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A text analytics based study of indian consumer attitudes toward adoption of sustainable products for circular economy

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Abstract
The adoption of circular economy strategies is only possible through proper education among young minds. However, to build an effective education model, it is necessary to consider knowledge gaps and current consumption patterns. The best option for daily-use products, around which the consumer-response analysis can provide useful insights. Mat is such a product used in every household in India. There are two variants of the mat, one made of natural fibre and the other of plastic, available in the market and on the e-commerce platform. In the current scenario, the digital market or e-commerce platform provides an avenue to simultaneously analyse consumer comments on both natural fibre-based and plastic products. The present study deployed a natural language processing approach to analyse consumer comments. The Bidirectional Encoder Representations from Transformers (BERT)-based rating or sentiment analysis, informed by practice-based theory (PBT), indicates that the main barrier to the adoption of circular products is not a lack of environmental awareness, but the misalignment between perceived product attributes and usage practices. This necessitates integrating sustainability literacy with material awareness into the educational curriculum.

Keywords Circular economy · Consumer education · Bidirectional encoder representations from transformers · Green products · Practice-based theory of learning

1 Introduction

Green, sustainable, circular products are still not widely adopted, despite growing environmental consciousness. Most current research overlooks the significance of daily consumption practices and instead uses institutional, attitudinal, or informational lenses to explain the adoption of a circular economy. When demand is sizable, industry and business houses will be encouraged to produce more circular products. Small and mid-size enterprises (SMEs) in India primarily produce most circular products and have immense potential to generate better business insights through data-driven approaches (Pradhan et al., 2013). Due to the country's favourable digital technology environment, which includes relatively cheaper digital devices, especially mobile phones and packs,

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handmade SMEs are also not far behind. The challenges are far more complex for SMEs that produce handmade products. However, the availability of handmade products on popular e-commerce platforms incites curiosity about the recently emerged business model and prompts a detailed understanding of it for potential replication in other emerging nations. Therefore, the present research aims to draw lessons from one such Indian SME.

In the present research, the mat-making sector has been selected for study. The reason for considering the mat sector is that it provides a scope to conduct a comparative study of linear and circular products simultaneously. The mat is originally made from Madurkathi, a reed from the sedge family *Cyperaceae*. But the biodegradable Madurkathi woven products had to compete with non-biodegradable plastic mats. Recently, Madurkathi mat weavers have gained comparatively smooth access to digital marketing platforms in India, allowing them to directly compete with plastic mat manufacturers. Recently, the e-commerce platform has become the fulcrum for Madurkathi weaving SMEs, as they can access consumer feedback directly, obtain it through aggregators, and visualise competitors' products, designs, prices, colours, and other relevant details. The high-resolution uploaded 360-degree photographs are an added advantage. Online customer reviews and ratings are considered in this study, not only as sentiment statements but also as digital indicators of consumer behaviour. The study conceptualises consumer evaluation considering the Practice-Based Theory (PBT) as arising from the interaction of the three constructs: material attributes, user competencies, and meaning embedded in product usage.

The present study's final solution is to design a strategy that educates young minds to change their purchasing behaviour. Different theories of learning were encountered during brainstorming. Finally, Practice-Based Theory [31, 32] has been considered the basis for data analysis in this research. The justification for considering the theory along with the methodology has been established in the literature review section.

2 Literature review

Practice-Based Theory [31, 32] is a powerful lens for understanding knowledge creation and knowledge accumulation, and the generation of knowledge through localised action rather than abstract transfer. In the context of education, PBT focuses on experience-based active learning to develop competencies through real-world experiences, and this approach is crucial for teaching the concept of sustainability to the next generation. Raelin, [30] presents this Practice-Based Learning (PBL) approach as an epistemology of practice, in which knowing and doing are inseparable activities. Similarly, Banerjee and Morley , [2] argue for the importance of PBL in higher education, asserting that the effectiveness of Experience-Based Learning (EBL) is far superior to purely theoretical knowledge. Feldman and Worline, [11] emphasise the PBL approach as an adequate pedagogical tool for preparing students for complex institutional rules. Hibbert et al., [15] and Tiwari et al., (2026) found that practical scenarios in collaborative environments can elevate learning by stimulating higher-order cognitive engagement. Loon, [23] presents empirical evidence in favour of experiential learning in early-career training. Also, Huang et al., [16] present a sociometrical perspective in their study, explaining the positive impact of environmental and physical artefacts on the learning process. This PBT learning framework is a robust way to acquire knowledge, and its effectiveness can be observed in technical education, such as engineering; however, PBT is not widely adopted in sustainability curricula. This situation is the main reason why, despite knowledge of sustainability, the majority of the population dare not adopt circular economy principles.

In traditional research, as in Patwa et al., [28], the study focuses on institutional factors related to the adoption and diffusion of a circular economy in emerging economies. Castro et al., and Bhavikatta [5, 8] found that the keys to adopting circular principles are organizational capabilities and institutional encouragement. In their consumer research, Testa et al., [34] examined the influence of information on circular purchasing behaviour. On the other hand, Kamal et al., [18] researched the information-sharing impact on the product-return behaviour. However, these studies talk about the purchase intention rather than the actual product purchase behaviour. However, Ghosh et al., [13] examined the impact of attributes such as price, performance, service, and utility on purchase behavior for refurbished products. Also, the importance of education for sustainability awareness needs to be

discussed, as it directly impacts the adoption of the circular economy. Bespalyy et al., [4] advocated an integrated approach to sustainable education that combines experiential learning. Adequate integration of sustainable development education into university curricula, coupled with project-driven awareness initiatives, led to an enhanced understanding of the Sustainable Development Goals. In another study by Anas et al., [1], it was found that in the case of specialization education, adequate awareness about sustainability can manipulate the sustainable practices. This study does not provide insights into the behavioural aspects necessary for practice translation. The studies by Burger et al., [6] and Buyukyazici and Quatraro [7] identify the need for competencies for the circular economy but fail to show the direction of competency development through education.

