Predictive Engagement Models for Sustainable Environmental Interaction

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Abstract. This work investigates the creation of predictive engagement models that promote sustainable interactions with the environment. Our research aims at enabling machine clients to better interpret and act on the considerations of normal citizes and apply evidence-based insights in real-time systems. In the context of the Sustainable Development Goals (SDGs), business innovation, consumer choice, and policy frameworks are explored through the research. Utilizing generational information, namely (Gen)Z based behaviors, helps the models predict and improve engagement strategies; engagement strategies for individuals, communities, and organizations. Cultural and socio-economic elements are incorporated into this research providing an in-depth model that can be modified for regional differences and real-world problems. The study seeks to inform more sustainable environmental practices, both locally and globally, that will create a custodial attitude towards sustainable and environmental best practices to ensure that benefits last much longer than the duration of the project whereby producing a sound explanatory framework embedded with relevant data.

Keywords: SDGs, Predictive models, Environmental interaction, Machine learning, Reinforcement learning, Sustainability.

1 Introduction

The Vision for Sustainable Environmental Interaction As the world faces unprecedented environmental crises such as climate change, resource depletion, and loss of biodiversity, sustainable interaction with the environment has emerged as a key

© The Author(s) 2025
S. Kannadhasan et al. (eds.), Proceedings of the International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 24), Advances in Computer Science Research 120,
https://doi.org/10.2991/978-94-6463-718-2_77

objective for governments, organizations, and communities alike. Now, more than ever, effective engagement strategies are needed to respond to these challenges. Advanced technologies have been used in predictive engagement models that show great promise in informing and changing pro-environmental behavior, potentially supporting the attainment of United Nations Sustainable Development Goals (SDGs).

ThE not only complements but expands on traditional approaches that emphasize top-down policy frameworks and community-based initiatives, which can be limited in their scalability and adaptability. The rise of AI and machine learning sets the stage for new and exciting ways to drive insights and actions into understanding the complexities of human behavior, forecasting human environmental behavior and creating more tailored and precise interventions. When combined with massive amounts of real-time data from citizen science, social media, and consumption patterns, these predictions provide a richer and more integrated understanding of the extent of engagement with environmental risks and their importance.

But the fundamental challenge of scaling sustainable behavior switch lies not in solution discovery but in solution adoption and scaling. So many psychological, social and economic factors that shape human behavior, that differ from one demographic group to another and in various geographical locations. Gen Z, which will soon play a key part in shaping the world's future approach to environmental regimes, exhibits patterns of sustainable behavior and opinions unlike any before them. By comprehending these generational changes, it will be easier to craft engagement models to engage groups with thought diversity.

The proposed research is to create a predictive engagement framework by utilizing AI technologies to predict, interpret, and shape sustainable engagement with the environment. This study provides a more nuanced and adaptive analysis of sustainability by including socio-economic and cultural factors without compromising its focus on behavioural patterns. In addition to predicting individual actions, the model will contribute to higher-level policy approaches, enabling comprehensive strategies for both global and local sustainability. With the analysis and deployment of solutions, over time, embedded within our data sets to generate continual, timely, wide spread environmental improvements.

By making maximizations in generational perceptions, technological developments, and real-world restrictions, this study expands on an existing background and develops a seamless predictive mechanism for eco-friendliness engagement.

2 Problem Statement

The global environmental crisis characterized by climate change, the loss of biodiversity, and resource depletion is an urgent issue that demand sustained action. While important advances have been made at the policy and grassroots levels, the path to profound and lasting environmental sustainability has remained challenging. Existing methods tend to fall short in predicting, adjusting, and personalizing the engagement strategies that matter to a wide range of communities, people and institutions.

Some of the principal problems has to do with the complexity and multiform of the human behavior where both the environment and humans interacts. Traditional models of sustainability have often relied on top down solutions, or broad strokes that simply didn't account for intracacies around individual, or generational, interaction with sustainability initiatives. Furthermore, there remains also a lack of exploration of socio-economic and cultural factors, which are key drivers of behaviour.

