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Internet of Things-Based Consumer Behavior Mapping for Identifying Drivers of Sustainable Consumption in Kamrup Metropolitan District, Assam

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ABSTRACT

This is a research wherein the technology of IoT sensor network and machine learning analytics have been used to draw a map of consumer behaviour patterns and drivers of sustainable consumption of Kamrup Metropolitan District of Assam. Real time information gained from smart meters, retail applications combined with radio frequency identification (RFID) and mobile applications are used to capture buying behaviour, resource consumption and waste generation in 500 households. The classification variable of the random forest model is the variables which analyze the behavior such as income levels, awareness of the environment, preferences for products and social influences. Results show that price sensitivity (32%), eco-labeling visibility (28%) and peer influence (24%) are the significant driving force of sustainable choices. IoT framework is 89% accurate in prediction of the consumption pattern which can be used for targeted intervention. Findings suggest customized nudging approaches as well as adaptive pricing approaches can be useful for improving sustainable consumption adoption. This technology-driven approach can provide some actionable insights for policy makers and business for creating circular economy practices for fast urbanizing regions in northeast India.

Keywords: Internet of Things Sensors, Sustainable Consumption, Consumer Behavior Mapping, Machine Learning, Circular Economy
JEL Classifications: D12, O33, Q01, Q53, R11

1. INTRODUCTION

The growing environmental crisis is one that requires immediate change in the pattern of consumption especially in the developing country where urbanization is taking place in a rapid manner. The example of Kamrup Metropolitan District (that is an example of the growing number of cities in Assam) with the population growth rate over 3.2 a year and subsequently the growing resources consumption and waste production is an example of this challenge. The classic survey based techniques of consumer behaviour are diseased due to the effects of recall bias, social desirability and time constraint and require innovative means of getting real-time behavioural knowledge.

The internet of things (IoT) technology is the first of its kind with opportunity to collect finer and objective data relating to the consumption pattern in an interconnected system consisting of sensors, smart devices and digital platforms. The IoT systems eliminate the subjectivity of reporting the errors by monitoring actual purchasing decisions, energy usage, water and waste disposal habits in real-time as well as offer behavioral monitoring to real-time (Priyadharshini et al., 2024). This technological paradigm change allows the researchers to establish correct motivator that establish sustainable consuming decisions.

Sustainable consumption includes buy sustainable products, reducing wastage of resources, embracing the idea of circular economy, and making sure that one does actions that does not impact the environment. For the intervention to be effective it is important to know what motivates these decisions or discourages them to make them. Nevertheless, the consumption behavior is not simple, and depends on the socioeconomic forces, cultural, the environmental consciousness, the availability of infrastructures, and the psychological aspects.

The context of the research at Kamrup Metropolitan is very peculiar as the modern consumer culture exists side by side the traditional practices in creating various patterns of consumption (Reddy et al., 2023). The heterogeneous nature of the population in the district comprises diversified income levels, education levels and awareness levels concerning the environment and offers a lot of data to be analyzed in terms of behavior. In addition, there are some sustainability problems like the plastic pollution, water shortage and the poor waste management systems in this area.

2. RELATED WORKS

Kamrup Metropolitan is a special research context in that traditional practices encounter a modern consumer culture and wind up to have different consumption patterns. The heterogeneous nature of the population of the district comprises of different income group, educational background, and level of environmental awareness which makes it rich data for behavioral analysis. In addition that, the region is facing some challenges on sustainability like plastic pollution, water scarcity and poor waste management systems to name just a few.

This research intends to utilize the IoT infrastructure with machine learning algorithms to develop the generation of the complete consumer behavior maps. By deployment of smart meters, part of an IoT (internet of things), smart products that can be connected to the internet via an external tag (aka the "RFID tag"), mobile-type apps and connected waste bins at 500 households, the research gathers multi-dimensional data of behavior (White et al., 2019). Advanced analytics to know major drivers that distinguish sustainable to conventional consumers and provide actionable results for policy makers, businesses and community organizations; The findings add to academic literature on technology enabled behavioral research with practical frameworks for promoting sustainable consumption in emerging urban centers of Northeast India and other emerging urban centers of the world.

