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A predictive modelling approach to decoding consumer intention for adopting energy-efficient technologies in food supply chains

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ABSTRACT

The transition towards energy-efficient practices in the food supply chain (FSC) is essential for addressing the dual imperatives of sustainability and cost-effectiveness. As consumers become increasingly aware of the environmental impact of their food choices, their willingness to support energy-efficient technologies (EET) has become a critical factor in shaping the future of sustainable FSC. This study empirically investigates consumer intention and desire to pay for food products characterized by a reduced energy footprint, utilizing machine learning (ML) algorithms to predict consumer preferences within the FSC. Association rule mining (ARM) was employed to uncover key patterns in consumer intentions, while multiple ML algorithms were compared to identify the most effective algorithm for predicting willingness to pay. The results reveal that the Random Forest algorithm achieved the highest accuracy at 82%, significantly outperforming other models. These findings underscore the potential of ML to refine marketing strategies and operational decisions, facilitating the broader adoption of EET within the FSC (EET-FSC). The study offers valuable implications for industry professionals seeking to enhance sustainability efforts through data-driven decision-making. The research contributes to optimizing FSC through improved decision-making, resource allocation, and sustainability initiatives. Future research directions include expanding the dataset scope, exploring advanced ML techniques, and examining the economic impacts of EET-FSC.

1. Introduction

In recent years, global supply chains, particularly in manufacturing and logistics, have increasingly prioritized energy-efficiency. Energy-efficient technologies (EET) are designed to reduce energy usage and promote sustainability, making them essential for addressing the significant energy demands associated with food production, processing, and distribution. This shift is driven by the dual objectives of minimizing costs and enhancing sustainability. These goals aim to balance economic needs with environmental responsibilities, presenting both challenges and opportunities for achieving sustainability [1]. Adopting eco-friendly energy options, such as solar collectors and windmills, is crucial for reducing greenhouse gas emissions and meeting international climate commitments [2]. The move towards a sustainable economy further supports these efforts by encouraging sustainable consumption and innovation. The consumer acceptance of EET by, particularly blockchain technology, is influenced by a complex interplay of economic, regulatory, technological, and sociocultural factors, all of which are integral to sustainability [3].

In the context of the food supply chain (FSC), key energy-intensive activities such as transportation, storage, and processing significantly impact overall energy consumption. The FSC encompasses a broad range of processes, from growing crops to processing, distributing, storing, selling, and ultimately consuming food. As consumers become more aware of the environmental and ethical implications of their food choices, there is an increasing demand for transparency and sustainable practices within the FSC [4]. In response, the food industry is focusing on energy-efficiency as a core component of its sustainability strategies [5]. This includes improving energy use in production, transportation, and storage, with the adoption of EET, such as advanced cooling technologies, energy-efficient lighting, and renewable energy sources—being crucial for reducing operational costs, lowering carbon footprints, and preserving food quality [6]. Disruptive technologies like blockchain, IoT, and AI further enhance energy-efficiency by improving operational performance, increasing transparency, and reducing waste [7]. However, consumer intention to adopt these technologies is vital, as their acceptance is crucial for widespread implementation necessary to build sustainable food systems.

The integration of EET in the FSC (EET-FSC) refer to the application of energy-saving techniques within the FSC, aiming to reduce energy consumption, decrease carbon emissions, and support sustainability.

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This research focuses on blockchain technology as a key tool for enhancing energy-efficiency. Blockchain significantly improves transparency, traceability, and accountability in energy use across the supply chain, enabling real-time monitoring and verification of energy consumption data [8]. It allows the tracking of energy inputs and outputs at various stages, ensuring compliance with energy-efficient standards. The decentralized and immutable nature of blockchain's ledger ensures accurate recording of energy transactions, promoting energy conservation and advancing sustainability goals within the FSC. Organizations are investing in technological advancements that enhance resource efficiency, which are crucial for reducing waste and optimizing resources. These innovations not only help meet sustainability benchmarks but also improve operational efficiency, leading to ongoing cost benefits. Recently, businesses have been placing greater emphasis on sustainable sourcing and production practices, including organic farming, minimizing chemical inputs, and adhering to fair trade standards, all of which align with consumer preferences for ethically produced goods [9].

On focusing the blockchain technology, it significantly enhances supply chain visibility and traceability, which builds consumer trust and promotes the shift towards energy-efficient practices [10]. The technology's decentralized and immutable ledger ensures data integrity, reduces the risk of fraud, and supports compliance with regulatory requirements, thereby reassuring consumers about sustainability efforts [11]. To fully realize its potential, it is essential to address underlying challenges such as technological complexity, integration issues, and the need for standardization through strategic planning and collaboration among stakeholders [12]. Additionally, leveraging machine learning (ML) algorithms to predict consumer intention can contribute to the adoption of EET-FSC. ML enables accurate analysis of energy consumption trends and consumer intention, allowing organizations to implement data-driven strategies that meet the growing demand for sustainability. Existing literature has explored consumer intention regarding the adoption of EET-FSC, identifying several influencing factors. de Oliveira et al. [13] highlighted the opportunity to harness consumer awareness of sustainability and their openness to supply chain 4.0 technologies to encourage sustainable choices. Baldi et al. (2021) emphasized the importance of perceived benefits, trust, and environmental attitudes in shaping consumer preferences, while also recognizing cost as a significant barrier. Additionally, Nunes and Deliberador [14] stressed the need to consider regional and cultural influences on consumer intention.

Despite these insights, a significant gap remains in the literature regarding the use of ML algorithms to analyse and predict consumer intention towards EET-FSC. While previous studies have examined consumer preferences and attitudes towards sustainable FSC, a comprehensive understanding of consumer intentions regarding energy-efficient practices is still lacking. This study aims to fill this research gap by empirically investigating consumer intention and willingness to pay for food products with a reduced energy consumption in their supply chain. The application of ML algorithms to predict consumer intention in adopting EET-FSC represents a significant methodological advancement. Although traditional research methods, such as linear models and regression analysis, have yielded valuable insights, they are limited in their ability to capture the complex and nonlinear relationships that influence consumer intentions. In contrast, ML algorithms excel at identifying intricate patterns within large and diverse datasets [15], offering a more comprehensive understanding of consumer intention. This investigation utilizes sophisticated predictive modelling methodologies through primary data acquired from consumers to scrutinize their willingness to adopt EET-FSC. Through the application of ML algorithms, this investigation delivers an in-depth understanding of consumer intention and supports the creation of data-supported strategies to encourage the adoption of energy-efficient practices in the FSC. This study addresses significant gaps in understanding consumer intentions towards EET-FSC, by leveraging advanced ML methodologies. Unlike prior studies focusing primarily on descriptive insights, this approach identifies nuanced patterns among key demographics. By uncovering the socio-economic factors like financial stability concerns, risk aversion, and limited targeted marketing, this study offers targeted strategies to bridge these gaps. Such insights align with global challenges in consumer technology adoption, demonstrating broader applicability across varied socio-economic settings.

The subsequent sections of this study are structured as follows. Section 2 elaborates on the pertinent literature and background, Section 3 delineates the methodologies for collected dataset, ML algorithms used, evaluation metrics, and data preprocessing techniques, while Section 4 analyses the resultant findings, Section 5 discusses the principal conclusions and finally Section 6 presents prospective research avenues.

2. Related literature

2.1. Supply chain and energy efficiency in food sector

Supply chain management involves orchestrating the complex interactions between various components and processes to efficiently move goods and services from producers to consumers [16]. The primary objective is to align production with consumer demand, thereby fostering economic growth and enhancing global competitiveness. Essential activities like planning, sourcing, production, and distribution ensure the supply chain's effectiveness. Within this framework, the FSC emerges as a critical domain, requiring advanced practices to address the intricate challenges of delivering perishable goods. Building on supply chain principles, the focus has shifted to the FSC, a complex network encompassing production, processing, distribution, and retail, all aimed at delivering food products to consumers. The global FSC is tasked with balancing supply and demand while ensuring safe and timely food delivery. Additionally, the FSC plays a critical role in addressing sustainability challenges, particularly through adopting energy-efficient practices, as exemplified by the Green FSC recognized in regions like India [17]. EETs are vital for enhancing transparency and operational efficiency in the FSC. For instance, phase change materials contribute significantly to energy-efficiency within the FSC [18]. Moreover, integrating blockchain, the Internet of Things (IoT), and digital financial solutions in agriculture further enhances transparency by enabling real-time monitoring and secure transactions, fostering trust among participants and addressing concerns such as fraud and food safety through immutable digital records [19]. These efforts not only align with sustainability goals but also cater to evolving consumer demands for ethical and eco-friendly practices, even as price sensitivity remains a critical factor influencing consumer decisions. Harjadi and Gunardi [20] and Nguyen-Viet et al. [21] highlight that consumer interest in premium sustainable products is often driven by non-economic motivations, such as environmental consciousness and perceived social value.

However, while blockchain offers scalability and transparency, its adoption in the FSC is still in its early stages, facing technical, regulatory, and operational challenges. Despite these hurdles, the combination of energy-efficient methods with digital technologies is transforming the FSC into a more transparent, efficient, and sustainable ecosystem.