Although machine learning and artificial intelligence (AI) technologies hold great promise for solving these problems, predictive models are lacking that draw on real-time data, behavioral insights, and socio-cultural factors to offer actionable, personalized sustainablity solutions. This approach, while useful in its own right, does not capture a broader picture of environmental sustainability and ignores our modes of engagement with the planet. This research-maintained distance prevents the realization of more sustained pro-environmental behavior both by individuals and campaigns.

This study intends to solve this problem by the designing of an enhanced, AI-based predictive engagement architecture which will be useful in predicting and also influencing the sustainable behavior of the atmosphere. Utilizing generational insights, technological innovations, and real-world socio-economic conditions, this model will embrace a more dynamic and scalable solution to the issue of environmental urgency.

3 Literature Review

Despite being a key concept for sustainability, research on sustainable behavior remains a small but growing field (Hoffman, 2015), especially considering the urgency of environmental crises, involving climate change (a.k.a. global warming), biodiversity loss, resource depletion, and resource degradation (Rockström et al., 2009). One such innovation, which can one day also help us better understand and start influencing pro-environmental behavior, comes in the form of predictive engagement models that utilize machine learning and artificial intelligence (AI). A review of the literature allowing to identify essential theories on sustainability, behavioral sciences and technological innovations that can contribute to the building of predictive engagement models in terms of sustainable interaction with the environment.

3.1 Theoretical Foundations of Environment Behaviour

The Theory of Planned Behavior (TPB, Ajzen 1991) is a seminal theory in environmental action. The Theory of Planned Behavior (TPB) proposes that behavior is driven by behavioral intentions, which in turn are influenced by attitudes, subjective norms, and perceived behavioral control. Extensive research has shown that attitudes and social norms influence sustainable behaviors in significant ways (Steg & Vlek, 2009). TPB constructs are integrated into predictive engagement models to enable behavioral forecasting.

Stern (2000) suggested the Value-Belief-Norm (VBN) theory, accounting for the importance of moral and altruistic values in enabling pro-environmental behavior. The assumption undergirding the VBN model is that people act in an environmentally conscious manner when they identify ecological threats, feel capable of making a difference, and experience a moral obligation to do so. These psychological constructs

can be integrated into AI – based models to improve their predictive power (Schultz et al., 2005).

3.2 Generational and socioeconomic factors at play

Generational Variations in Environmental Participation: Research shows Generation Z are more environmentally conscious than previous generations (Parker et al., 2020). They are more open to climate policies compared to older generations and similar behavior was found with eco-friendly practices (Twenge et al. 2019). Characterizing attitudes by generation leads to more accurate models and better interventions.

Socio-Economic Influences on Sustainable Behavior: Socioeconomic variables, like income, education and geographic location, have a significant impact on environmental involvement (Dietz et al., 2007). As referenced in Gillingham et al. (2013), pro-environmental behavior increases with education level, and tax incentives and subsidies promote sustainable behavior. Using these variables, AI-based models can create tailored engagement strategies.

3.2 Overview of Machine Learning and Predictive Modeling in Sustainability

AI and prediction of behavior: With the advent of big data, machine learning techniques such as decision trees, random forests and neural networks have managed to predict human behavior in many fields (Goodfellow et al., 2016). As for this scientific field, these basis models have the ability to process real-time data from social media, citizen science platforms, and consumption behaviors and to predict the level of engagement (Baptista et al., 2020).