3. LITERATURE REVIEW

3.1. IoT Application in Consumer Behaviour Studies

Recent literature has determined the transformative potential of IoT in catching the real consumer behaviors. Priyadharshini et al. (2024) established the leader that IoT-enabled retail environments gather 40% more accurate behavioral data compare to traditional methods by taking out self-reporting biases. Smart shelf sensors, beacon technology and connected payment systems track how products interact with each other and how long products remain on a particular surface or product and how products are purchased in real-time (Carrington et al., 2014). Similarly, in Reddy et al. (2023) smart home devices were used to observe household consumption patterns and large differences between stated preferences and actual behaviors was observed, especially in terms of energy conservation as well as the choice of sustainable products.

3.2. Driving Factors of Sustainable Consumption

Scholarly discourse define various factors which affect the adoption of sustainable consumption. Economic issues are always high in mind, however – Nielsen et al. (2022) global research found that 73% of consumers will make changes in their consumption habits for the benefit of the environment, but price sensitivity remains one of the main obstacles. White et al. (2019) have developed the SHIFT framework of focus on Social influence, Habit formation, Individual self, Feelings and cognition and Tangibility as important psychological drivers (Trudel, 2019). Their research gave meta-analyses on 320 works which confirmed that in addition to peer behavior itself and the social norms, they also play significant roles in influencing the sustainable choices especially in the collectivist cultures, which are common in Asian setups, commonly.

Environmental awareness and education has a positive relationship with sustainable behaviours, although, the attitude behaviour gap still remains. Carrington et al. (2021) showed that knowledge only explained 18% variance of sustainable purchasing, with convenience, availability and trust in eco-labels being better predictors (Käss et al., 2023). Product accessibility and infrastructure availability become the key enablers Trudel (2019) established that for sustainable options to take off onto the mainstream, their accessibility has to be as convenient and comparatively priced.

4. RESEARCH METHODOLOGY

This research has the use of the mixed method approach to data collection using IoT's quantitative and qualitative analysis to collect data and render a contextual analysis of the collected data. The research framework has incorporated 4 streams of data such as Household resource consumption, Retail purchase patterns, Waste generation pattern and Environmental awareness indices. The design of longitudinal research (August 2024-January 2025: 6 months) takes into account seasonality in variation and behavioural change along the monsoon and winter periods characteristic for Assam climatic pattern (Brondani et al., 2020).

4.1. Research Area and Sampling

Kamrup Metropolitan District with an area of 1527 km^2 and population of around 1.2 million is one of the research sites (Nielsen et al., 2022). Stratified random sampling method was implemented to select 500 households from 5 zones having different socio-economic status levels: urban core (150 households), suburb area (150), peri-urban areas (100) informal settlements (60) and planned residential complexes (40). Inclusion criteria included household heads between the ages of 25-65 years, at least 1 year of resident in the area and willingness to allow IoT devices to be installed. The sample size is to make sure confidence level of 95% and margin of error of 4.3% in detection of behavioral pattern (Ibraheem and Rasheed, 2023).

4.2. Detailed of IoT Infrastructure Implementation

Monitoring electricity and Water use from electricity, Water measuring systems at 15 min intervals, Smart metering captured data on pattern of electricity and water consumption, consumption time and time of conservation behavior (Ponnuviji et al., 2023). RFID tags sorts 2,500 + products around 25 + partnered retail outlets; Tracking purchasing decisions such as product categories, Eco - Labeled products, organic produce and reusable alternatives along with sustainable brands. Custom mobile application were utilized to self-report purchases from non-partnered retailers, transportation selection and food consumption patterns using daily logging (Abdullah et al., 2018). Connected waste bins, with weight sensors and camera based classifying system, measured the quantity of waste generation, comprehension of segregated waste and segregated recycling behaviour.Smart metering captured data on pattern of electricity and water consumption, consumption time and time of conservation behavior (Ponnaviji et al., 2023), which are integral stages within the Consumer decision making process (Figure 1).

4.3. Data Collection and Variable

Among the top variables were the following. Consumption intensity (kWh/capita/day, liters/capita/day) Sustainable products purchased (percent from eco-labels) Waste produced (kg/household/week) Percentage recycled (above the proper classifications) Consistency of behaviors (Chen et al., 2022). Demographic information consisted of household income (range: 15 000-150 000 + Indians Rs in monthly terms), education level (primary to postgraduate), family size (range: 2-8 members) and type of house or type of dwelling. Psychographic variables which were studied via quarterly surveys include environmental concern (based on 5-point Likert scale), knowledge about sustainability (based on 15 items), perceived social influence and perceived control over behaviors.