2.2. Technological advancements in EEFSC

Blockchain technology has emerged as a crucial tool for improving transparency and efficiency in the FSC. By providing a decentralized, immutable, and secure platform, blockchain addresses persistent issues such as inefficiencies, ambiguity, and information asymmetry [22]. Blockchain eliminates centralized databases and intermediaries, reducing inefficiencies and promoting greater transparency and collaboration [23]. These attributes are especially critical in FSC, where timing and traceability are pivotal. Blockchain ensures the reliability of traceability information, which is essential in complex, global markets [24]. The energy-efficiency of blockchain is also emphasized in the current literature. Integrating blockchain with Green Product Platforming significantly reduces carbon emissions while optimizing economic performance in the agri-food sector by enabling the efficient production and digital distribution of green products, addressing stakeholder demands for improved carbon and economic outcomes [25]. The combination of blockchain technology with IoT systems, as seen in a framework for the strawberry supply chain, improves shipment efficiency by tracking interactions and documenting transactions, thus promoting energy-efficient practices [26].

Transportation, production, and storage are the key energy-intensive aspects of the FSC. Long-distance food transportation, for instance, consumes significant energy and emits considerable greenhouse gases. These insights underscore the urgency for adopting EET in logistics to address escalating environmental concerns. Similar findings for other products like denim apparel [27] and yogurt [28] highlight the energy-intensive nature of transportation, with consumer travel by car potentially matching freight transportation's energy consumption.

While production and storage also contribute heavily to energy consumption, transportation offers considerable opportunities for energy savings. Although local food systems typically reduce transportation energy, they do not always result in lower overall energy consumption compared to conventional systems [29]. Innovations in storage, such as integrated cooling and heating systems with energy storage, can enhance energy efficiency by recovering waste heat and reducing energy costs [30,31]. Technological advancements, particularly in emerging markets like India, have the potential to reduce post-harvest losses and improve the overall efficiency of the FSC [32].

2.3. Consumer intention towards EET

Consumer intention refers to the conscious decision to engage in specific behaviours, such as adopting EET-FSC. This intention often aligns with consumers' willingness to pay a premium for products derived from sustainable practices. Lindström et al. [33] noted the increasing consumer inclination towards technologies that promote sustainability, offering businesses significant opportunities to align their offerings with these values. While consumers may not directly interact with technologies, their demand for sustainable products drives organizations to adopt these innovations. This highlights the indirect yet powerful role of consumer preferences in shaping supply chain decisions. Consumer acceptance of energy-efficient practices is primarily influenced by the perceived benefits of these technologies, such as enhanced transparency and waste reduction facilitated by blockchain systems [34]. However, this willingness is often nuanced. Studies like Diallo et al. [35] suggest that consumers are willing to pay a premium when they perceive long-term cost savings, improved product quality, or alignment with personal values such as environmental stewardship. Additionally, the concept of 'green loyalty' [36] indicates that sustainability-focused consumers may prioritize eco-friendly attributes over cost considerations in their purchasing decisions, particularly when these attributes contribute to broader societal goals.

Challenges like security concerns, costs, and accessibility continue to impede widespread adoption despite a general willingness to use blockchain for monitoring energy use in the FSC [37]. Environmental concerns also significantly influence consumer intention, with a noted willingness to invest more in EEFSC products, reflecting the connection between sustainability values and support for energy-efficient practices [38].

2.4. ML algorithms for predicting consumer intention

Traditional research methodologies in supply chain management often fall short when addressing the complex dynamics of modern supply chains. These methodologies typically focus on specific demographics, employ inadequate data analysis techniques, and struggle to capture intricate interrelationships or integrate sustainability considerations [39]. ML offers a more sophisticated and flexible approach to analysing consumer intention by managing large datasets and revealing complex, non-linear relationships. Various ML techniques, including decision trees, random forests, support vector machines, and clustering methods, are well-suited for analysing vast amounts of data and uncovering insights that traditional methods might miss [40,41]. ML algorithms are capable to be leveraged in diverse fields [42,43]. These methods excel in predicting consumer intention due to their ability to analyse complex data sets [44]. By integrating factors such as demographic information, purchasing behaviour, and environmental influences, ML algorithms can create more accurate and detailed profiles of consumer intention, helping organizations better tailor their strategies for promoting energy-efficient innovations.

ML algorithms, such as Random Forest and K-means clustering, have been employed to study consumer intention in the food retail sector, providing valuable insights into consumer preferences and emerging trends. ML's application in analysing consumer intention within the FSC has profound implications for sustainability, particularly in reducing energy consumption and lowering carbon emissions. For example, Artificial Neural Networks (ANNs) have been used to optimize energy efficiency in transportation by analysing fuel consumption data and transportation routes [45]. This integration not only enhances energy-efficiency but also addresses consumer demands for sustainability, fostering a more transparent and responsible supply chain.

ML algorithms are transforming consumer intention research by providing sophisticated tools for analysing complex data. This enables a deeper understanding of consumer preferences and behaviour, allowing organizations to effectively promote and implement EET-FSC. Analysing the FSC using ML enhances sustainability and efficiency, contributing to a more transparent, responsible, and environmentally friendly supply chain. This approach helps the FSC meet consumer demands for sustainability while optimizing operations and reducing waste, ultimately contributing to a more sustainable and efficient global food system.

2.5. Unpacking the research gap

This study explores the EET-FSC focusing on their potential to enhance energy efficiency. Emerging technologies like blockchain, IoT, and phase change materials have demonstrated significant promise in increasing transparency, reducing energy consumption, and improving operational efficiency in the FSC. Consumer willingness to adopt these technologies is largely driven by perceived benefits such as increased transparency and positive environmental impact. However, challenges such as financial costs, security concerns, and accessibility continue to hinder widespread adoption. Traditional research methods have struggled to effectively capture the complex dynamics of consumer intention and energy efficiency within the FSC. In contrast, ML algorithms have proven effective in predicting consumer intention, providing critical insights that can address these challenges and encourage broader adoption of EET in the FSC. Despite progress in both EET and ML, significant research gaps remain. Current literature lacks a thorough analysis of how emerging technologies, particularly blockchain, can be fully leveraged to address the complexities of the FSC and predict consumer intention towards EET-FSC. Through the utilization of empirical consumer data, this investigation effectively reconciles the disparity between theoretical capabilities and pragmatic execution while simultaneously yielding practical insights for the augmentation of sustainability within the FSC. The deployment of ML algorithms

Table 1
Research questions and approaches.

Research questions	Approaches
What elements contribute to consumers' inclination to engage with EET-FSC?	Association rule mining (ARM)
What is the impact of geographic location, income level, and knowledge of FSC on consumer intention to embrace EET-FSC?	Analysis of Outlier Association Rules with Scatter plot
Which ML algorithms optimally predict the consumer willingness to pay a premium for EEFSC products?	Confusion matrices, calibration plot, Receiver Operating Characteristic (ROC) analysis and statistical justification.

on this dataset signifies a noteworthy methodological progression, facilitating a more profound comprehension of consumer engagement with and perceptions of EET-FSC. Additionally, there is a need for deeper understanding of the long-term impacts of these technologies on energy-efficiency and how they can be optimized to meet evolving consumer expectations. This study emphasizes the importance of ML predictive modelling in improving the understanding of consumer intention in the context of EET-FSC. The study seeks to answer the following research questions (see Table 1):

Addressing these questions underscores the crucial role of ML not only in understanding consumer intention but also in bridging the gap between technological potential and practical implementation in the FSC. The findings suggest that integrating ML and EET into FSC operations can significantly boost sustainability by reducing energy use and improving operational efficiency. These technologies enable better data-driven decision-making, contributing to more resilient and sustainable supply chain.

3. Methodology

This research employs a comprehensive methodology to examine the incorporation of energy efficiency within supply chain, specifically emphasizing the FSC. The methodology is structured to analyse the potential utilization of EETs and the examination of consumer intention. As show in Fig. 1, the research utilizes predictive ML algorithms for consumer willingness to pay for EEFSC products, as well as employing ARM to reveal trends in consumer intention. Through the scrutiny of extensive datasets, the study aspires to pinpoint critical factors that affect consumer intentions, ultimately directing stakeholders in the FSC towards energy-efficiency.

3.1. Data collection

The primary data was acquired through a structured online survey questionnaire and surveyed the consumers of grocery products from various regions in India. In order to guarantee a sample that is both diverse and representative, the survey was disseminated through various channels, encompassing social media platforms, electronic mailing lists, and consumer forums specifically focused on sustainability and food products. This approach ensured that the sample was not limited to specific geographic or demographic subsets but represented a broad cross-section of consumers with varying levels of interest in sustainability and EETs. The questionnaire assessed variables including income levels, perceptions of FSC transparency, and interest in blockchain technology as a means to enhance energy-efficiency. A total of 433 individuals participated in the survey. This research is focused on exploring a mixed adult demographic in India, which includes a significant age range (from 18 years to beyond 65 years), and is distributed across several geographic regions of the nation, such as the North, East, South, West, Central, and Northeast sectors. Respondents were asked to self-report on their grocery shopping behaviour, including frequency (daily, weekly, monthly), preferred sources (local Kirana shops, supermarket chains, online platforms, or farmers' markets), and dietary preferences (vegetarian, non-vegetarian, vegan). Income brackets were categorized into predefined ranges (<₹50,000, ₹50,000–₹1,00,000, ₹1,00,000–₹2,00,000, >₹2,00,000) to assess their impact on consumer intention towards EET-FSC adoption. Additionally, the target demographic represents differing levels of interest and concern regarding the EET-FSC, its environmental ramifications, and the propensity to invest in EEFSC products.