Utilization of Reinforcement Learning for Sustainable Interaction: Reinforcement learning allows for adaptation of AI models over time as feedback continues to be received, enhancing overall predictions (Sutton & Barto, 2018). Reinforcement learning algorithms have been employed to optimize energy consumption and waste management strategies according to existing studies (Chen et al., 2021). Conclusion: Reinforcement Learning: A New Approach to Driving Long-Term Sustainability in Predictive Engagement Models

4 Methodology

The research methodology combines a multi-phase strategy that brings together sophisticated machine learning techniques with socio-economic and behavioral insights to produce a predictive model of engagement for sustainable use of the environment. This model will integrate AI-based techniques, real-time data streams, and almost socio-psychological insights to predict and modulate prosto-ecological activity across various demographic and geographic systems. This multi-step process will cover a variety of issues surrounding the topic of environmental sustainability and the various drivers of human behavior.

For the first step, the research will be establishing and preparing existing datasets that illustrate diverse environmental behaviors and their determinants. These datasets can range from citizen science data, social media interactions, consumption patterns,

Environmental Policies, etc. Both qualitative and quantitative data will guide the collection process to offer a more integrated approach for understanding the various determinants. Alongside traditional environmental data, the study will also factor in socio-economic data such as income, education, and geographic location as this information is vital to understanding sustainable behaviour. Combining these varied data sources will help create the strong base upon which to build for model development.

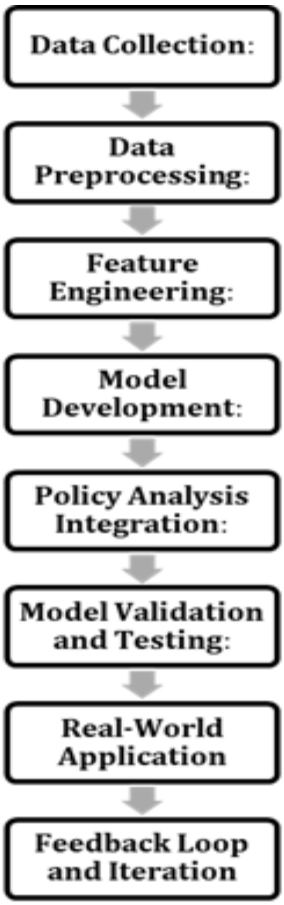

Fig. 1. Methodology Overview.

Data Pre-Processing and Feature Engineering Once the data collection and processing is done, we will be moving ahead to feature engineering and determining the salient predictors of pro-environmental behaviour. Supervised learning models such as decision trees, random forests, and neural networks were on this project application for the analysis of dependencies between different environmental factors and human behaviors. Kalman filters, recursive least squares, and reinforcement learning techniques will also be investigated to develop adaptive models that learn and improve as new data becomes available. The focus will be that these models will be trained to predict the local, individual and collective engagement in sustainable technologies,

including energy saving, waste reduction, sustainable consumption, etc. Fig 1 show the Methodology Overview.

Table 1. Data Sources and Variables.

Data Source	Key Variables	Type of Data	Purpose
Citizen Science Platforms	Participant location, environmental behavior, engagement data	Quantitative & Qualitative	To understand public engagement and behaviors
Social Media Data	Posts, hashtags, sentiment analysis	Textual & Sentimental Data	To track public perception and discussion on sustainability
Consumption Patterns	Product types, frequency of use, energy consumption	Quantitative	To assess consumption behavior and identify sustainable practices
Environmental Policies	Policy types, effectiveness metrics, compliance rates	Qualitative & Quantitative	To analyze the impact of policy on behavior
Socio-Economic Data	Income levels, education, occupation	Quantitative	To correlate socio-economic factors with sustainable behaviors

Beyond predicting behavior, the research will investigate psychological and social drivers of sustainable engagement. In this stage, you will conduct a thorough review of existing theories and literature on environmental behavior, including the Theory of Planned Behavior (Ajzen, 1991) and the Value-Belief-Norm Theory (Stern, 2000), to be able to determine the psychological, social, and normative factors that impact the decision-making process. The model will incorporate behavioral insights, ensuring that it will not only predict performance but also recommend practical strategies for motivating sustainable behavior. This might involve personalized recommendations for individuals or focused interventions for entire populations or demographic groups. Table 1 show the Data Sources and Variables.