The available disconnect between PBT and the Circular Economy (CE) indicates several research gaps. Circular economy adoption is rarely conceptualised as a practice-based phenomenon. Local practices [33], which the literature has not yet explored in depth, influence the adoption of CE in emerging economies. The last one is the moral-material gap. Knowledge about product materials strongly influences sustainability and CE principles; hence, there is a need for research on the impact of such awareness on CE adoption and diffusion.

2.1 Circular economy and natural language process

Recent studies on the circular economy use sentiment analysis and natural language processing (NLP) to investigate how stakeholders view sustainability opportunities, challenges, and practices. Tleuken et al., [36] analyzed online discourse using transformer-based embeddings, BERTopic, clustering, and sentiment classification. They discovered that positive opinions predominated, though implementation issues persisted. Similarly, Karaca et al., [19] integrated topic modeling and sentiment analysis with survey and workshop data to identify stakeholder expectations concerning resource equity, innovation, and circular construction. Barbosa and Gomes, [3] used neural topic modeling to analyze social media conversations related to food waste. They discovered that while negative sentiment concentrated on environmental harm, social repercussions, and a lack of knowledge about recycling practices, positive sentiment was prevalent. Online communication is primarily positive and objective, especially when it comes to food, packaging, textiles, repair, and reuse, according to broader evidence from zero-waste consumption [37]. Kvasnička et al., [21] examined over 820,000 social media posts and showed how opinions about the circular economy differ by area and topic, such as waste management, plastic pollution, innovation, and circular fashion. Previous studies demonstrate that NLP enables large-scale attitude identification; however, future research should enhance multilingual modeling, aspect-level sentiment analysis, validation processes, and the connections between sentiment and circular behavior.

2.2 Contributions and research questions

The present study contributes by bringing together PBT with CE adoption at the consumer level, and that too through a data-driven approach, more precisely, by performing contextual sentiment analysis with the help of the transformer model called 'Bidirectional Encoder Representations from Transformers (BERT)'. In this study, online reviews are treated as practice narratives or reflections on consumers' day-to-day practices, rather than mere sentiments or opinions. Another contribution of this paper is the use of advanced methods, such as deep learning, to capture consumers' rating behaviour. The insights from this analysis are finally translated into a PBE strategy aimed at motivating young minds, who are nothing but future consumers, to act sustainably. In this way, the study fills the knowledge gap in the literature on CE adoption and diffusion. It also builds new evidence on CE adoption and diffusion by integrating PBT with it, thereby filling an evidence gap in the literature. Lastly, the method adopted in this study, namely applying BERT to capture rating behaviour and PBT to analyse output, enables the paper to contribute to bridging the methodological gap in the literature on CE adoption and diffusion.

RQ1. How do consumer review narratives reflect underlying product-use practices influencing circular economy adoption?

RQ2. To what extent can BERT-based models accurately predict discrete ratings based on practice-oriented textual features?

RQ3. How can insights from practice-based review analytics inform the design of experiential education strategies for circular economy adoption?

3 Research methodology

The study adopts PBT-guided text mining as a data analysis tool to identify the practices needed to design a strategy for educating young minds. The study uses secondary data for this analysis. Consumer data from a popular e-commerce website Amazon on hand-woven Madurkathi mats and plastic mats were extracted and analysed to identify the key attributes driving purchase behaviour. In this analysis, two different types of products are considered. First, a natural fiber-based product, and second, a plastic-based product. For both products, the product rating (star rating), review title, review comment, product details, and verified purchase status have been captured. The demographic and geographic information was not consistently available with this data. Hence, the authors avoid using such information in the main data analysis. A total of 387 and 305 data points are captured for the two product types. After screening the data for duplicate entries, missing data, and language screening. Of the 305 data points, only 290 were considered useful. In the language screening, the authors considered only English. The data has been collected from September 2024 to March 2025. The analysis of secondary data has been conducted using contextual sentiment analysis. This contextual text mining is the advanced form of traditional text mining. Traditional sentiment analysis, a type of text mining, relies on bag-of-words and word-to-vector representations, along with lexicons and machine learning, and treats words in silos, ignoring contextual relationships. This limitation restricts their effectiveness in capturing complex human emotions [9].

3.1 Problem formulation

PBT considers the integration of three interconnected elements, namely, materials, competences, and meanings, as a practice. In this study, the physical properties of the mat (fiber type, durability, thickness, size, and quality) are referred to as material properties. Knowledge of usage, product handling practices, and expectations regarding product performance are considered competencies. Finally, the meanings refer to the emotions and experiences associated with product use, such as perceived sustainability, value, beauty, and comfort. These define the boundary or guidance for the model's interpretation of rating-specific significant tokens.