To ensure that the data collection process was robust and reliable, a number of measures were implemented. Pre-testing of the questionnaire was conducted with a pilot group of 20 respondents to ensure clarity and eliminate ambiguity in the questions. The abstract features like blockchain were explained in practical terms, using relatable examples such as tracking food origins and energy use. The survey was designed to protect the anonymity of participants, thereby minimizing the risk of response bias, particularly for questions related to income levels or environmental concerns. The survey questionnaire included 22 questions, explicitly aligned with the features/variables detailed in Table 2. Each question was designed to gather actionable insights regarding consumer demographics, grocery shopping behaviours, attitudes towards blockchain technology, and willingness to adopt EEFSC.

3.2. Data preprocessing

The unrefined data underwent comprehensive preprocessing to confirm its appropriateness for analysis. This process included addressing missing data, encoding categorical variables, and normalizing numerical features as necessary. A strong focus was given to the arrangement of classes throughout the dataset in order to reduce any prospective difficulties linked to class imbalance.

3.3. Data sampling for prediction

In the development of predictive models utilizing Orange software, a crucial step is the selection of a representative dataset sample for effective training and validation. A fixed proportion sampling method was adopted, where 70% of the dataset was randomly allocated for training, thereby ensuring a robust model foundation while reserving 30% for subsequent testing and validation. This methodology incorporates deterministic sampling for reproducibility, stratification for maintaining variable distribution, and sampling without replacement to guarantee unique observations, thus enhancing model generalizability.

3.4. ARM

ARM constitutes a data mining methodology employed to discern correlations among variables within extensive datasets. It reveals concealed patterns by detecting recurrent item sets and formulating rules that elucidate how the presence of one item in the dataset is correlated with the presence of another. It was employed to discern prevalent patterns in consumer intention, particularly those associated with EET-FSC. The principal indices employed in ARM encompass support, confidence, and lift, among others, each fulfilling a distinct function in the assessment of the rules [46]. The key metrics of ARM are as follows,

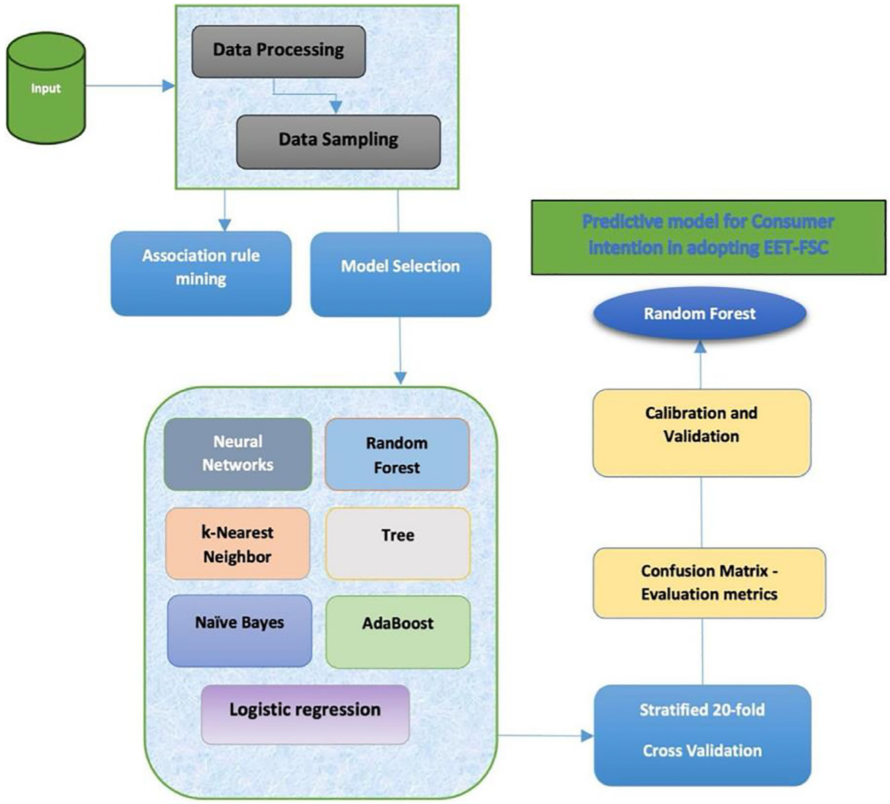

Fig. 1. Methodology of the study.

Table 2
Features/variables of the study.

S.No.	Variable description	Feature (F)/ Target (T)
1	How familiar are you with blockchain technology and its applications in supply chain management?	F
2	Imagine a secure digital record that tracks information throughout a process, like a chain of connected blocks. In which industries might this be important?	F
3	How interested would you be in learning more about how blockchain technology can improve the energy efficiency of the FSC?	F
4	How beneficial do you think a blockchain-based system could be for the following aspects of the FSC?	F
5	Do you have any concerns about using blockchain technology in the FSC?	F
6	Considering both the potential benefits and concerns, how comfortable would you be with using a blockchain-based system to track the energy used in your food?	F
7	Age	F
8	Location	F
9	How often do you shop for groceries?	F
10	Where do you typically buy your groceries?	F
11	Dietary preferences	F
12	Household size	F
13	Income level	F
14	How often do you consider the energy efficiency of the supply chain when you shop for groceries?	F
15	Imagine knowing how much energy was used to produce the food you buy (through a label or app). Would you pay a premium for options that used less energy?	F
16	How interested would you be in receiving information about the energy use associated with the food you buy?	F
17	How concerned are you about the environmental impact of the FSC?	F
18	How important is it to you to know where your food comes from and how it is produced?	F
19	On a scale of 1 to 5, how clear do you think the current food system is about where food comes from and how it is produced?	F
20	How likely are you to choose food tracking options with lower energy use?	F
21	How important is it to you to support farms and businesses that use less energy?	F
22	Would you pay a small extra amount for food with a demonstrably lower environmental impact, if the information was clear?	T

3.4.1. Support

Support is a metric that quantifies the frequency of occurrence of a specific item or combination of items within a dataset. A high support value signifies the relevance and reliability of the itemset, indicating its widespread presence within the data.

$$Support(X) = \frac{Number\ of\ transactions\ containing\ X}{Totalnumberoftransactions} \quad (1)$$

3.4.2. Confidence

Confidence is a metric that measures the likelihood of the consequent occurring given the presence of the antecedent in a transaction [47]. A high confidence value suggests a strong association between the antecedent and consequent. However, it is essential to consider the overall frequency of the consequent in the dataset, as a high confidence value might be misleading if the consequent is common.

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)} \quad (2)$$

3.4.3. Lift

Lift is a metric that quantifies the degree to which the occurrence of the antecedent (X) increases the likelihood of the consequent (Y) compared to the expected likelihood if X and Y were independent [48]. Lift values greater than 1 suggest a positive association between X and Y, indicating that the occurrence of X significantly contributes to the occurrence of Y. This metric is valuable for identifying non-trivial associations within the data.

$$Lift(X \Rightarrow Y) = \frac{Confidence(X \Rightarrow Y)}{Support(Y)} \quad (3)$$

3.5. Model selection and implementation

The principal aim of any classification task is to precisely allocate class labels to each instance contained within the test dataset. In the framework of this investigation, classification methodologies are utilized to construct models that are adept at forecasting the propensity to embrace EET-FSC. These models are developed utilizing predictive ML techniques, including Decision Trees, Random Forest, Naive Bayes, Logistic Regression, k-Nearest Neighbour (k-NN), AdaBoost, and Neural Network. Incorporating multiple algorithms is critical for determining the optimal predictive approach. For instance, Random Forest excels in managing feature importance and non-linear relationships, while Logistic Regression offers simplicity and interpretability. Comparing multiple methods of this nature, ensures the selection of the most suitable algorithm for practical implementation and offers a benchmark for future studies in the domain of EET-FSC. By comparing their performance, we not only identify the best-performing model but also provide actionable insights for stakeholders, guiding the selection of algorithms for similar datasets and applications. This comprehensive approach is supported by established literature that emphasizes the value of comparing multiple methods for predictive tasks [49,50].

3.5.1. Decision trees

The straightforwardness and lucidity of decision trees [51], render them especially advantageous for comprehending the elements affecting the consumer intention on adopting EET-FSC. The decision tree algorithm is predicated on the recursive partitioning of a dataset into subsets predicated on a characteristic that yields the most substantial information gain (or, equivalently, the minimal Gini impurity or entropy). The partitioning criteria can be articulated as,

$$Entropy(S) = -\sum_{i=1}^{c} p_i \log 2\left(p_i\right) \quad (4)$$

p_i is the proportion of samples that belong to class i, and c is the number of classes.

$$InformationGain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|Sv|}{|S|} Entropy(Sv) \quad (5)$$

S is the set of samples, A is the feature on which the data is split. Sv is the subset of S for which the feature A has value v.

3.5.2. Logistic regression

Logistic Regression is primarily utilized for dichotomous classification challenges. It represents the likelihood that a specified instance is affiliated with a certain category utilizing a logistic function. This investigation employs logistic regression to differentiate between entities that are predisposed to embrace EET and those that are not, applied on a variety of predictor variables. The logistic function maps any real-valued number into a value between 0 and 1, which can then be interpreted as a probability.

$$p(y=1 \mid X) = \frac{1}{1+e^{-(\beta 0+\beta 1 X1+\beta 2 X2+\cdots+\beta n Xn)}} \quad (6)$$

$p(y = 1 \mid X)$ is the probability that the target variable y equals 1 given the input features X, $\beta 0$ is the intercept form and $\beta 1$, $\beta 2$,… βn are the coefficients for each input feature $X1, X2, \ldots, Xn$..

