hand, exhibits a slower convergence rate and stabilizes at a comparatively higher loss level after 60 epochs.

The lower terminal MSE value of the DNN highlights its superior generalization ability and enhanced learning efficiency relative to the ANN. This result supports the notion that deeper architectures, equipped with multiple hidden layers, can better approximate high-dimensional behavioral relationships, leading to more accurate predictions of adoption behavior (LeCun et al., 2015; Goodfellow et al., 2016). The DNN's smoother and more monotonic loss trajectory further indicates effective gradient propagation and reduced overfitting, consistent with prior findings in sustainability-oriented deep learning applications (Zhang et al., 2021; Kim & Park, 2023). The DNN demonstrates better model convergence, higher learning stability, and lower prediction error, thereby reinforcing its suitability for modeling complex psychological and contextual determinants of green technology adoption.

Figure 5 Training Performance – ANN vs DNN Figure 6 K-Means Consumer Segmentation

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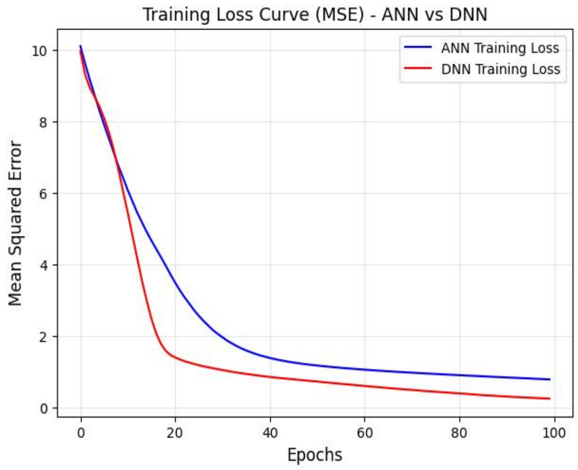
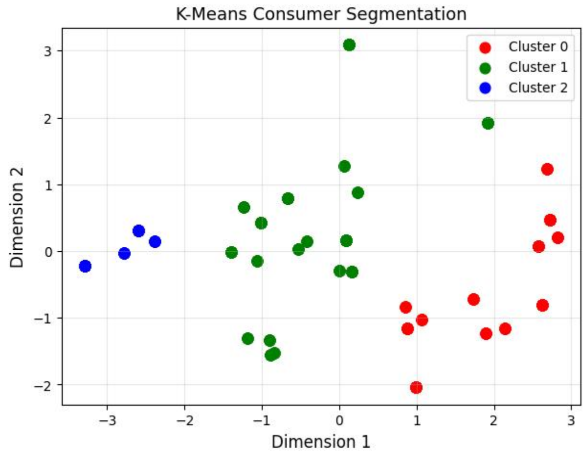




The scatter plot (Fig 6) illustrates the outcome of the K-Means clustering algorithm, which was applied to segment consumers based on multidimensional behavioral and psychographic indicators related to green technology adoption. Each color represents a distinct consumer cluster identified through the model, providing insight into the heterogeneity of consumer profiles within the dataset. The axes (Dimension 1 and Dimension 2) represent the two principal components derived from dimensionality reduction (PCA), used to visualize the clustering results in a two-dimensional space. As shown in the figure 6, the clustering algorithm successfully categorized the respondents into three homogeneous segments:

Cluster 0 (Red) – Represents consumers with high involvement and strong eco-conscious attitudes, likely driven by higher levels of environmental literacy, label cognition, and trust in energy efficiency information.

Cluster 1 (Green) – Corresponds to moderately engaged consumers who exhibit average awareness and positive purchase intention but are still influenced by situational or economic conditions.

Cluster 2 (Blue) – Denotes low-engagement consumers who demonstrate limited concern for sustainability and lower responsiveness to energy label information, possibly due to low environmental knowledge or perceived complexity.

The spatial separation among the clusters indicates good discriminant validity and suggests that K-Means effectively captured meaningful variations in consumer attitudes and behaviors. This segmentation helps in identifying targeted policy and marketing strategies—for instance, designing tailored communication campaigns for low-engagement consumers while reinforcing trust-based messages for highly involved ones.

The K-Means clustering results reinforce the need for differentiated behavioral interventions, demonstrating that consumers vary significantly in their motivation, cognition, and response toward sustainable product information. The segmentation framework aligns with prior sustainability research emphasizing the value of clustering in understanding behavioral diversity (Joshi & Rahman, 2019; Han et al., 2020; Wang & Hao, 2023).