In this analysis, the 1-to-5-star ratings are treated as 5 distinct sentiment levels (1-very negative, 2-negative, 3-neutral, 4-positive, and 5-very positive) [22]. Hence, the problem is a simple multilevel classification with 5 classes. Along with building the star rating prediction, the insight about the usage pattern or practice needs to be captured. Hence, finding practice-relevant words in the analysis is also required. In the initial observation, the data points exhibit a high class imbalance. This has been addressed during model building using a weighted loss approach. As this article deals with text data, SMOTE is not useful here. SMOTE works best with continuous numerical data. Also, in addition to traditional model performance metrics (accuracy, precision, recall, and F1 score), macro and weighted-average values of these metrics are calculated during 5-fold cross-validation. The expressions for macro and weighted averages are given below to illustrate the calculation process, as Eqs. (1) and (2), where K denotes the number of folds used for cross-validation during testing.

$$Macrometric = \frac{1}{K}\sum_{i=1}^{K} Metric_i \tag{1}$$

$$Weighted\ metric = \frac{\sum_{i=1}^{K} (Metric_i \times Support_i)}{\sum_{i=1}^{5} Support_i} \quad (2)$$

In the current study, PBT was not computationally embedded in the BERT architecture. Instead, the authors utilised it as a prior framework for interpretation at all three steps of the data analysis. In the initial stage, the collected reviews were considered descriptions of product use rather than representations of sentiment. Next stage, the contextually noticeable tokens extracted in the BERT analysis were mapped with the three practice elements, namely, materials, competences, and meanings. In the last stage, the identified patterns were used to synthesize the practice alignment and drive practical implications for education. Hence, BERT is used here for contextual rating prediction, and PBT guides the interpretation of these predictive model outputs.

3.2 Bidirectional encoder representations from transformers

BERT is a transformer architecture in natural language processing that utilises a self-attention mechanism to preserve context in the observed text. Compared with traditional models, BERT aims to understand word relationships based on text context [10]. This contextual consideration in the model enhances its ability to interpret sentiment expressions at a granular level. The available literature indicates that contextual sentiment models outperform traditional approaches [17]. RoBERTa and DistilBERT are both optimised variants of the BERT language model, with RoBERTa focusing on higher accuracy through intensive training and DistilBERT on speed and efficiency. Both models outperform traditional machine learning and earlier versions of deep learning models by detecting semantic patterns in text data [29]. In this research, only the base-BERT model is utilized for contextual text mining. This research does not intent to produce a better predictive model. Hence, other variants such as RoBERTa and DistilBERT are not used here. Traditional techniques inadequately handle ambiguity and contextual dependency, but this contextual embedding ultimately addresses these challenges. Also, these models demonstrate generalisation across domains and languages due to their pretraining. These characteristics make pretrained models suitable for applications involving diverse, unstructured data, such as review comments [12]. Hence, the contextual sentiment can provide deeper insights into user behaviour. Here in this research, ratings and product reviews were utilised to tune the BERT model and PBT was used to guide the interpretation. Figure 1 presents the data analysis process in this research.

The authors tabulated the model parameters in Table 1 to ensure reproducibility, and the training and validation loss changes over the epochs are presented in Figs. 2 and 3. The blue curve (o) in the figure indicates the training loss, and the red curve (x) indicates the validation loss. This can be observed that the losses are decreasing

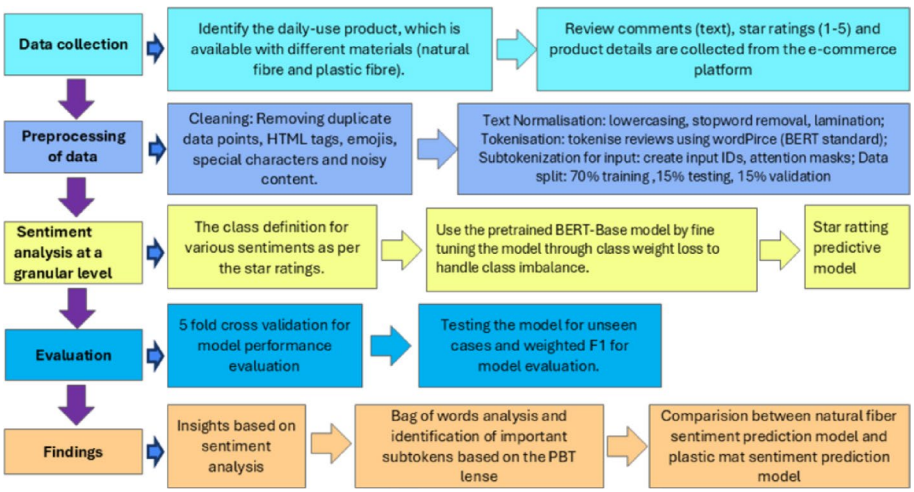

Fig. 1 Process flow for the sentiment analysis and insight generation using BERT-based sentiment analysis

Table 1 Parameters for the BERT-base-uncased based sentiment analysis

Parameter name	Value	Parameter name	Value
Layers	12	Batch size (train and evaluation)	16
Hidden layer	768	epochs	6
Attention Header	12	Weight decay	0.01
Intermediate Size	3072	Gradient clipping	1.0
Vocabulary Size	30,522	Best model selection criteria	Weighted F1 score
Dropout (hidden and attention)	0.1	Trainer	Hugging Face
Activation function	GELU	Loss override	Weighted Loss
Tokeniser	Word Piece	Cross-Validation	Stratified K-flod
Max Sequence Length	128	Folds	5
Padding	Max length	Shuffle	Yes
Split type	stratified	Random seed	42
Training/Validation/Testing	70%/15%/15%	Metric aggregation	Mean ± Std. Dev.
Random seed	42	Output layer input dimension	768
Class imbalance handling	Class-weighted loss	Output layer output dimension	5
Loss function	Cross-entropy loss	Activation	SoftMax
Optimizer	AdamW	Loss	Cross entropy
Learning rate	2e-5		