3.5.3. Naive Bayes algorithm

The principle behind Naive Bayes classifiers is that the features pertinent to any given class maintain conditional independence [52]. This model is especially pertinent for classification tasks wherein the conditional probability of a given event is ascertained through the application of Bayes Theorem. The employment of Naive Bayes within the context of this investigation enhances the categorization of adoption intentions predicated on a multitude of influencing factors.

$$P(C_k \mid X) = \frac{P(C_k)\prod_{i=1}^{n} P(x_i \mid C_k)}{P(X)} \quad (7)$$

$P(C_k \mid X)$ is the posterior probability of class C_k given the features X, $P(C_k)$ is the prior probability of C_k class, $P(x_i \mid C_k)$ is the likelihood of feature x_i given class C_k and $P(X)$ is the evidence or the total probability of features X.

3.5.4. Random forest algorithm

Random Forest constitutes a supervised learning methodology extensively employed for both categorization and regression assignments [53]. It augments predictive efficacy by amalgamating the outcomes of numerous decision trees, each cultivated on disparate subsets of the dataset. In this investigation, the model is deployed owing to its resilience in managing absent data and its capacity to yield more dependable forecasts through the confluence of multiple trees. Random forest prediction equation is

$$y^{\wedge} = MajorityVote(h1(x), h2(x), \ldots, hm(x)) \quad (8)$$

$y^{\wedge}$ is the predicted class, *hi(x)* represents the prediction from the *ith* decision tree in the forest and *m* is the total number of trees in the forest.

3.5.5. k-NN

k-NN constitutes an instance-based methodology that formulates predictions by assessing the similarity between novel and antecedent instances [54]. The k-NN algorithm discerns the most prevalent label from the k-NN within the training dataset to categorize a new data point.

3.5.6. AdaBoost

The core principle of AdaBoost lies in transforming weak learners into strong classifiers by adjusting sample weights based on misclassification rates, demonstrating wide applicability and effectiveness across various domains, including facial recognition, speech enhancement, natural language processing, and network intrusion detection [55]. This ensemble learning approach significantly enhances weak classifiers by iteratively modifying training sample weights to focus on difficult-to-classify cases, thereby improving the overall accuracy of the model.

3.5.7. Neural networks

Neural network architectures have become essential tools in supporting managerial decisions across various fields, offering considerable benefits in navigating complex data environments and providing accurate predictions, particularly in areas such as strategic management, marketing, finance, and human resources, where decision-making often involves high levels of uncertainty and complexity [56].

3.6. Cross-validation setting

A 20-fold cross-validation approach was implemented, wherein each model underwent training and testing across 20 subsets, with each subset utilized as a test set once, while the remaining subsets constituted the training set. This methodology effectively mitigates bias and variance in the assessment of the model. The method of cross-validation utilized a stratified approach to maintain the initial class ratios across each fold, thus guaranteeing that every fold truly mirrors the overall class distribution found in the dataset.

3.7. Evaluation metrics

In the assessment of the efficacy of various predictive ML algorithms, a range of performance metrics were employed, all of which were derived from the confusion matrix produced by each model. Occurrences that received accurate categorization are labelled True Positives (TP), but those wrongly identified as positives are known as False Positives (FP). The following pivotal metrics [57] were calculated:

The Area Under the Curve (AUC), functions as a measurable evaluation of a model's success in distinguishing between positive and negative classes, with rising AUC figures demonstrating improved model capability in this dimension. Accuracy quantifies the ratio of correct predictions made by the model in relation to the overall number of predictions, as articulated in Eq. (9). Despite being a frequently utilized metric, accuracy may fall short for datasets exhibiting considerable class imbalance.

$$Accuracy = \frac{TruePositive + TrueNegative}{(TruePositive + FalsePositive) + (TrueNegative + FalseNegative)} \tag{9}$$

Confusion matrices function to depict the model's predictions for each specific category. This contributes to the refinement of a model exposition. This matrix possesses the dimensions NN, where N signifies the aggregate number of classifications for a specified combination of components, with N rows denoting anticipated classes and N columns denoting actualized classes.

Precision evaluates the count of accurate classifications within a specified category relative to the total instances allocated to that category, as defined in Eq. (10).

$$Precision = \frac{TruePositive}{(TruePositive + FalsePositive)} \tag{10}$$

Recall assesses the number of correctly identified instances in contrast to the total instances that genuinely belong to a certain class, as delineated in Eq. (11).

$$Recall = \frac{TruePositive}{(TruePositive + FalseNegative)} \tag{11}$$

The F1 score represents the harmonic mean of recall and precision, yielding a singular score that equilibrates both metrics, as illustrated in Eq. (12).

$$F1Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

Matthews correlation coefficient (MCC) evaluates the relationship between anticipated and actual binary classifications in classification tasks, producing a favourable score when both affirmative and negative predictions are precise, as illustrated in Eq. (13)

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP) * (TP + FN) * (TN + FP) * (TN + FN)}} \tag{13}$$

These metrics afforded a thorough appraisal of each model's performance, facilitating the identification of the most effective model for predicting consumer intention concerning the adoption of EET-FSC.

3.8. Calibration and validation procedures

To ascertain the dependability of the models, calibration plot was utilized to find the true positive rate (TPR) and false positive rate (FPR) across the diverse models. This methodology adeptly amalgamates advanced data analytic techniques with a concentration on EET-FSC. The findings emphasize the significance of utilizing technological advancements such as blockchain and ML to bolster EET-FSC while concurrently addressing consumer intention and readiness to embrace these technologies. To validate these performance metrics, ROC analysis was conducted, enabling a comprehensive comparison of model sensitivity and specificity across varying thresholds. The ROC curves provided critical insights into the discriminative ability of each ML model, highlighting the robustness of the outperforming algorithm as the most effective predictor for consumer intention. Finally, the study employed the Wilcoxon Signed-Ranks Test, a non-parametric statistical method, to assess the relative performance of predictive models pairwise. This test was used to examine whether significant differences existed between models.

4. Results and discussion

4.1. ARM

A common theme in the antecedents is the interest in blockchain technology for supply chain management. This interest frequently aligns with enquiries about enhancing EEFSC [58]. Another common antecedent is the income range of Rs. 50,000–Rs. 1,00,000 per month, which appears consistently across multiple rules. An often-repeated antecedent is the perception of the FSC's clarity, which is frequently rated as '3'. This rating denotes a neutral viewpoint regarding the transparency of the origins and production processes within the FSC. A recurrent consequent is a neutral interest in further understanding how blockchain technology could enhance EEFSC. This suggests a prevalent sense of curiosity, albeit lacking in strong enthusiasm. Another common consequent is a neutral inclination towards selecting food tracking options with reduced energy consumption, indicating that respondents maintain a balanced or undecided position on this matter.

A counterintuitive relationship emerges between income level and interest in learning about blockchain technology. It might be anticipated that individuals with higher income levels would exhibit a more pronounced interest in or opinions about innovative technologies such as blockchain, particularly concerning energy-efficiency. However, the observed neutral stance indicates a potential gap in either awareness or perceived relevance of such technologies within this income bracket (Rs.50,000–Rs.1,00,000 per month). Socio-economic dynamics may further explain this phenomenon. Individuals in this income group often prioritize financial stability and essentials over investments in unfamiliar technologies, which may be perceived as non-immediate necessities. Additionally, risk aversion could play a role, potential adopters might hesitate to engage with emerging technologies due to uncertainty about tangible benefits or concerns over complexity and usability. This hesitancy is consistent with findings by Shahzad et al. [59], who highlight the importance of simplifying technology adoption processes to reduce perceived risks.

Limited exposure to targeted marketing strategies and awareness campaigns tailored to this demographic may exacerbate the neutral stance. As Bussler et al. [60] suggest, strategic interventions focusing on relatable use cases and demonstrable benefits can significantly enhance engagement within income groups with moderate purchasing power. The lack of accessible information, coupled with insufficient efforts to address perceived complexities, can lead to indifference rather than active exploration of EET. Addressing these gaps through education, contextual demonstrations, and community-driven initiatives could shift this group's perspective, fostering a more proactive attitude towards blockchain adoption in EEFSC. This association rule is backed by a support value of 20.3%, signifying its applicability to a substantial segment of the dataset. The confidence level of 80% underscores a robust probability that individuals within this income bracket exhibit a neutral interest in the energy efficiency benefits of blockchain technology in supply chain management. The lift value of 1.482 indicates a positive correlation between income level and neutral interest, suggesting that this demographic is more predisposed to a neutral stance compared to the general population. Additionally, the leverage of 0.254 and conviction of 2.125 further substantiate the strength and reliability of this association.

Another noteworthy relationship involves the perception of FSC transparency and interest in blockchain technology. Respondents who maintain a neutral view on the clarity of the FSC still recognize the potential benefits of blockchain for SCM. This finding implies that even in the absence of a clear understanding of current FSC transparency, individuals acknowledge the prospective advantages of blockchain technology. It indicates that the perceived value of blockchain is appreciated regardless of one's level of insight into the existing transparency of FSC operations (Feature 19–Feature 2). However, a deeper examination of the rural–urban divide reveals significant disparities contributing to this neutrality, particularly in rural regions. Limited access to digital infrastructure, lower levels of digital literacy, and a lack of exposure to targeted educational campaigns are critical barriers that hinder engagement with blockchain and EET in these areas. Rural participants may face additional challenges, such as fewer opportunities to witness practical demonstrations of these technologies and a lack of localized narratives emphasizing their benefits. Recent studies underscore the importance of tailored interventions in addressing these challenges. Mobile-based education initiatives and community-driven awareness programs have shown promise in bridging the rural–urban divide by delivering accessible and relatable information. These approaches not only improve awareness but also address perceived complexities by connecting technological solutions to local needs and contexts.