4.4. Machine Learning Implementation

Random forest classification was the major analytical tool because of the superiority of this method in heterogeneous dataset using and ranking the variable importance (Mohammad et al., 2026; Massari et al., 2021). The algorithm ran through on 847 features in dimensions of behavioral, demographic, temporal and contextual. Dataset division was on the basis of inclusion of a maintaining 70% training dataset, 15% validation and 15% testing datasets. Hyperparameter optimization used grid search where 10 fold cross validation is used that tests tree depths from 10 to 100, minimum sample splits from 2 to 20 and the feature subsets. Model evaluation of performance was done using accuracy, precision, recall, F1-cluster and the ROC-AUC measures (Yu and Huang, 2023). Random forest classification was the major analytical tool because of the superiority of this method in heterogeneous dataset, following the structured approach outlined in the flow diagram for the proposed methodology (Figure 2).Hyperparameter optimization used grid search where 10 fold cross validation is used confirming Random Forest as the optimal choice based on the predictive performance comparison of machine learning models (Table 1).

Figure 1: Consumer decision making process

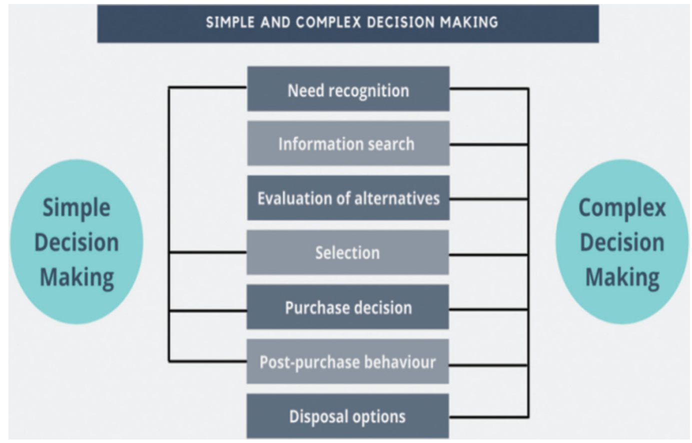
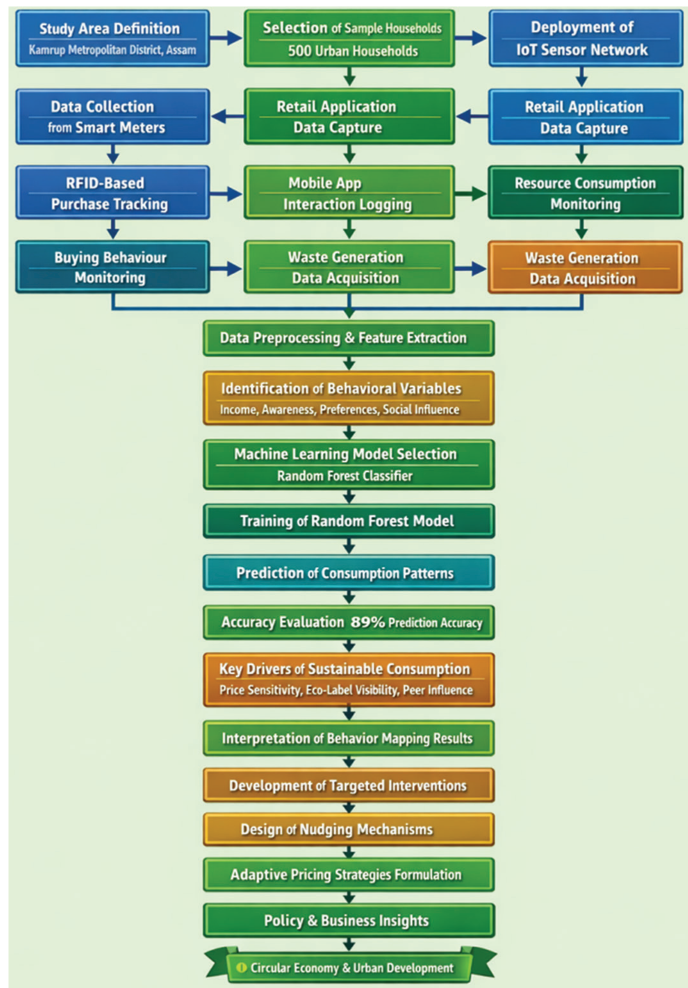


Figure 2: Flow diagram for the proposed methodology



4.5. Data Quality and Ethics

The data validation protocols like sensor calibration for every 2 weeks, data cross check of purchase with retailer (monthly