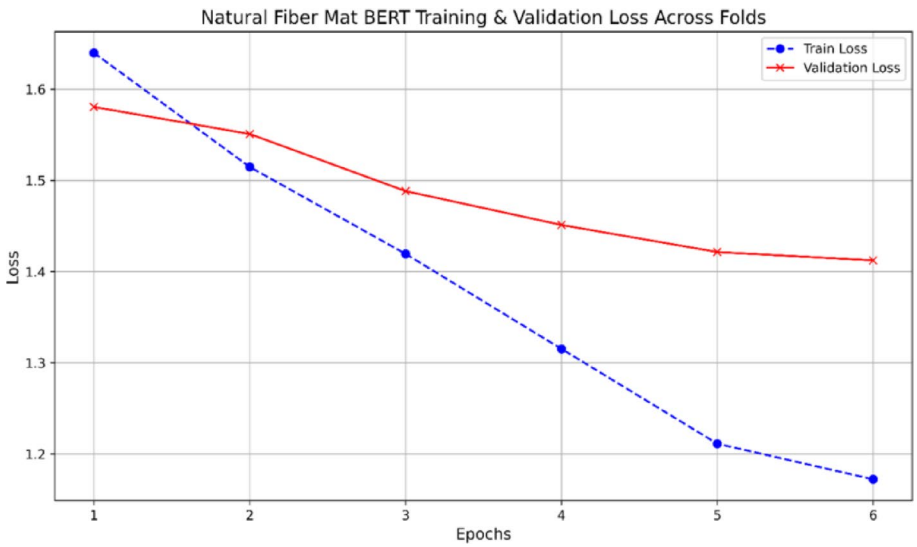

Fig. 2 Training and Validation loss of BERT base uncased model with Natural fiber mat data

with the epoch values for both training and validation. This is a clear sign that the models are learning and surely avoiding overfitting. There is a difference between the training loss and validation loss, as the validation process is trying to generalize itself for the unseen observations, and this is quite normal in the case of training any machine learning model.

3.3 Operationalizing practice-based theory

The operationalization of PBT has been achieved through a theory-based coding framework, consisting of three interconnected components, namely, materials, competences, and meanings. This coding framework or schema was formulated before the classification of the process of identification of the important tokens. The coding schema is presented in Table 2.

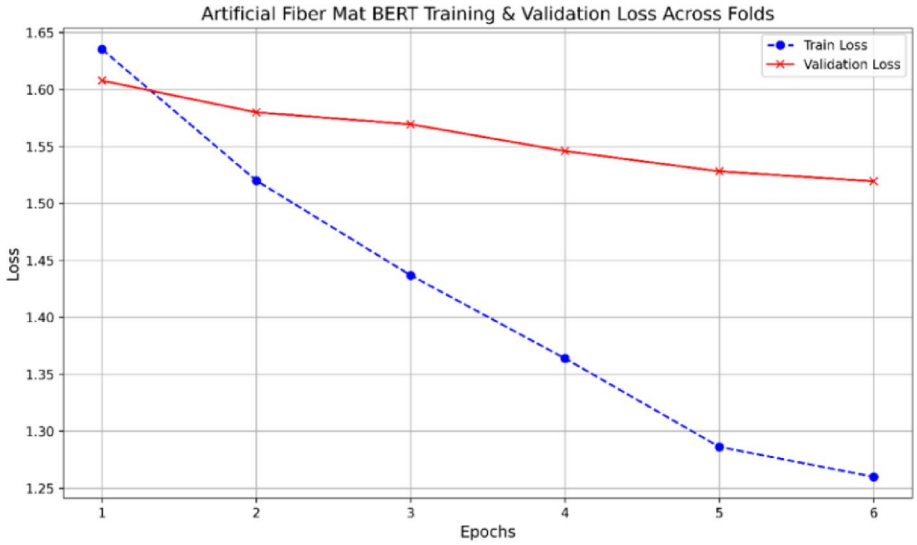

Fig. 3 Training and validation loss of BERT base uncased model with artificiall fiber mat data

Table 2 Codebook description for practice based theory (PBT)

Components	Operational definition	Definition
Materials	Physical properties, objects, infrastructures and material conditions involved in product use	Fiber, thickness, size, quality, durability, breakage, damage, colour, design, physical condition
Competences	Skills, practical knowledge, handling procedures, maintenance knowledge and capacity to use the product appropriately	Use, handling, folding, sitting, cleaning, placement, maintenance, or suitability for a particular activity
Meanings	Emotional, aesthetic, symbolic, normative, and value based interpretations attached to the product	Beauty, comfort, satisfaction, environmental value, perceived inferiority, prestige, authenticity or value for money
Overlap	A token-in-context that simultaneously reflects two or more PBT elements	Can not be adequately represented by one category

The BERT based identified important clean tokens are examined through original review context and classified using this coding schema. Two independent coders complied this classification separately. Inter-rater agreement was assessed using Cohen's κ value (0.76 substantial agreement)([14]. Tokens that reflected more than one practice element were classified as overlapping rather than being forced into a single category. This procedure distinguished computational token identification from theory-guided interpretation. Also, while interpretation of the results, some of the counter examples or construct overlap was observed and for better understanding a simple table has been added as Table 3 for improving the readability.

3.4 Baseline model

A Term Frequency-Inverse Document Frequency (TF-IDF)-based bag-of-words model with multinomial logistic regression serves as the baseline for this sentiment prediction. This strategy differs from the widely used BERT-based strategy in that the decision model is not pretrained. The parameter list for the sentiment prediction baseline model is presented in Table 4. This process starts with data preprocessing (lowercase and punctuation removal) and then TF-IDF vectorisation (1–2 g). The next step is to train a logistic regression model with L2 regularisation using a balanced approach. Then, using 80% of the data for training, train the model and test it on 20% of the data with 5-fold cross-validation. Further calculate the performance metrics based on the prediction results.