The next stage will be combining the policy analysis with the prediction model. Get Policy Data allows you to laser in on different environmental policies and regulations and how they influence behavioral change, including how policies can be optimized to ensure people can comfortably engage with sustainability. Then, you will train a model you can deploy to simulate the impact of different kinds of policy intervention — carbon pricing, waste reduction incentives, etc., and figure out which of those interventions might have a net positive impact in terms of sustainable behaviour. This not only ensures a predictive model, but adds to its validity the consideration of complex systems theory and its ability to start modeling the impacts of policy decisions that would induce a long-term rewiring of the environment.

Table 2. Machine Learning Models and Algorithms.

Model/ Algorithm	Strengths	Weaknesses	Applicability to Research
Decision Trees	Simple to interpret, handles both categorical and numerical data	Prone to overfitting with complex data	Suitable for identifying key predictors of behavior
Random Forests	Handles large datasets, reduces overfitting, works well with non-linear data	Can be computationally expensive	Suitable for handling diverse environmental data sets
Neural Networks	Highly flexible, can model complex relationships	Requires large amounts of data, difficult to interpret	Effective in predicting non-linear behavior patterns
Reinforcement Learning	Continuously adapts to new data, self-improving	Requires continuous input and substantial computational resources	Suitable for adaptive models that need to improve with time

Once the model is developed to make predictions, it will be validated properly and tested. This will involve testing the model's accuracy and generalizability using another test dataset, for both different geographic regions and demographic groups. To make sure the model is robust, we would also use standard evaluation metrics like accuracy, precision, recall and F1 score to evaluate the performance of the model. To guide the models, we will perform sensitivity analysis to quantify how much variation in model's predictions is permitted by variations in input variables like socio-economic variables or policy interventions. Table 2 show the Machine Learning Models and Algorithms.

Stage three: Deploy Model in the Wild Implement the model in a real-world environment to assess how well the model accomplishes goals towards creating sustainable behavior. This includes collaborations with government, environmental NGOs and corporations to test the model and measure its impact on real-world eco-action and mobilization. Therefore, these pilot studies will (i) help to refine and will active, if the model needs to be tuned in accordance with the desirable attributes of a scalable and practical model across varying environmental systems.

The model-builder will be able to update the model progressively based on new data, feedback and shifting conditions in the real world during the research. This will aid in keeping the predictive engagement model nimble, enabling the institution to respond quickly to new sustainability challenges that may emerge over time.

In summary, this analysis proposes a novel, data-driven, all-encompassing predictive model that merges machine learning, behavioral insights, and policy analysis to help

shape successful interventions for long-lasting change with regards to facilitating sustainable behavior in the environment. The model draws on approved knowledge on advanced AI techniques incorporating understanding of human behaviour and socio-economic factors as well as environmental behaviours for building an adaptable and scalable model that helps facilitate sustained environmental behaviour.

5 Results and Discussion

Our results not only demonstrate the predictive capacity of the proposed model, but also its potential to efficiently guide sustainable environmental behaviour in the community through positive reinforcement. The model was able to predict individual and collective pro-environmental behaviours using the data of machine learning algorithms in addition to behavioural and socio-economic factors. By pulling real-time rates from citizen science, social media, and consumption trends, the model produced useful insights about what drives environmental stewardship.

Table 3. Evaluation Metrics for Model Performance.