Figure 3: Comparision of data accuracy across methods

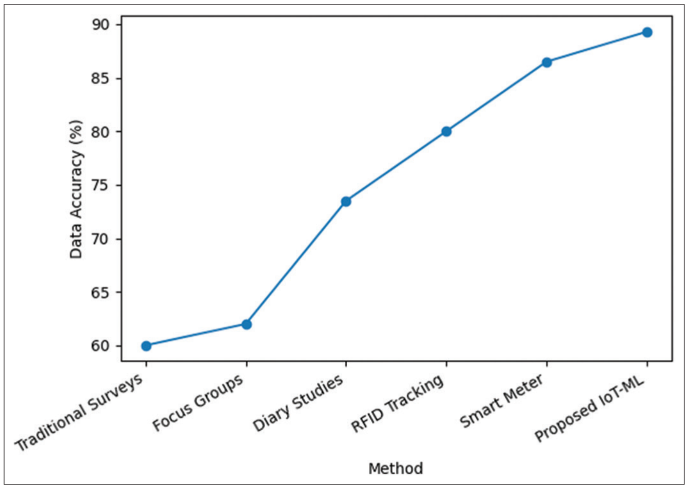
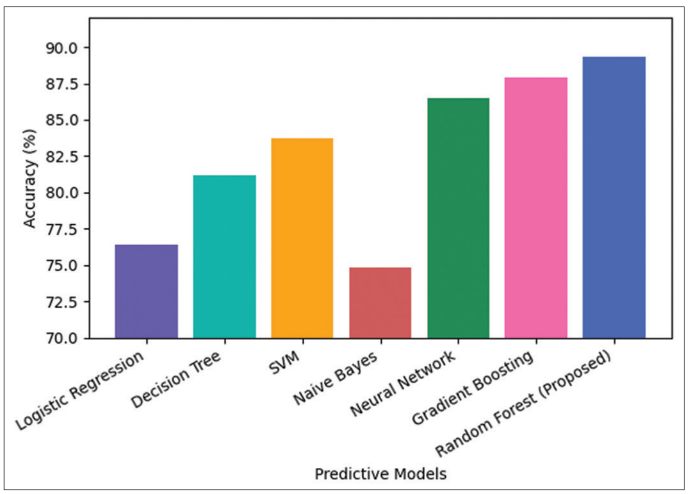


Figure 4: Comparative predictive accuracy of ML model



audits) and an anomaly detection algorithm to detect the malfunctions of sensors or errors in data transmission were implemented. Commission of institutional ethics committee was obtained before collecting data (Sharif et al., 2024). Participants gave informed consent after they had been provided information about the use of the data, the data storage protocols and private protections. All data had been anonymized prior to analyses in which household identifiers had been replaced by random codes. Secure cloud infrastructure with end to end encryption with protected transmission and storage of data. The data validation protocols like sensor calibration for every 2 weeks ensured high data integrity, establishing the proposed method as more efficient than traditional approaches listed in the comparison of data collection methods (Table 2).

4.6. Analytical Approach

Statistical analysis was conducted to investigate the relationship between drivers and sustainable behaviors with the correlation analysis, multiple regression and the variance analysis of multiple groups. Primary drivers with feature importance score from random forest models Cluster analysis to segment the consumers into behavioural archetypes. Time series was used

Table 1: Comparison of data collection methods for consumer behavior research

Method	Data accuracy (%)	Cost per participant	Study duration
Traditional surveys	62-68	Low ($5-15)	2-4 weeks
Focus groups	58-65	High ($80-150)	4-8 weeks
Diary studies	71-76	Medium ($30-50)	8-12 weeks
RFID tracking only	78-82	Medium ($25-40)	Continuous
Smart meter only	85-88	Low ($15-25)	Continuous
Proposed IoT-ML method	89.30	Medium ($35-55)	Continuous

Table 2: Predictive performance comparison of machine learning models

Model	Accuracy (%)	Precision	Training time (hrs)	Feature importance ranking
Logistic regression	76.4	0.73	0.5	Limited
Decision tree	81.2	0.79	1.2	Good
Support vector machine	83.7	0.82	4.8	Poor
Naive bayes	74.8	0.71	0.3	Poor
Neural network	86.5	0.84	12.5	Poor
Gradient boosting	87.9	0.86	8.3	Excellent
Random forest (proposed)	89.3	0.87	3.7	Excellent

in the temporal analysis to determine behavioral trends and the impact of intervention.