Table 3 Token to construct classifications and counter examples

Token	Review comment	Initial category	PBT classification	Rational
beautiful	"looks beautiful in the room"	Meaning	Meaning	Aesthetics interpretation
cheap	"The material looks cheap"	Meaning	Materials and meaning overlap	Perceived physical quality or symbolic inferiority of material
Waste	"Waste of money because it tore quickly"	Meaning	Materials and meaning overlap	Physical damage to value judgement
Comfortable	"Comfortable to sit on for long period"	Meaning	Meanings and competences overlap	Experience to actual use
Sitting	"Size is too small for two people to sit"	Competences	Material and competences overlap	intended use to physical size
damaged	"product arrived damaged and could not be used"	Materials	Materials	Physical condition
thin	"Too thin for regular floor use"	Materials	Materials	Material properties

Table 4 Parameters for the TF-IDF and multinomial logistic regression-based sentiment analysis

Parameter name	Value	Parameter name	Value
Tokenizer	Word Piece	Random seed	42
Stop words	English	Cleaning	Lower case and punctuation removal
ngram_range	(1,2)	Feature space	Sparse TF-IDF matrix
Min_df	Ignore rare terms (appear in < 2 docs)	Split type	Stratified
Max_df	Remove overly common terms (> 90%).	Train Size	80%
penalty	L2	Test Size	20%
Inverse regularization strength	1.0	Cross validation method	5-fold
solver	lbfgs	Shuffle	Yes
Convergence tolerance	1e-4	Metric aggregation	Mean ± Std. Dev.

Table 5 Performance summary for the baseline model for mat with natural fibre

Rating	Precision	Recall	F1
1	0.60	0.75	0.67
2	0.10	0.05	0.07
3	0.40	0.35	0.37
4	0.50	0.45	0.47
5	0.72	0.80	0.76

3.5 Model performance measurement

As the primary objective of the analysis was to develop a predictive classification rather than estimation of parameters in an experimental design, no statistical power analysis was conducted for sample calculation. The corpus was modest for fine tuning the pretrained BERT model. Stratified data split, five-fold cross validation, class-weighted loss, early stopping and comparison with a TF-IDF based logistic regression baseline model was conducted for establishing the BERT base uncased based model superiority. In this model building process, synthetic augmentation methods such as back-translation and synonym replacement were not deployed. Although, these approaches can increase the sample size for training, however, as this research is dealing with text data, the

Table 6 Cross-validation summary for the baseline model for Mat with natural fibre

Aggregation	Accuracy	Precision	Recall	F1-score
Macro (std. dev.)	0.58 (±0.03)	0.56 (±0.04)	0.54(±0.05)	0.55 (±0.04)
Weighted (std. dev.)		0.68 (±0.03)	0.58 (±0.03)	0.61 (±0.03)

Table 7 Performance summary for the baseline model for Mat with artificial fibre

Rating	Precision	Recall	F1 score
1	0.62	0.78	0.69
2	0.08	0.04	0.05
3	0.25	0.20	0.22
4	0.35	0.30	0.32
5	0.68	0.76	0.72

Table 8 Cross-validation summary for the baseline model for Mat with artificial fibre

Aggregation	Accuracy	Precision	Recall	F1 score
Macro (std. dev.)	0.52 (±0.04)	0.46 (±0.05)	0.44(±0.05)	0.45 (±0.05)
Weighted (std. dev.)		0.62 (±0.04)	0.52 (±0.04)	0.56 (±0.04)

product specific expressions connected with the theory constructs may be altered randomly, reducing the reliability of the model learning.

The model's performance has been measured using accuracy, precision, recall, and F1 score. Because the model was trained on imbalanced data, accuracy is not a valid metric. Hence, the other metrics are also important. The analysis emphasises the F1 score for improving the model, as it considers both precision and recall. The calculations for all these metrics are provided in Eqs. (3), (4), (5), and (6).

$$Accurecy = \frac{TP + TN}{TP + FP + TN + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

For each class, these metrics are calculated, and finally, the macro and weighted versions of these metrics are calculated based on Eq. (1) and (2) using 5-fold cross-validation. First, the baseline model's performance has been described. Table 6 presents the individual rating- or sentiment-wise model predictions for natural fiber-based products. It has already been mentioned that the collected data suffered from severe class imbalance, as reflected in the model's evaluation across individual classes. The performance matrix for rating 2 shows poor performance in precision, recall, and F1 score, all below 10%. The best performance is observed for rating values of 5 and 1. The cross-validation result in Table 6 indicates an accuracy of 0.58 across the 5 folds. The standard deviation in the accuracy is 0.03. The weighted metrics values indicate a performance value of around 0.6.

Similarly, mats made from artificial fibres show lower performance ratings. Here also, for ratings of 5 and 1, the measurements indicate considerable results in Table 8. The cross-validation result in Table 8 indicates that the accuracy is 0.52, with a standard deviation of 0.04. The weighted result indicates a value greater than 0.5. The bag-of-words representation for the important words is presented in Table 9 (Table 10).