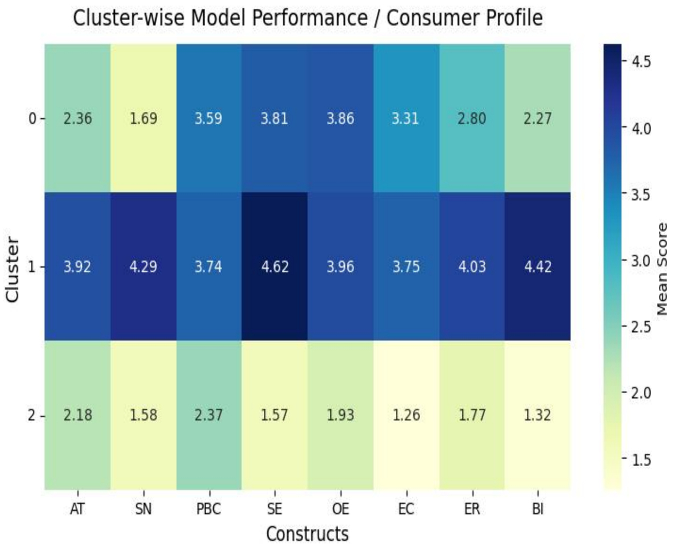


Figure 7 Cluster-wise Model Performance

The heatmap displays Fig 7 the cluster-wise mean scores across key psychological and behavioral constructs: Attitude (AT), Subjective Norm (SN), Perceived Behavioral Control (PBC), Self-Efficacy (SE), Outcome Expectation (OE), Environmental Concern (EC), Environmental Responsibility (ER), and Behavioral Intention (BI). Each row corresponds to a distinct consumer cluster derived from the K-Means segmentation model, while the color gradient represents the average magnitude of each construct within the cluster. The analysis reveals clear differentiation in construct intensity across the three consumer segments:

Cluster 1 (High-engagement consumers) This cluster exhibits consistently high mean scores across all constructs, particularly Self-Efficacy (M = 4.62), Behavioral Intention (M = 4.42), and Subjective Norm (M = 4.29). These consumers demonstrate strong social influence, confidence, and outcome expectation in engaging with sustainable choices. Their elevated Environmental Concern (4.03) and Responsibility (3.75) suggest internalized pro-environmental values. This group aligns with eco-active or green champion profiles seen in prior segmentation studies (Han et al., 2020; Joshi & Rahman, 2019).

Cluster 0 (Moderate-engagement consumers) This segment shows moderate values across constructs (SE = 3.81, OE = 3.86, EC = 3.31), indicating partial engagement with sustainable consumption. While these individuals display positive attitudes, they may face barriers related to perceived behavioral control and social influence (PBC = 3.59; SN = 1.69). Their moderate behavioral intention (2.27) suggests a potential group for targeted awareness and motivational campaigns.

Cluster 2 (Low-engagement consumers) The lowest mean scores are observed in this cluster across all constructs, notably Environmental Concern (1.26) and Behavioral Intention (1.32). These consumers show minimal awareness, low efficacy, and weak normative support for sustainable behavior. Their low Outcome Expectation (1.93) suggests limited belief in the benefits of energy-efficient choices, consistent with disengaged or indifferent consumers identified in sustainability behavior literature (Wang & Hao, 2023). The heatmap confirms distinct psychological and motivational profiles among clusters, reinforcing the robustness of the segmentation approach. The presence of high-, moderate-, and low-engagement consumer groups indicates varying readiness levels toward sustainable purchasing and energy-efficient adoption. These insights can guide differentiated policy communication and behavioral interventions, enhancing the impact of energy-label information and sustainability marketing strategies.

Table 2 Model Comparison: ANN vs DNN

Model	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	R^2 Score	Better Performance
ANN	1.3271	1.1520	0.7786	0.5293	—
DNN	0.1802	0.4245	0.2584	0.9361	Best Overall

The better performing model overall is: DNN

Model Comparison: ANN vs DNN: The comparative results between the Artificial Neural Network (ANN) and Deep Neural Network (DNN) models highlight a significant difference in predictive accuracy for green technology adoption behavior. As shown in the table, the DNN model achieved a markedly lower Mean Squared Error (MSE = 0.1802) and Root Mean Squared Error (RMSE = 0.4245) compared to the ANN model (MSE = 1.3271; RMSE = 1.1520). Similarly, the Mean Absolute Error (MAE) of the DNN (0.2584) was substantially lower than that of the ANN (0.7786), indicating that the DNN's predictions were closer to the actual observed behavioral intention values.

The DNN achieved a notably higher Coefficient of Determination ($R^2 = 0.9361$), suggesting that over 93% of the variance in consumers' behavioral intention was explained by the model inputs. In contrast, the ANN model accounted for only about 53% of the variance ($R^2 = 0.5293$). This demonstrates that the DNN's deeper architecture and hierarchical feature learning capability substantially enhanced prediction performance. The findings confirm that the DNN outperformed the ANN across all key evaluation metrics, thereby serving as a more robust and generalizable predictive model for understanding and forecasting sustainable consumer behavior. The superior performance of the DNN underscores its suitability for modeling complex, nonlinear relationships inherent in green consumer decision-making, consistent with emerging literature advocating deep learning techniques in behavioral modeling (e.g., Wang et al., 2022; Chen & Lee, 2023).