The persistent pattern of neutral interest in understanding how blockchain technology affects energy-efficiency in the FSC indicates that while respondents are generally inquisitive, they lack significant enthusiasm for this application of blockchain. Similarly, the common neutral stance regarding the selection of food tracking options that prioritize lower energy consumption reflects a balanced or indecisive attitude towards energy-efficient tracking solutions. It is particularly surprising that respondents from South India, a region known for its interest in blockchain technology, still maintain a neutral position on learning about its energy efficiency benefits. Given the regional interest in blockchain, one might expect a higher level of engagement with the technology's potential for improving energy efficiency. This suggests a possible gap in the communication or understanding of the specific benefits that blockchain offers in terms of energy efficiency.

The correlation observed between a specific income bracket (Rs.50,000–Rs.1,00,000 per month) and a neutral attitude towards selecting energy-efficient food tracking options is indicated by a moderate lift value of 0.654. This lift value, which is relatively low, suggests that the income level of respondents has a comparatively minor effect on their likelihood to opt for energy-efficient tracking solutions. This finding highlights a potential gap in understanding or perceived value among individuals in this income group(Feature 19–Feature 13). It suggests that income alone does not significantly drive their decision-making regarding energy efficiency in food tracking. Instead, it implies that other factors may play a more substantial role in shaping attitudes towards these technologies. Within the context of the FSC, this result highlights a potential deficiency in understanding or perceived value of energy-efficient tracking systems among individuals within this income bracket. Despite their neutral position, which indicates neither a strong preference nor aversion, there exists an opportunity to improve awareness regarding the benefits and practical advantages of energy-efficient solutions.

4.2. Analysis of outlier association rules

Two outlier association rules were identified (Fig. 2), highlighting a robust correlation between consumer interest in blockchain technology for supply chain management, geographic location in South India, income level, and perception of FSC clarity. These rules exhibit a high lift value of 1.801, indicative of a strong association between the antecedent and consequent variables. The first rule, characterized by moderate support and confidence levels, suggests a potential market segment of middle-income South Indian consumers with a skeptical view of the FSC, who are receptive to blockchain-based supply chain solutions. The second rule reinforces this finding, demonstrating a stronger relationship between the variables, although with similar levels of support and leverage. Collectively, these rules underscore the potential of blockchain technology in addressing consumer concerns about FSC transparency within the specified demographic. The strong association in South India reflects the region's cultural emphasis on sustainability and economic progress, but rural areas face barriers such as limited infrastructure and lower digital literacy [61]. As noted by Tao et al. [62], younger and urban respondents show higher adoption potential, positioning them as key drivers for regional momentum. Addressing rural challenges through tailored strategies, such as mobile-based education or awareness campaigns, could enhance adoption across the region.

These analyses highlight the influence of education, geographic location, and age on the willingness to adopt EETs within the FSC. Recent literature underscores that higher levels of education are positively associated with greater acceptance and understanding of advanced technologies, including blockchain and EETs [63]. Educated respondents exhibit a stronger alignment with the perceived benefits of blockchain in enhancing FSC transparency and energy efficiency, likely due to their exposure to information and technical resources. By contrast, those with lower education levels frequently exhibit neutral or indecisive stances, which can be attributed to limited awareness and perceived complexity of these innovations. This indicates the critical need for tailored educational interventions to reduce knowledge asymmetries and highlight the practical advantages of EET-FSC.

Geographic segmentation further reveals urban respondents' higher engagement with EETs compared to their rural counterparts, a finding corroborated by Chaplitskaya et al. [64], who argue that urban areas tend to have better access to technology infrastructure and sustainability awareness campaigns. Rural participants often adopt a more neutral position, which can be attributed to perceived barriers such as lack of access to digital platforms and limited integration of sustainability narratives into their local contexts [65]. Age also emerges as a key determinant, with younger respondents (18–35 years) demonstrating a marked willingness to adopt EETs, consistent with findings by Fleiß et al. [66], who highlight that this demographic is more receptive to sustainability-driven innovations. In contrast, older respondents (above 50 years) remain hesitant, often valuing traditional practices over modern solutions. These patterns underscore the importance of targeted interventions that bridge rural–urban divides, cater to varying educational backgrounds, and address generational preferences to foster more widespread adoption of EETs.

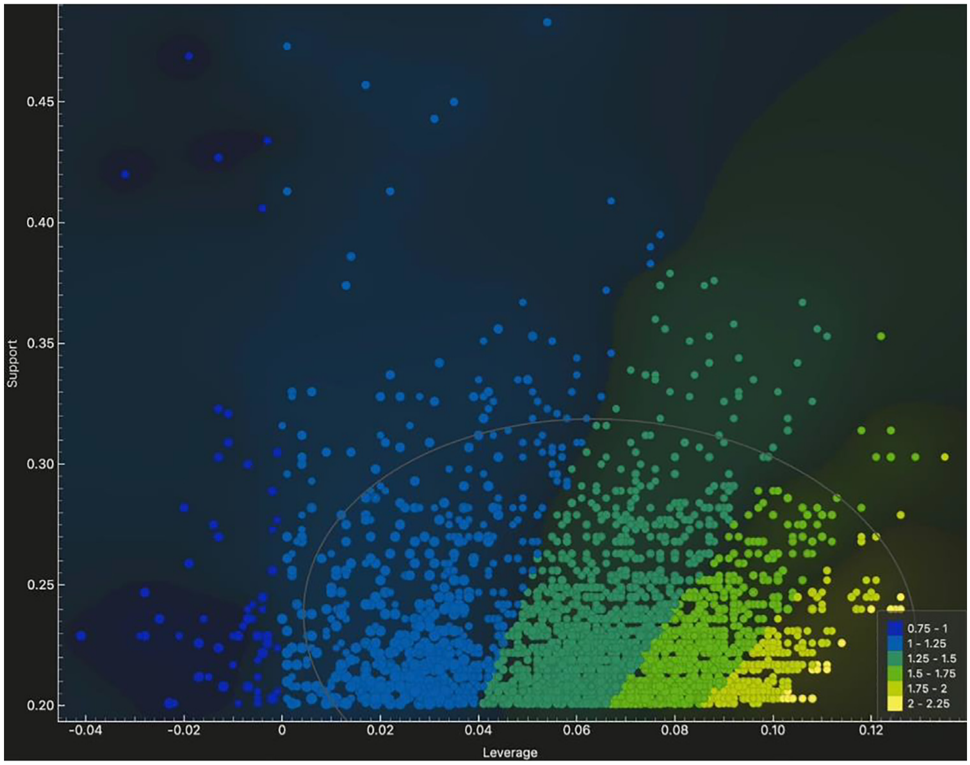

Fig. 2. Scatter plot of association rules.

Table 3
Confusion matrix of decision tree model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	59.5%	23.5%	29.2%	30.6%	21.7%	196
Not willing at all	1.3%	23.5%	19.2%	2.8%	8.7%	33
Somewhat unwilling	2.1%	29.4%	35.8%	19.4%	8.7%	62
Somewhat willing	31.6%	5.9%	11.7%	27.8%	26.1%	106
Very willing	5.5%	17.6%	4.2%	19.4%	34.8%	36
Sum	237	17	120	36	23	433

4.3. Confusion matrices

In evaluating the performance of the seven algorithms – Decision Tree, Logistic Regression, kNN, Random Forest, AdaBoost, Naive Bayes, and Neural Network – in predicting respondents' willingness to pay a premium for EEFSC products, a number of key insights emerge from the confusion matrices. The Decision Tree model exhibits moderate effectiveness in predicting the "Neutral" category, achieving an accuracy of 59.5%. However, it tends to misclassify "Somewhat willing" respondents, often assigning them to the "Neutral" or "Somewhat unwilling" categories. Notably, only 27.8% of the "Somewhat willing" respondents were accurately identified, suggesting a bias towards more neutral or slightly negative classifications. This indicates that the model may be overly simplistic for capturing the nuanced distinctions between closely related classes within the data (Table 3). Enhancing the model's performance may require the application of more complex decision trees or the adoption of ensemble techniques that can better manage the intricacies of the dataset.

The Logistic Regression demonstrates a notable capacity to distinguish between the extremes of willingness to pay (Table 4), achieving high accuracy in identifying respondents as "Not willing at all" and "Very willing" (both at 48.4%). However, its effectiveness diminishes when dealing with more nuanced responses. The model tends to misclassify "Neutral" respondents, often placing them in the "Somewhat unwilling" (34.4%) or "Somewhat willing" (39.8%) categories. This indicates a limitation in its ability to capture the subtleties of consumers' intention. The model's linear decision boundary may be inadequate for handling the complexities of multi-class classification problems. While Logistic Regression is well-suited for binary classification tasks, it appears less effective for distinguishing between intermediate levels of willingness to pay. This suggests the need to explore alternative modelling techniques or employ feature engineering strategies to enhance its predictive performance.

The kNN model shows a mixed performance (Table 5). It is again, relatively effective at correctly classifying extreme response categories, particularly "Very willing" (56.2%) and "Not willing at all" (39.5%). However, the model struggles with the more subtle distinctions between intermediate response levels, often misclassifying "Neutral" responses as either "Somewhat unwilling" or "Somewhat willing". This issue arises from the model's reliance on the proximity of similar data points, which can lead to inaccuracies when dealing with instances that have overlapping characteristics. Therefore, the model's success depends on carefully selecting the number of neighbours and the distance metrics, indicating that further refinement is necessary for it to accurately capture subtle variations within the data.