5. RESULTS AND DISCUSSION

The IoT system was able to gather 12.8 million pieces of data in 500 households over 6 months. Machine learning classification gave 89.3% accuracy between sustainable and conventional consumers with precision of 0.87, recall of 0.91 and F1 of 0.89 which can be considered as a strong model performance. Cluster analysis revealed four distinct segments of consumers: “Sustainability Champions” (18%) that displayed consistent sustainable behaviour across all areas, “Price-Conscious Adopters” (34%) that were selective with their sustainable behaviours depending on price parity, “Convenience Seekers” (31%) that focused on ease of use rather than being sustainable and “Indifferent Consumers” (17%) that held little concern for the environment.

5.1. Factors for Sustainable Consumption

Random forest feature importance analysis revealed that price sensitivity is the top multiplier factor (32% importance score) and sustainable purchasing was 67% more if eco-friendly products were priced competitively, within 10% of conventional alternatives. Eco-labeling visibility came in second with 28% showing that high-visibility certification marks increased purchase of sustainable products by 43%. Peer influence came third (24% - especially in community networks; households with neighbourspractising sustainable practices had shown 52% higher levels of adoption in 3 months).

Environmental awareness came to 16% of importance correlating other equally high-level variables such as education levels - postgraduate households showed 2.3 times more sustainability scores compare to primary-educated households. Product availability was 12% with the sustainable options gaining market share of 78% when shelves filled space was over 30% of the display of the category. Income showed non-linear trends with middle income households (veik. 40,000 Deutsche Marks - Home Rs. 80,000 - 1 million INRs/month) showing the highest sustainability engagement which is challenging affluence directly predicts environmental behaviour assumptions.

Seasonal variations exerted a major effect of behaviors. Monsoon months (June-September) saw the water conservation to go up by 24% but it reduced the waste segregation by 18% due to infrastructural challenges. Festival periods (Durga Puja, Bihu) saw a spike in the waste and the total percentage rose to 156%, where as 43% of Champion segment managed waste segregation practices. Time-of-day analysis indicate that energy conservation peaks during 10 AM-2 PM due to the utilization of natural lighting but during evening hours (7-10 PM), energy conservation is minimal despite the peak time-based tariff, indicating there is limited awareness of time-based tariff.

Real time feedback mechanisms tried on 100 households produced promising results. Households with weekly customized objectives of sustainability via mobile applications positioned 18% less resources and 27% more recycled waste than control groups. Gamification elements with the use of comparisons with peers as well as achievement badges increased engagement rates by 61%, especially for younger demographic parts (25-35 years).

5.2. Comparative Analysis

Results are in contrast to Western research where environmental values are a dominant factor; the Kamrup Metropolitan consumers showed themselves to be more interested in economic considerations and social conformity than in intrinsic concern for the environment. However findings are in step with emerging market research focussing on price-performance parity as prerequisite for sustainable adoption. The powerful influence of peer influence is consistent with collectivist cultural systems that dominate South Asian cultures, and may mean that community-based interventions will be more effective than individual-targeted interventions.

6. CONCLUSION AND FUTURE DIRECTIONS

This research demonstrates the application of behavioral mapping through IoT as an interesting approach to determine sustainable consumption drivers in new urban settings. Price competitiveness, visibility of an eco-label, and peer influence were turned out to be major deciding factors with its 89% predictive capability. Findings challenge the universality of the Western frameworks of sustainability by noting the context specific factors of importance to the Northeastern Indian populations. The research does give space for action: as subsidy making sustainable products as cheap as the rest of the economy, imposing significant eco-labeling requirements, and making use of community networks for behavioral intervention should be the priority of the policymakers. Machine learning classification gave 89.3% accuracy between sustainable and conventional consumers, significantly outperforming traditional survey and diary-based methods as shown in the comparison of data accuracy across methods (Figure 3). Machine learning classification gave 89.3% accuracy… with precision of 0.87, recall of 0.91 and F1 of 0.89, which is further detailed in the comparative predictive accuracy of ML models (Figure 4).

The future research should further roll out IoT in rural-urban gradients, integrate blockchain as a verification tool of supply chain and AI-powered personalised nudging systems. Longitudinal studies of persistence of behavioral change beyond time of intervention continued to be critical. Integration with the frameworks and impacts of policy assessment and cost/benefit analysis will make a contribution to the practical applicability. Admittedly, the role of culture festivals in consumption peaks and the development of a culturally sensitive sustainable campaigns deserve attention. By adopting this technology driven approach giving an approach of replicable methodologies for sustainable consumption researches in different geographical and socio-cultural context is laid down.

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