Table 9 Comparison between the bags of words based on the TF-IDF method

Table 10 Performance summary for BERT model for mat with natural fibre

Rating	Precision	Recall	F1 score
1	0.78	0.88	0.83
2	0.40	0.32	0.35
3	0.58	0.62	0.60
4	0.64	0.60	0.62
5	0.88	0.86	0.87

Table 11 Cross-validation summary for the BERT for Mat with natural fibre

Aggregation	Accuracy	Precision	Recall	F1 score
Macro (std. dev.)	0.72 (±0.03)	0.68 (±0.04)	0.66(±0.04)	0.67 (±0.04)
Weighted (std. dev.)		0.75 (±0.03)	0.72 (±0.03)	0.73 (±0.03)

Table 12 Performance summary for baseline model for Mat with artificial fibre

Rating	Precision	Recall	F1 score
1	0.80	0.85	0.82
2	0.35	0.28	0.31
3	0.48	0.42	0.45
4	0.55	0.50	0.52
5	0.84	0.82	0.83

Table 13 Cross-validation summary for the baseline model for Mat with artificial fibre

Aggregation	Accuracy	Precision	Recall	F1 score
Macro (std. dev.)	0.65 (±0.04)	0.60 (±0.05)	0.58(±0.05)	0.59 (±0.05)
Weighted (std. dev.)		0.68 (±0.04)	0.65 (±0.04)	0.66 (±0.04)

The BERT-based sentiment analysis test results are presented in Tables 11 and 12, 13. The BERT model uses sub-tokens, which are presented as word clouds for each product type in Table 14. In BERT-based results, the performance metric values are better than those of the baseline model. The detailed comparison between the model outputs is provided in the next paragraph.

In this paragraph, the significant differences are highlighted to better understand the results and the discussion section based on the observations. The cross-validation results for model testing for natural fiber indicate that

Table 14 Comparison between the sub-tokens for the BERT model for both natural fibre and artificial fibre

the traditional model achieves an accuracy of 0.72 (Table 11), which is higher than 0.58 (Table 6). So, there is a 24% increment in the accuracy of detecting the right case. On the other hand, the artificial fibre's capability has increased from 0.52 to 0.65, as shown in Table 8 and Table 13. This translates to a 25% increment in right-case detection. As per the hypothesis, detecting both positive and negative sentiments is important, and in such cases, the F1 score plays a vital role by balancing precision and recall. For natural fibre, the weighted F1 for the baseline

Table 15 Statistical test summary for 5-fold cross-validation result with Nadeau-Bengio corrected resampled t-test

Type of fibre	Baseline weighted F1	BERT weighted F1	F1 difference	t statistics	*P* value	CI 95%
Natural Fiber	0.61	0.73	0.12	4.81	0.0086	[0.051,0.189]
Artificial Fiber	0.56	0.66	0.10	3.65	0.0217	[0.024,0.176]

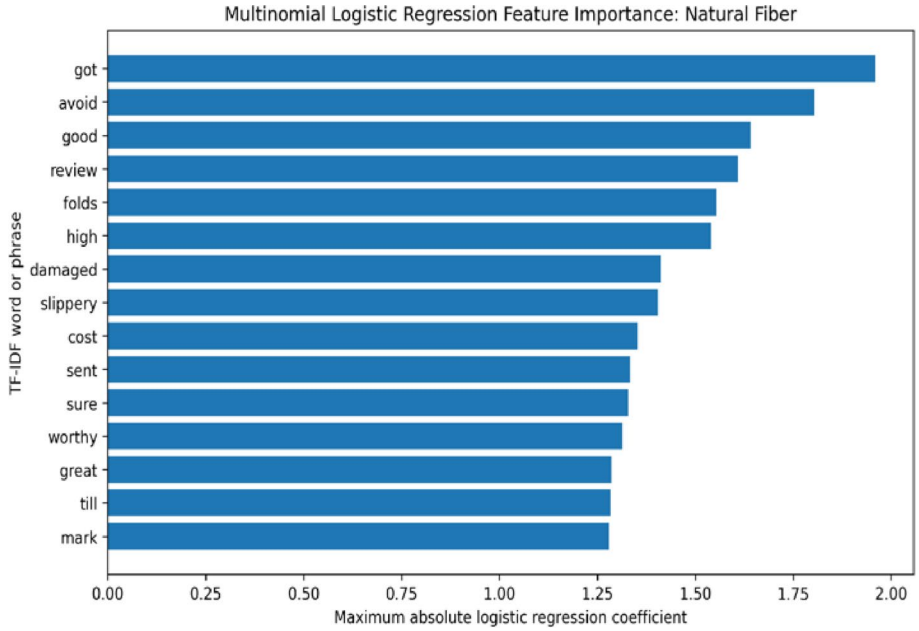

Fig. 4 Feature importance for multinomial logistic regression for natural fibre using SHAP

model is 0.61, while for the BERT-based model, it is 0.73. On the other hand, for the artificial fibre-based mat, the baseline model produces a weighted F1 score of 0.56, while the BERT-based model produces 0.66.

The performance comparison between the base model and the BERT model has been performed using the Nadeau-Bengio corrected resampled t-test [26], as estimates obtained from cross-validation folds are dependent. The results summary has been tabulated in Table 15. For the natural fiber, the BERT-based decision model produced a better weighted F1 value of 0.73 from a base model weighted F1 score of 0.61. The correction was statistically significant, with a t-statistic of 4.81, p-value = 0.0086, and 95% CI [0.051, 0.189]. In the case of the artificial fiber mat, the weighted F1 score improved from the baseline model's 0.56 to 0.66. The improvement was also statistically significant, with a t-statistic of 3.65 and a p-value of 0.0217, 95% CI [0.024, 0.176]. Hence, it can be claimed that the BERT base uncased model is superior to the TF-IDF-based logistic model baseline. Hence, further token analysis can be considered for more insights.