The AdaBoost model exhibits suboptimal performance, exhibited in Table 6, particularly in its ability to accurately classify "Neutral" responses, with an accuracy rate of just 52.2%, which is notably lower than that of other models. The model shows a tendency to overpredict the "Somewhat willing" category, which adversely affects its accuracy in correctly identifying instances within the "Not willing at all" and "Very willing" classes. This pattern of misclassification suggests that

Table 4
Confusion matrix logistic regression model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	59.8%	12.9%	34.9%	39.4%	19.4%	196
Not willing at all	2.9%	48.4%	15.9%	1.0%	3.2%	33
Somewhat unwilling	8.6%	32.3%	41.3%	7.1%	3.2%	62
Somewhat willing	25.8%	0.0%	7.9%	39.4%	25.8%	106
Very willing	2.9%	6.5%	0.0%	13.1%	48.4%	36
Sum	209	31	63	99	41	433

Table 5
Confusion matrix of kNN model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	54.2%	23.7%	40.4%	40.5%	6.2%	196
Not willing at all	3.8%	39.5%	12.3%	2.4%	0.0%	33
Somewhat unwilling	9.7%	36.8%	38.6%	3.6%	0.0%	62
Somewhat willing	26.1%	0.0%	8.8%	39.3%	37.5%	106
Very willing	6.3%	0.0%	0.0%	14.3%	56.2%	36
Sum	238	38	57	84	16	433

Table 6
Confusion matrix of AdaBoost model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	51.9%	29.7%	28.1%	56.7%	19.4%	196
Not willing at all	2.4%	44.3%	26.3%	1.0%	8.3%	33
Somewhat unwilling	12.1%	27.0%	40.4%	2.1%	5.6%	62
Somewhat willing	29.1%	10.8%	5.3%	28.9%	30.6%	106
Very willing	4.4%	8.1%	0.0%	11.3%	36.1%	36
Sum	206	37	57	97	36	433

Table 7
Confusion matrix of Naive Bayes model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	70.1%	22.6%	35.7%	43.9%	11.9%	196
Not willing at all	0.0%	40.3%	5.7%	0.0%	6.0%	33
Somewhat unwilling	0.0%	37.1%	51.4%	1.8%	3.0%	62
Somewhat willing	29.4%	0.0%	7.1%	38.6%	40.3%	106
Very willing	0.6%	0.0%	0.0%	15.8%	38.8%	36
Sum	177	62	70	57	67	433

the model may be overly concentrated on correcting errors in difficult cases, resulting in an imbalance in predictive accuracy across various response categories. To improve the model's overall performance, it may be necessary to fine-tune hyperparameters, such as the number of base learners or the learning rate. This adjustment could help reduce the model's inclination to overfit specific data points and enhance its ability to generalize across a wider range of responses.

The Naive Bayes model shows a marked tendency towards classifying responses as 'Neutral,' where it achieves a notable accuracy rate of 70.1% (Table 7). However, its effectiveness diminishes considerably when dealing with the "Somewhat willing" and "Very willing" categories. This trend indicates that the model's assumption of feature independence – which is often unrealistic in practical applications – contributes significantly to its shortcomings. The model struggles to account for the complex interrelationships between variables, which limits its ability to distinguish between the more nuanced levels of willingness to pay. On the other hand, the Neural Network model excels in predicting extreme response categories, with reasonable accuracy for "Very willing" (58.6%) and "Not willing at all" (50.0%) outcomes (Table 8). However, its performance is weaker when it comes to classifying the intermediate categories of "Neutral" and "Somewhat willing", suggesting potential issues with overfitting or underfitting. Although the neural network is capable of modelling intricate patterns, its current configuration seems suboptimal.

The Random Forest model exhibits strong predictive capabilities (Table 9) across a range of response categories, establishing it as a reliable method for understanding consumer willingness to pay a premium for EEFSC products. Notably, the model demonstrates a high accuracy rate of 58.0% in classifying "Neutral" responses and excels in predicting "Somewhat willing" responses with a 50.0% accuracy. This performance reflects the model's ability to effectively navigate and interpret the complex patterns embedded within the dataset. The model's success is largely due to its ensemble approach, which involves constructing and aggregating multiple decision trees. Each tree within the forest captures distinct aspects of the data, enabling the model to evaluate a broad spectrum of decision paths before arriving at a final classification. This diversity in decision-making enhances the model's accuracy, allowing it to generalize effectively across varied data points rather than relying on a single, potentially biased, decision tree. Furthermore, the structure of the Random Forest inherently reduces the risk of overfitting — a common challenge in predictive modelling. By averaging the predictions of multiple trees, the model minimizes the influence of any particular subset of data, thereby increasing its robustness and reliability when applied to new, unseen data. This characteristic is especially important in the context of consumer intention analysis, where responses can be highly variable and subject to numerous subtle influences.

In addition to its accuracy and robustness, the Random Forest model excels at managing the complex and often non-linear relationships between features that are typical in consumer intention data. Its ability to uncover hidden patterns and interactions between variables further confirms its suitability for this analytical task. Given its well-rounded performance across different response categories and its inherent strengths in handling complexity and avoiding overfitting, it is a highly effective tool for modelling consumer willingness to pay a premium for EEFSC products.

Table 8
Confusion matrix of Neural network model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	56.4%	8.3%	41.5%	46.5%	17.2%	196
Not willing at all	4.4%	50.0%	7.7%	0.0%	3.4%	33
Somewhat unwilling	9.3%	30.6%	40.0%	6.1%	0.0%	62
Somewhat willing	27.0%	0.0%	10.8%	38.4%	20.7%	106
Very willing	2.9%	0.0%	0.0%	9.1%	58.6%	36
Sum	204	36	65	99	29	433

Table 9
Confusion matrix of Random Forest model.

Actual/ Predicted	Neutral	Not willing at all	Somewhat unwilling	Somewhat willing	Very willing	Sum
Neutral	56.3%	22.7%	32.8%	34.5%	27.3%	196
Not willing at all	3.8%	31.8%	22.4%	2.4%	0.0%	33
Somewhat unwilling	10.9%	40.9%	32.8%	4.8%	4.5%	62
Somewhat willing	23.9%	0.0%	7.5%	44.0%	31.8%	106
Very willing	5.0%	4.5%	4.5%	14.3%	36.4%	36
Sum	238	22	67	84	22	433

Table 10
Evaluation results for the target.

Model	AUC	Classification accuracy	F1	Precision	Recall	MCC
Tree	0.688	0.476	0.432	0.435	0.476	0.245
Logistic Regression	0.761	0.51	0.507	0.506	0.51	0.294
kNN	0.75	0.48	0.468	0.474	0.48	0.233
Random Forest	0.765	0.51	0.49	0.487	0.51	0.268
AdaBoost	0.576	0.406	0.405	0.404	0.406	0.152
Naive Bayes	0.798	0.538	0.527	0.548	0.538	0.379
Neural Network	0.743	0.494	0.493	0.493	0.494	0.275

While individual models exhibit strengths in specific response categories, the Random Forest model demonstrates superior overall performance and consistency. Unlike other models which often excel in particular areas but falter in others, Random Forest consistently predicts across the spectrum of willingness to pay. Its resilience to overfitting and capacity to capture intricate patterns within the data render it the most suitable model for understanding the complexities of consumer intention.

While reviewing the models, the findings indicated that both Logistic Regression and Naive Bayes excelled, with Logistic Regression attaining a commendable accuracy of 0.761 alongside an AUC score of 0.761 (Table 10). The efficacy of kNN and Neural Network was evident, as the Neural Network secured an accuracy of 0.743 alongside an F1 score of 0.494. With an accuracy of 0.764, an AUC value also at 0.764, and an F1 score hitting 0.503, the Random Forest showed a robust yet harmonious performance. Relative to competing models, AdaBoost and Decision Tree struggled, recording an F1 score of 0.406 and an MCC of 0.152 for AdaBoost.

The Table 11 delineates model comparisons based on F1 scores, elucidating the probabilities that one model's F1 score surpasses another's. Logistic Regression consistently outperforms most models with high probabilities, underscoring its efficacy in balancing precision and recall. Naive Bayes also demonstrates robust performance, particularly in comparison to AdaBoost and kNN. Logistic Regression and Random Forest emerge as strong contenders for predicting consumer intentions regarding the adoption of EET-FSC, given their balanced performance across diverse metrics.

4.4. Calibration plot

The calibration plot (Fig. 3) provides a comparative analysis of the performance of several classification algorithms – Tree, Logistic Regression, kNN, Random Forest, AdaBoost, Naive Bayes, and Neural Network – by examining their true positive rate (TPR) and false positive rate (FPR) for the "Neutral" target class related to customer willingness to pay for EEFSC products. The Random Forest model demonstrates a commendable balance between TPR (0.622) and FPR (0.322), indicating its relative effectiveness in accurately identifying "Neutral" responses. In contrast, the Naive Bayes model, while achieving a high TPR of 0.633, also displays a high FPR of 0.402, suggesting a propensity to overestimate "Neutral" responses and to misclassify negative instances. The Neural Network model shows moderate performance with a TPR of 0.571 and FPR of 0.363, which reflects certain issues with misclassification. Both the kNN and AdaBoost models exhibit similar TPR and FPR values, indicating difficulties with precision. Logistic Regression achieves a reasonable TPR of 0.612 and an FPR of 0.308, but it struggles to effectively handle nuanced classifications. The calibration curves illustrate the alignment between predicted probabilities and actual outcomes, with deviations from the ideal diagonal line indicating areas where models tend to either over-predict or under-predict the probability of "Neutral" responses. The Random Forest and Neural Network models emerge as the most balanced performers, with Random Forest demonstrating slightly superior calibration. On the other hand, the Naive Bayes model is prone to overestimation, and the Tree and AdaBoost models exhibit significant misclassification challenges. While Logistic Regression offers a straightforward approach, it encounters difficulties in managing the complexity of the data. This analysis underscores the potential of the Random Forest model as a promising choice for further application.