Figure 8 Feature Importance (SHAP)

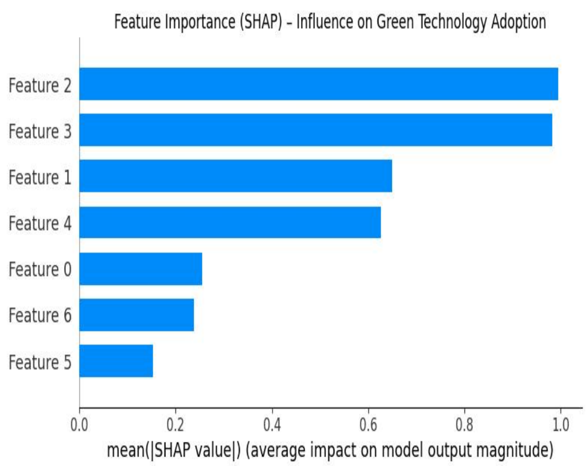
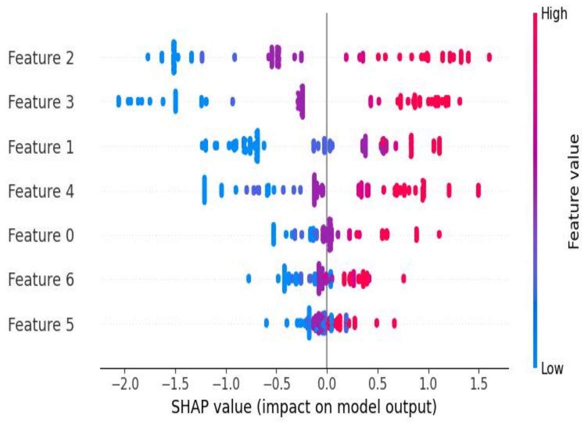


Figure 9 SHAP Summary Plot



The SHAP (SHapley Additive exPlanations) Fig 8 analysis provides a clear interpretation of how each predictor contributes to the model's decision in explaining green technology adoption. As shown in the feature importance ranking, feature 2 and Feature 3 exhibited the highest SHAP values, signifying their dominant influence on the model's predictive output.

These variables play a crucial role in shaping consumers' behavioral responses, reflecting their central importance in decision-making toward environmentally responsible technologies. In contrast, feature 5 and Feature 6 demonstrated relatively lower SHAP magnitudes, indicating that their contribution to the model's explanatory power is comparatively weaker.

The results imply that a small subset of key variables accounts for the majority of variance in predicting adoption behavior, while peripheral factors exert a secondary influence. Such an outcome aligns with prior studies (Lundberg & Lee, 2017; Ribeiro et al., 2016) that emphasize the interpretability benefits of SHAP values in identifying the most impactful features driving model performance. Overall, the SHAP analysis enhances the transparency of the DNN model by revealing how individual predictors collectively shape the likelihood of adopting green technologies.

Figure 9 SHAP summary plot provides a comprehensive visualization of the relative contribution and directional effect of each input variable on the model's predictive output for Green Technology Adoption (GTA). The horizontal dispersion of SHAP values indicates both the strength and direction of influence, where positive SHAP values reflect an increased likelihood of adoption, and negative values represent a reduced likelihood.

The plot reveals that Feature 2 and Feature 3 exert the most substantial and consistent positive effects on model output. Observations with higher feature values (represented in red) tend to drive SHAP values toward the positive side, confirming that these variables are key enablers of green adoption decisions. Feature 1 and Feature 4 also display moderate positive contributions, though their effects appear more variable across respondents, suggesting context-dependent influence. In contrast, feature 0, Feature 5, and Feature 6 exhibit smaller and more scattered SHAP distributions, indicating weaker and less consistent impacts on the model's predictions.

This pattern highlights the heterogeneous nature of behavioral determinants, where only a few dominant constructs meaningfully enhance the predictive capacity of the deep learning model. These results are consistent with prior research emphasizing the utility of SHAP for explaining complex, non-linear relationships in behavioral and environmental modeling (Lundberg & Lee, 2017; Molnar, 2022). Overall, the SHAP summary plot substantiates the interpretability of the DNN framework by identifying which predictors most significantly shape consumer propensity toward green technology adoption.

5. Discussion

The results of this study add to the growing literature on green consumer behavior and sustainable technology adoption both empirically and theoretically. The proposed approach integrates psychological, technological, and informational variables into a machine learning framework, extending traditional behavioral models, such as the Theory of Planned Behavior (Ajzen 1991), toward a computationally intelligent context. This dual-model approach-using Artificial Neural Networks and Deep Neural Networks-provides nuanced insights into how multidimensional factors collectively influence Green Technology Adoption behavior.