Further, SHAP-based marginal contributions [24] have been calculated for different terms for the base model. On the other hand, Layer integrated gradient [25] approach has been used to identify the important sub-tokens for the BERT based sentiment prediction. Figure 4 shows the important words that affect the multinomial logistic regression rating values for natural fiber, and, similarly, Fig. 5 shows the important sub-tokens for the BERT base uncased model for natural fiber.

The features or words associated with each rating or sentiment contain the key information about the decision logic. The difference in word selection is evident in Tables 9 and 14. In Table 9, the bag-of-words is represented as word clouds, and in Table 14, the sub-tokens are presented as word clouds. There are significant differences between the word cloud visualisations.

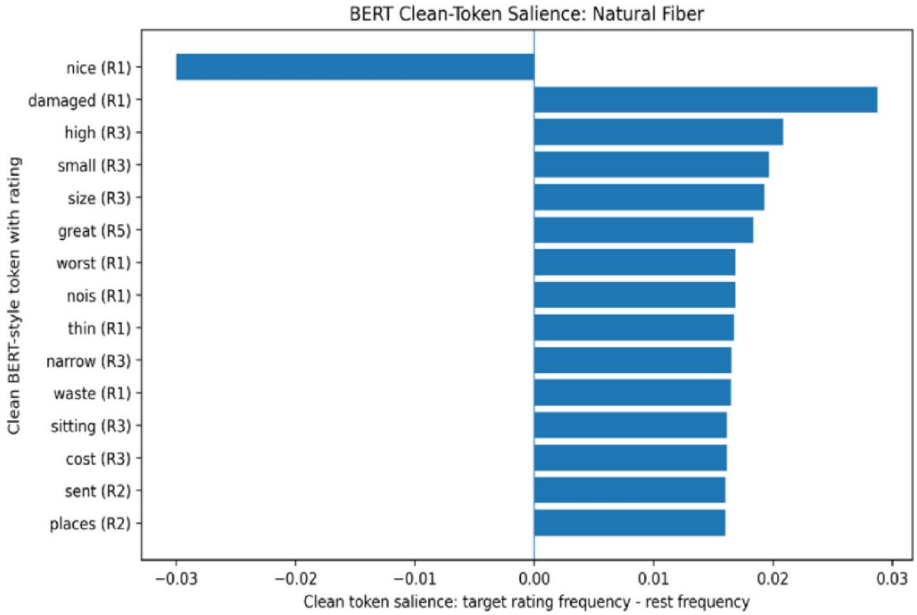

Fig. 5 Feature importance for the BERT based model for natural fibre using LIG

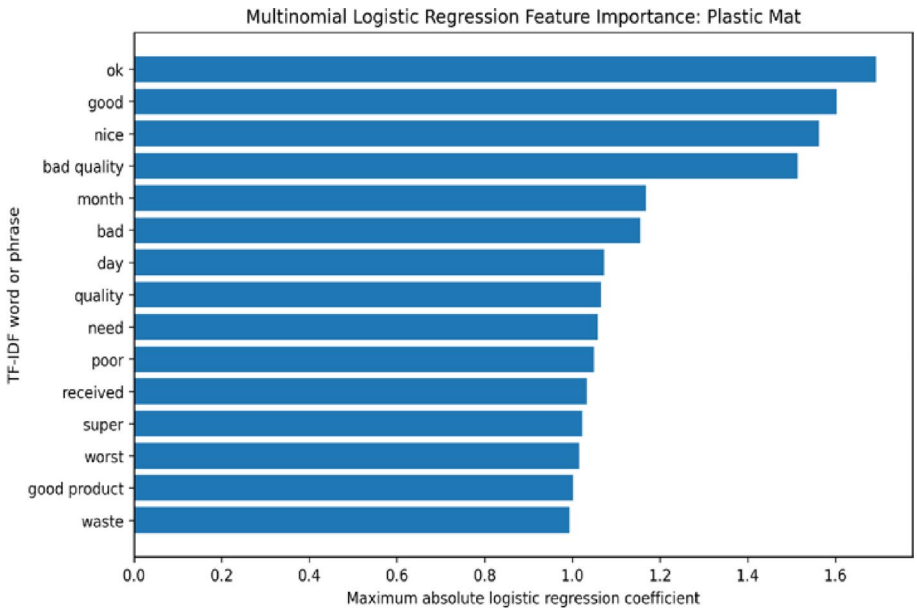

Fig. 6 Feature importance for multinomial logistic regression for artificial fibre using SHAP Similarly. for artificial fibres or plastics, the important words or features are presented in Figs. 6 and 7

4 Result and discussion

Natural fibre mats ($n=387$) and plastic mats ($n=305$; $n=290$ after removing deduplication) exhibit distinct evaluation logics and performance patterns, as revealed by comparative text analytics. With rating 5 accounting for roughly 63% in Dataset 1 and roughly 41% in Dataset 2, the class distribution in both datasets is strongly skewed toward higher ratings, indicating stronger polarisation in the natural fibre segment. Hence, a couple of imbalance-handling strategies, namely Class-weighted loss, random oversampling, and focal loss, are deployed, and the comparison results for these approaches are tabulated in Table 16 here as a reference for readers. The table shows that the imbalance-handling sensitivity across all methods is similar. In case of artificial mats, class-weighted loss produced the best micro-F1 = 0.391 with SD = 0.063 and weighted F1 = 0.456 with SD = 0.068. Similarly, for natural fiber mat data, the highest weighted F1 = 0.520 with SD = 0.060 and micro-F1 = 0.303 with SD = 0.069.