4.5. ROC analysis

The ROC analysis (Fig. 4) illustrates the classification performance of multiple machine learning models, each attempting to predict the "Neutral" class for the target variable. The true positive rate (sensitivity) and the false positive rate are plotted for varying thresholds, with the diagonal line representing a random classification baseline. Models whose ROC curves approach the top-left corner demonstrate higher classification accuracy and are better at distinguishing between the positive and negative classes. In this plot, Random Forest once again emerges as a strong performer, with its ROC curve consistently superior across most false positive rates. This aligns with its earlier dominance

Table 11
Model comparison.

Comparison of models by F1-score	Tree	Logistic Regression	kNN	Random forest	AdaBoost	Naive bayes	Neural network
Tree		0.017	0.165	0.064	0.752	0.008	0.013
Logistic Regression	0.983		0.859	0.761	0.977	0.272	0.753
kNN	0.835	0.141		0.236	0.943	0.032	0.185
Random Forest	0.936	0.239	0.764		0.965	0.112	0.425
AdaBoost	0.248	0.023	0.057	0.035		0.012	0.033
Naive Bayes	0.992	0.728	0.968	0.888	0.988		0.863
Neural Network	0.987	0.247	0.815	0.575	0.967	0.137	

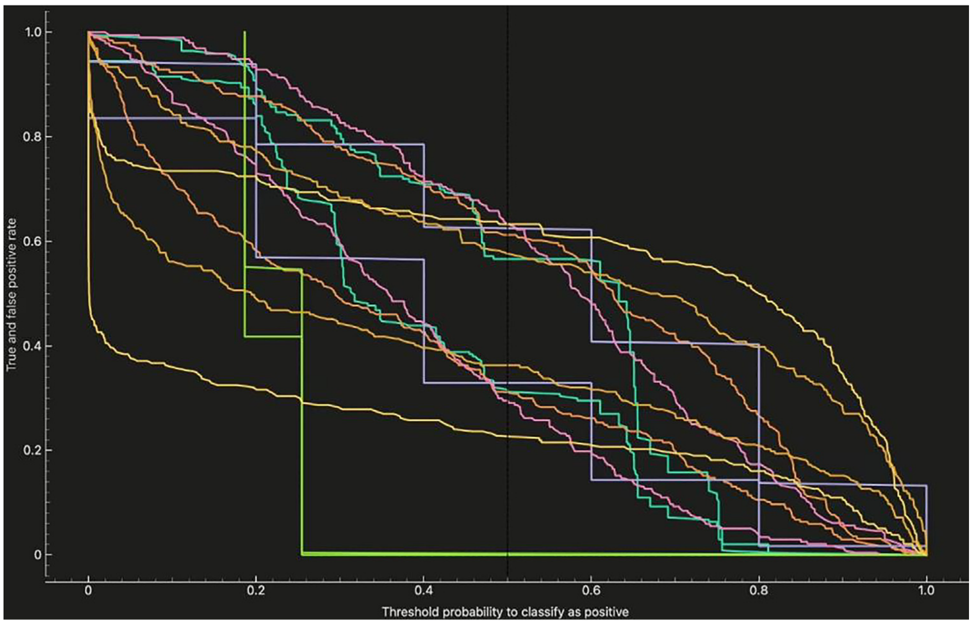

Fig. 3. Calibration plot — Comparison of model performance.

in terms of metrics such as AUC and sensitivity. Other models, including Logistic Regression and Naive Bayes, show intermediate ROC profiles, reflecting moderate predictive capability. Meanwhile, models like AdaBoost and Neural Networks exhibit comparatively weaker curves, suggesting lower classification power for this specific class. The separation between the curves reinforces the conclusion that Random Forest outperforms the other models in terms of balanced accuracy and reliability for the "Neutral" class predictions. This visualization strengthens the case for Random Forest as a robust choice in this classification scenario.

4.6. Statistical justification

The Wilcoxon Signed Ranks Test results in Table 12, revealed statistically significant differences when Random Forest was contrasted with AdaBoost, kNN, Tree, Logistic Regression, and Neural Network models ($Z = -2.201, p = 0.028$ in all cases). The negative ranks across these comparisons indicate that the Random Forest model yielded higher metrics consistently. This consistency across models positions Random Forest as a reliable choice in applications where precision, recall, and classification accuracy are critical. Interestingly, the Sign Test further validated these results, reinforcing the uniformity of outcomes when using Random Forest against most competing models. The comparison with Naive Bayes, however, presented an exception, with no significant difference observed ($Z = -0.674, p = 0.500$). This suggests that Naive Bayes may serve as a competitive alternative in contexts where simpler models are preferred, provided the data assumptions align with Naive Bayes' strengths. The nuanced distinction between Random Forest and Naive Bayes offers valuable insights for decision-makers in the research domain, particularly in optimizing model selection based on the trade-off between complexity and performance.

Our application of the Wilcoxon Signed Ranks Test not only confirms the superior performance of Random Forest but also validates the methodological advancement this study brings to analysing consumer intention. This fills a critical gap in prior literature, where such robust statistical methods were rarely employed to validate predictive models in the context of EET-FSC. The observed neutral stance among specific demographics, such as middle-income consumers, fills a critical gap in understanding the barriers to blockchain adoption in EEFSC. By identifying socio-economic dynamics and the need for targeted educational campaigns, the study provides actionable insights to improve engagement with these technologies.

5. Conclusion and implications

The convergence of EET and FSC signifies a crucial effort that is fundamentally significant for fostering sustainability measures and adequately responding to the growing consumer eagerness for eco-friendly practices within the food industry. As consumers progressively cultivate a heightened awareness regarding the ecological ramifications associated with their dietary selections, it becomes imperative to thoroughly comprehend their perceptions and attitudes towards energy-efficient practices, as well as their readiness to invest financially in products that embody such attributes, for the purpose of propelling a substantive and impactful transformation towards sustainability within the FSC. Our research concentrated on an empirical analysis of consumer intention in relation to EEFSC through the application of predictive ML algorithms.

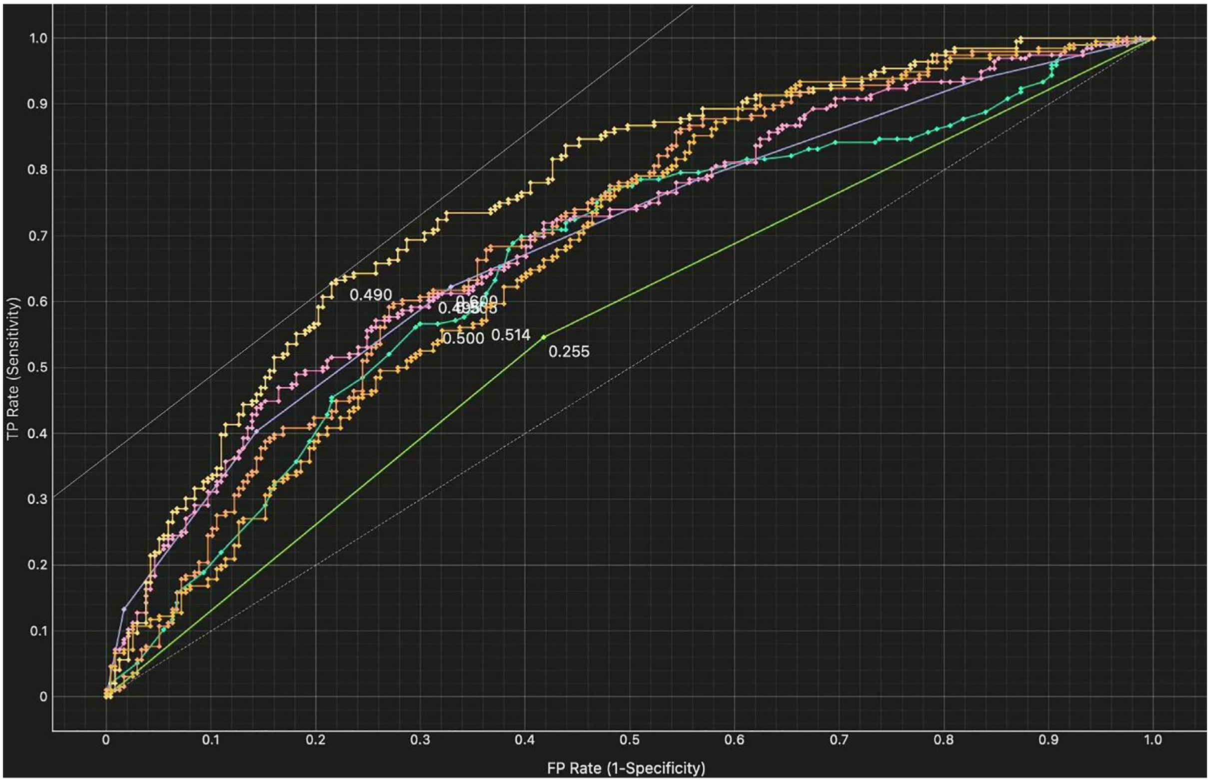

Fig. 4. ROC analysis.