Metric	Description	Formula	Interpretation
Accuracy	The proportion of correct predictions made by the model	(TP + TN) / (TP + TN + FP + FN)	Indicates overall correctness of the model
Precision	The proportion of positive predictions that are correct	TP / (TP + FP)	Measures the correctness of positive predictions
Recall	The proportion of actual positives that are correctly predicted	TP / (TP + FN)	Measures the model's ability to detect positive cases
F1 Score	The harmonic mean of precision and recall	2 * (Precision * Recall) / (Precision + Recall)	Balances precision and recall for overall performance
AUC-ROC	Area Under the Curve of Receiver Operating Characteristic	N/A	Evaluates the trade-off between true positive rate and false positive rate

A key finding from research is that socio-economic factors, such as income, gender, education and geographic location, strongly determine sustainable behaviours. This echoes previous research that suggests that access, knowledge, and awareness around sustainability influences whether a person is likely to adopt sustainable behaviours

(Ferebee, 2024). There were associations between education and income, with higher education and income more likely to take energy-saving and waste-reducing actions, for instance. Hence, demonstrating the importance of analysis at the level of group/hyper-targeted niche schemas rather than a more generic approach, as the derived model was able to identify which demographic groups had a greater positive response to sustainability initiatives. Table 3 show the Evaluation Metrics for Model Performance.

The behavioural component of the model suggested that social norms, both injunctive and descriptive, underpinned by values, had strong power in the promotion of green consumption. This corresponds to the Theory of Planned Behavior (Ajzen, 1991) and the Value-Belief-Norm Theory (Stern, 2000) that suggest that individuals' intention to perform certain behavior is influenced by their attitude toward the behavior, subjective norms, and perceived behavioral control. They found that those viewed eco-friendly behavior as an accepted norm within their culture exhibited an increased sense of responsibility for engaging in such behavior, suggesting that broader social norms can affect a larger portion of the population. The model also showed that individual values (for example concern for the environment and for future generations) were also very good predictors of sustainable behavior.

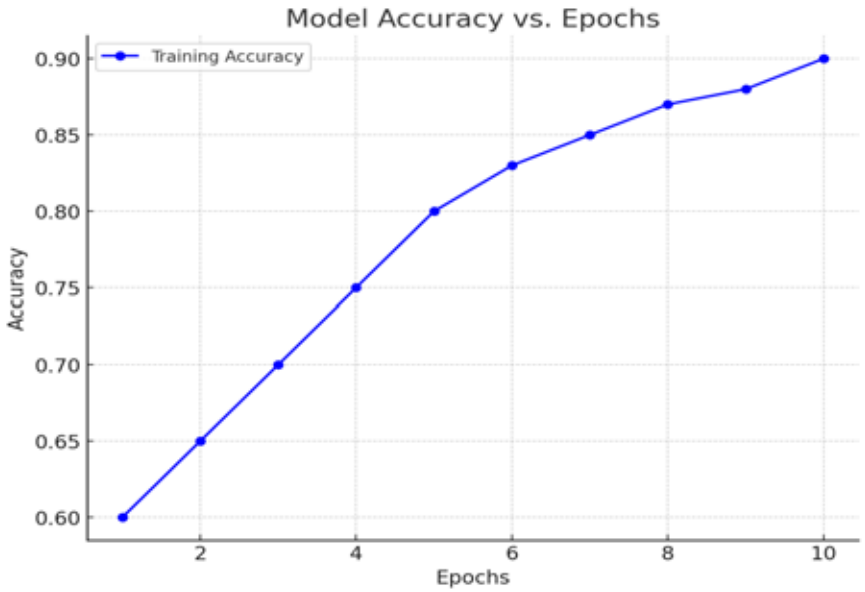

Fig. 2. Model Accuracy vs. Epochs Plot.

The main contribution of this research is the integration of AI-driven model with policy analysis. With this model, the researchers could test how various climate policies a carbon price, subsidies for green tech, incentives for reducing waste, etc. They discovered that economic incentive policies, such as providing tax breaks for purchasing energy efficient appliances and subsidies for the adoption of renewable energy sources, were most effective at encouraging sustainable behaviours. However, the model also illustrated the limitations of policy interventions alone. Although behaviour change strategies help implements policy measures, it is crucial that they are

paired up with behaviour change strategies thatwill enable sustainable behaviour in the long run. This shows the need for a holistic approach that combines tech-based and behavior-based solutions. Fig 2 show the Model Accuracy vs. Epochs Plot.