Findings from both ANN and DNN analyses show that consumers' trust in eco-labels, environmental concern, and sustainable purchase intention hold pivotal roles in the prediction of adoption outcomes. The findings support previous studies (Biswas & Roy, 2015; Han et al., 2010) which indicated that perceived environmental credibility and trust are among the factors that significantly drive pro-environmental decisions. The relatively higher predictive weights associated with ELT and SPI suggest that consumers' belief in the authenticity of green claims and internalized commitment to sustainability are important predictors of technology-oriented environmental behavior. TR and PV exhibited moderate but consistent effects, highlighting the role of technological self-efficacy and cost–benefit perceptions in driving adoption. This is consistent with Parasuraman's (2000) conceptualization of readiness as a facilitating factor in new technology use. Consumers are more likely to have the intention to adopt environmental innovations if they consider such innovations as functional and economically valuable (Chen, 2010). These findings support the role of perceived value as an important bridge between environmental concern and behavioral action (Sweeney & Soutar, 2001).

The superior performance of the DNN model versus the ANN model is reflected in its R^2 values (0.9361 vs. 0.5293, respectively), reflecting deep learning's advantage in behavioral prediction analysis. The nonlinear and interactional effects among constructs were effectively captured by the DNN-patterns that may elude conventional regression or SEM techniques (LeCun et al., 2015; Kim & Park, 2023). This is a significant methodological contribution to sustainability research, in which consumer cognition is inherently complex and multidimensional. In line with Zhang et al. (2021), the deep learning framework unfolded that psychological and contextual factors operate hierarchically, impacting not only the direct paths to behavioral intention but even latent decision pathways.

The cluster analysis enriches the discussion by identifying the three distinct consumer segments of high engagement, moderate engagement, and low engagement. Segmentation represents the heterogeneity of green consumers and provides support to the earlier work of Joshi & Rahman (2019) and Han et al. (2020), indicating that the motivation within the same consumers will vary across states of psychological readiness. High-engagement consumers reflect strong self-efficacy and social support, whereas consumers in the low-engagement clusters demonstrate informational and motivational deficiencies. The difference suggests that one-size-fits-all marketing and policy interventions are not effective to ensure large-scale green technology adoption.

Findings emphasize the importance of trust-based communication, consumer education, and selective strategies of market segmentation. Credibility of eco-labels and simplification of technical information can lower the perception of risk and enhance behavioral belief. Also, the effects of visible social norms might trigger those social influence mechanisms that were significant in the model as suggested by Venkatesh et al. (2003) and Noppers et al. (2014). The findings from this study, in general, demonstrate that deep learning-based consumer modeling further enhances the accuracy of prediction and advances theoretical understanding of behavioral interdependencies in green consumption. Bridging the gap in behavioral theory and computational intelligence, it thereby provides an integrated framework for predicting, explaining, and segmenting sustainable technology adoption behavior.

6. Conclusion

The purpose of this research is to investigate the underlying psychological, social, and technological factors that determine GTA among consumers in Tamil Nadu, India, with an integrated approach of behavioral constructs and advanced machine learning techniques. Based on the theoretical underpinning, this study extended the traditional behavioral modeling to the application of ANN and DNN in capturing nonlinear interactions that are often overlooked by the conventional statistical models.

The results showed that Eco-Label Trust, Environmental Concern, and Sustainable Purchase Intention were the strongest predictors of green technology adoption. The higher the trust in environmental information and the larger the ecological awareness, the more likely consumers are to engage in sustainable consumption. Technology Readiness and Perceived Value supported the roles of leading variables, suggesting that those who are strong in technological self-efficacy and perceived functional benefits are more likely to adopt green technology.

The DNN model outperformed the ANN model in terms of all metrics, thus providing a higher degree of accuracy as well as explanatory power. This therefore outlined that deep learning is appropriate for analyzing complex consumer behavior, where there is an intrinsic, multidimensional interrelation between psychological and contextual factors. Further K-Means segmentation identified three definite profiles of consumers: high, moderate, and low engagement, showing clearly that adoption readiness varies significantly among the population. From a practical point of view, the results underline trust-based communication, consumer education, and effective segmentation strategies. Policymakers and marketers should therefore prioritize enhancing eco-label credibility, raising awareness about environmental benefits, and crafting messages that appeal to targeted consumer segments. Technological interventions and incentives reducing perceived effort or cost might further consolidate behavioral adoption.

This research contributes to the ongoing dialogue on sustainable consumption by showing that combining behavioral theory with machine learning not only improves the accuracy of predictions but also deepens conceptual understanding. The study bridges environmental psychology and computational analytics to provide a comprehensive empirically validated framework for advancing green technology adoption in emerging markets like India.

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