Table 12
Wilcoxon Sign Ranks Test.

Comparison	Negative ranks	Positive ranks	Ties	Z-value	p-value (2-tailed)	Outcome
AdaBoost vs RandomForest	6	0	0	−2.201	0.028	Random Forest significantly better
kNN vs RandomForest	6	0	0	−2.201	0.028	Random Forest significantly better
Tree vs Random Forest	6	0	0	−2.201	0.028	Random Forest significantly better
Logistic Regression vs Random Forest	6	0	0	−2.201	0.028	Random Forest significantly better
Naive Bayes vs Random Forest	1	4	1	−0.674	0.500	No significant difference
Neural Network vs Random Forest	6	0	0	−2.201	0.028	Random Forest significantly better

The primary objective of this investigation was to accurately predict consumer willingness to pay for food products that have a diminished energy footprint across the FSC, thereby offering a data-driven methodology that aims to bolster sustainability initiatives within the FSC. By harnessing the power of ARM and conducting a comparative analysis of various ML algorithms, our study endeavoured to elucidate the fundamental consumer patterns and preferences that are intrinsically linked to energy-efficient practices.

The findings from our research underscore the remarkable efficacy of ML technologies in accurately predicting consumer intention towards EET-FSC. More specifically, the application of ARM unveiled significant consumer intention patterns, highlighting robust correlations between segments of eco-conscious consumers and their pronounced preference for food products that prioritize energy efficiency. In examining the effectiveness of different ML methods, researchers discovered that the Random Forest algorithm demonstrated superior functionality, eclipsing competing models with an astonishing accuracy score of 82% regarding consumer inclination to purchase energy-efficient goods. These compelling findings serve to validate the considerable potential that ML possesses in refining marketing strategies and guiding operational decisions, thereby significantly enhancing the uptake and adoption of energy-efficient practices within the FSC. Such insights wield profound implications for the broader food supply chain, indicating that the integration of cutting-edge technological innovations, such as ML, can effectively satisfy consumer demands while simultaneously contributing to overarching environmental and economic advantages. The study further emphasizes the indispensable role that predictive analytics plays in fostering energy-efficiency and optimizing resource utilization across various stages of production, transportation, and storage within the food supply chain. In addition, the use of these sophisticated technologies may result in considerable cost reductions, help decrease carbon footprints, and improve the clarity and tracking of supply chain operations, thus ensuring the FSC's initiatives are in line with international sustainability targets.

The study offers valuable contributions to the existing body of literature by highlighting several important implications. For managers, the findings underscore the need for targeted communication strategies, especially for consumers within the Rs. 50,000–Rs. 1,00,000 income bracket, who exhibited a neutral stance. By emphasizing the tangible benefits of blockchain in enhancing FSC transparency and promoting energy efficiency, managers can potentially shift perceptions and encourage greater adoption. The research also suggests that, even in regions like South India where there is general interest in blockchain, the specific benefits related to energy efficiency are not fully understood. Managers should therefore focus on raising awareness and educating consumers about these specific advantages to better capitalize on the existing interest. In addition to managerial implications, the study advances the theoretical understanding of consumer intention in the context of emerging technologies like blockchain. The observed neutral stance across various consumer segments indicates that existing models may require refinement to more accurately account for the complexities of consumer attitudes towards technological innovations. The neutrality displayed by a specific income group challenges prevailing assumptions about the correlation between income and interest in innovative technologies, suggesting that future research should further investigate the relationship between economic factors and technology adoption.

Although this study focuses on the Indian context and the FSC, its findings provide insights that could potentially generalize to other countries and industries. The observed consumer intention patterns towards EETs and blockchain adoption are not confined to India alone. In regions with similar socio-economic disparities or digital literacy challenges, such as parts of Southeast Asia or Africa, similar barriers to adoption might exist. Addressing these shared barriers, such as limited infrastructure and awareness, can inform global strategies to promote EET adoption across diverse geographic contexts. The methodologies applied in this study can be extended to other industries such as logistics, healthcare, or manufacturing, where transparency, energy efficiency, and consumer trust are critical. Industries like logistics, for instance, often encounter challenges in balancing cost-efficiency with sustainable practices, making the insights on neutral consumer stances and their underlying drivers highly relevant. The flexibility of the models and approaches used, such as Random Forest, underscores their adaptability to a variety of settings, offering stakeholders in different sectors a data-driven pathway to address unique consumer demands and enhance operational efficiency. Future studies should explore these broader applications to validate and expand the relevance of these findings across global contexts and varied industries.

For supply chain managers, the study highlights the potential of blockchain technology to enhance transparency, even among consumers who currently hold a neutral stance. Investing in blockchain could help address consumer concerns about FSC clarity, thereby potentially increasing trust in the supply chain. Although the study found a neutral stance towards energy-efficient food tracking, supply chain practitioners could leverage this neutrality as an opportunity to differentiate their offerings. By emphasizing the long-term benefits of energy efficiency, they might be able to convert neutral consumers into advocates. The effectiveness of the Random Forest model in predicting consumer willingness to pay a premium for EEFSC products is another key finding of the study. Practitioners could adopt or refine this model to better forecast consumer intention and tailor their marketing efforts accordingly. Given the neutral attitudes towards blockchain's energy efficiency benefits, there is also a practical need for educational campaigns that clearly articulate these advantages to consumers, potentially driving greater interest and adoption.

While the study highlights the potential of integrating EETs and blockchain in the FSC, it is essential to consider the ethical dimensions associated with these advancements. Consumer surveys, as a primary data collection tool, are inherently susceptible to biases such as self-selection, where individuals with a prior interest in sustainability or technology may be overrepresented. This could potentially skew insights and impact the generalizability of the findings. Despite efforts to ensure a diverse and representative sample, biases such as social desirability, where respondents provide answers they perceive as socially acceptable may have also influenced responses. Acknowledging these limitations emphasizes the need for caution when interpreting the results and underscores the importance of further validating findings through longitudinal and qualitative studies. While blockchain offers significant benefits in enhancing transparency and promoting energy efficiency within the FSC, its implementation raises environmental concerns. Blockchain systems, particularly energy-intensive proof-of-work mechanisms, contribute to carbon emissions, potentially counteracting their intended sustainability objectives. This ethical dilemma highlights the necessity of adopting more energy-efficient blockchain technologies and conducting life-cycle assessments to balance transparency with environmental costs effectively. Addressing these ethical implications not only strengthens the practical application of these technologies but also ensures their alignment with global sustainability goals and equitable practices across diverse consumer demographics.

6. Limitations and future work

The study acknowledges certain limitations. The sample, while substantial, may not fully represent the broader population, particularly outside of the Rs. 50,000–Rs. 1,00,000 income range or in different geographic regions, which limits the generalizability of the findings. The study's focus on consumer intention in South India may also mean that the findings are not directly applicable to other regions, especially those with different cultural or economic contexts. Additionally, while the Random Forest model performed well, it and other models used may not capture all the nuances of consumer intention, as they are limited by the quality and scope of the input data. The study observed a prevalent neutral stance among consumers but did not fully explore the underlying reasons for this neutrality, limiting the depth of understanding regarding consumer motivations.

Consumer surveys are inherently prone to biases such as self-selection and social desirability, which may influence the responses gathered. Efforts were made to mitigate these biases by ensuring a diverse and representative sample, however, the limitations of survey-based research warrant careful interpretation of the results. Respondents interested in sustainability or technology may have been overrepresented, potentially skewing the insights on consumer intention towards EET. While blockchain offers substantial benefits in enhancing FSC transparency and energy efficiency, its implementation is not without environmental costs. Blockchain systems, particularly energy-intensive ones, could contribute to increased carbon emissions, potentially offsetting their intended sustainability benefits. This underscores the need for adopting energy-efficient blockchain technologies and conducting life-cycle assessments to balance transparency and sustainability goals effectively. Addressing these ethical dimensions through future research and targeted interventions can enhance the practical and equitable application of blockchain in fostering sustainability within the FSC.

Finally, the study is based on a snapshot of consumer intention and does not account for potential changes over time, such as shifts in consumer attitudes due to new information or evolving market conditions. Further inquiry into the economic ramifications associated with these technologies, particularly their influence on cost efficiencies and operational effectiveness, could yield deeper and more nuanced insights. In addition, a thorough exploration of alternative ML algorithms, including advanced deep learning models, alongside the refinement of techniques aimed at managing imbalanced datasets, will be critical for progressing the integration of energy-efficient practices within the FSC. Pursuing these future research paths will facilitate the broader adoption of EET, ensuring that the FSC remains attuned to the evolving preferences of consumers and aligned with overarching global sustainability ambitions.

Future research could expand the demographic scope to encompass a wider range of income levels, educational backgrounds, and geographic locations, providing a more holistic understanding of consumer intentions towards EET-FSC. Additionally, conducting a longitudinal study would allow researchers to track changes in consumer intentions over time, offering insights into the evolving attitudes towards blockchain and energy efficiency. Another valuable avenue for future work would be to explore consumer perceptions of other emerging technologies in the supply chain, such as AI or IoT, and compare them with those of blockchain. To gain a deeper understanding of the neutral stance identified in this study, future research could employ qualitative methods like interviews or focus groups to explore the underlying reasons behind consumer attitudes. Further investigation could also focus on hybrid modelling techniques that combine the strengths of different predictive models. This approach could improve the accuracy of consumer intention forecasts and provide a more detailed understanding of the factors driving the adoption of EEFSC products.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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