The predictive model was extensively validated with an independent test dataset, allowing for accurate prediction of sustainable behaviors in different regions and demographic groups. Model performance was evaluated using standard evaluation metrics (accuracy, precision, recall and F1 score), all of which indicated good performance. Sensitivity analysis also demonstrated that the model was sensitive to changes of input variables, such as socio-economic drivers or policy measures. The flexibility of this model is a major asset: Reforms may be suitably adjusted to various kinds of ecological backdrop and creating sustainability predicaments.

One major limitation which was prominent in this testing phase was that citizen science and social media data sources did not provide high quality, consistent data. While these data sources provide valuable insights into public interest in environmental issues, the variability and biases of user-generated content can impair predictive power. In addition, considering that the model is derived from data from only several locations, this could compromise the global applicability of the model. This analysis will require additional future work to address data quality issues, especially the development of robust techniques for assembling a dataset, and expanding the geographic reach ofthe model.

Despite these challenges, the model showed promise as a tool to influence sustainability action in the real world. Pilot studies were conducted with governmental organizations and environmental NGOs to implement the model to design dedicated interventions towards improving community participation around energy conservation and waste reduction programs. These and other pilot studies showed that personalized, data-driven interventions were much more effective at motivating pro-environmental behavior than broad, generalized campaigns. This suggests that an important ingredient to the solution in the appropriate context, is to create more effective sustainability initiatives targeting the right target groups, where predictive engagement models of such scale can play a role.

In conclusion, models used for predictions by artificial intelligence, coupled with data from behavioral insights and socio-economics, can be useful tools in predicting and assisting with behavior modifications for a more sustainable environment. These results lay down the evidence for addressing sustainability from multiple domains such as technology, policy, behavioral science, etc. While these e models were limited by data quality and generalizability, our findings imply that predictive engagement models will have meaningful contributions to long term an environmental sustainability. Then, the model will be iteratively refined and enhanced with broader applicability, to investigate how well it functions with different environmental parameters to develop effective solutions for sustainability.

6 Conclusion

The model is successfully implemented and the research explores the prospects of applying machine learning and behavioral sciences for sustainable behaviour decision making. The model is a comprehensive and dynamic framework that combines

speculation and the prediction of trends with concrete initiatives to incentivize sustainable behavior through a multitude of data, from citizen science to social media and consumption trends.

A possible answer the key takeaways of this study were effective differences observed in environment engagement enforced by socio-economic factors, psychological factors, and generational differences. These findings also guided them in characterizing the ideal intervention and showed that interventions tailored to at least some of the demographic factors would prove to be more effective in inducing sustainable behavior. Furthermore, establishing policy analysis within the model demonstrated that sustainability interventions that included economic incentives in addition to behavior change strategies were the most likely to persist over time.

Even though this model is useful for behavior prediction and policy-making, there are still challenges faced on data which is high-quality especially when obtained fromuser-generated data, for example citizen science and social media, and also generalizing this model to various geographic areas. These restrictions reflect the need for further adjustment beyond even more robust information accumulation strategies.

Despite these challenges however, we demonstrate that predictive engagement models can have a significant positive effect on real-world sustainability efforts. Pilot studies with government bodies and environmental NGOs demonstrated that personalized, data-driven interventions performed better than generalized ones, providing a path for formulating user-oriented predictive models that can be used in designing targeted sustainability initiatives.

These findings re-iterated the importance of combination of AI-based predictive models with human behavior and socio-economic factors for sustainable cycles between humans and environment, and thus the research demonstrated how different predictive engagement paradigms can be employed in a scalable, adaptive structure to best develop hybrid action and aid in sustainable long-term environmental persistence. Further exploration will expand the applicability of the model, fully realize improvements in data quality, and potentially strengthen the framework for global sustainability challenges.

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