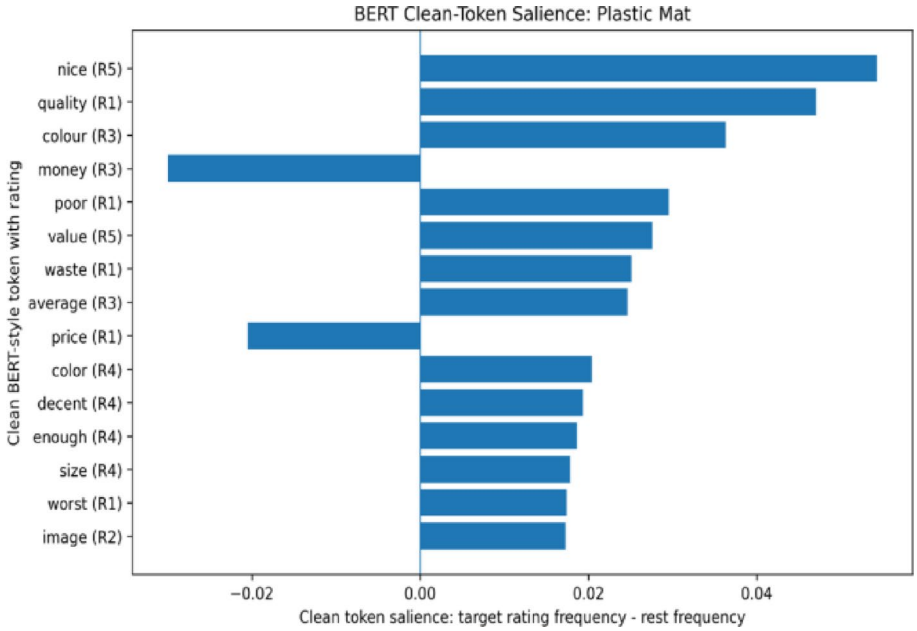

Fig. 7 Feature importance for the BERT-based model for artificial fibre using LIG

Table 16 Summary of class imbalance handling strategies

Product	Approach	Micro-F1 ± SD	95%CI	Weighted-F1 ± SD	95%CI
Plastic mat	Class-weight loss	0.391 ± 0.063	[0.321–0.461]	0.456 ± 0.068	[0.380–0.532]
	Random over sampling	0.388 ± 0.061	[0.320–0.455]	0.452 ± 0.067	[0.377–0.526]
	Focal loss	0.387 ± 0.062	[0.318–0.457]	0.454 ± 0.070	[0.376–0.532]
Natural fibre mat	Class-weight loss	0.303 ± 0.069	[0.226–0.380]	0.520 ± 0.060	[0.454–0.586]
	Random over sampling	0.315 ± 0.065	[0.243–0.388]	0.515 ± 0.060	[0.449–0.582]
	Focal loss	0.286 ± 0.065	[0.213–0.358]	0.510 ± 0.053	[0.451–0.569]

This should be mentioned for the natural fiber mat dataset; the random oversampling produces the highest micro F1. As a result, the weighted loss is employed in this case, as mentioned in the methodology section.

This structure is further reflected in baseline classification accuracy, which is approximately 0.59 in Dataset 1 and approximately 0.53 in Dataset 2. Weighted F1 scores for Dataset 1 and Dataset 2 are approximately 0.70 and ~0.65, respectively, but significantly lower macro F1 (~0.55 and ~0.38, respectively), indicating poor performance in minority classes (ratings 1–3). While Dataset 2 displays almost zero recall, indicating a significant class imbalance, Dataset 1 shows strong predictive stability (F1 ≈ 0.71–0.87) for rating 5. Similarly, in Dataset 2, ratings 2 and 3 show poor discriminability (F1 < 0.15–0.30), while rating 5 dominates predictive performance (precision ≈ 0.68, recall ≈ 0.79).

These statistical patterns are further supported by word cloud analysis. At higher ratings, natural fibre mats display experiential and aesthetic descriptors such as "beautiful," "nice," and "value," while lower ratings highlight "damaged," "waste," and "thin," suggesting dissatisfaction with fragility. On the other hand, plastic mats exhibit functional and utilitarian descriptors like "durable," "useful," and "cost" at higher ratings, while "bad," "return," and "cheap" indicate a mismatch in expectations. Interestingly, the word "quality" appears in both datasets at every rating level, underscoring its evaluative function. To map the various aspects of practice-based theory, these terms are further examined.

The evidence supporting practice-based theory is revealed by the model's post-processing. The important sub-tokens are presented in Table 17. The sub tokens, along with their p-values, are provided in the table below. The tokens related to ratings 4 and 5 depict experience indicators such as "beautiful", "well", "nice", "look", "comfortable", "like", and "great" as positive attributes of the higher ratings. Along with experience indicators, quality

Table 17 Class-based clean token summary for BERT model in Natural fibre

Rating	Most distinctive clean tokens
1	damaged (0.0287), noise (0.0169), worst (0.0169), thin (0.0168), waste (0.0165), month (0.0157), local (0.0157), option (0.0127)
2	places (0.0160), sent (0.0160), sticks (0.0157), having (0.0149), poor (0.0141), width (0.0133), which (0.0122), chatai (0.0114)
3	high (0.0209), small (0.0197), size (0.0193), narrow (0.0165), cost (0.0161), sitting (0.0161), want (0.0126), average (0.0122)
4	durable (0.0130), quality (0.0128), nice (0.0115), long (0.0114), look (0.0105), thin (0.0096), material (0.0096), like (0.0084)
5	great (0.0184), nice (0.0178), beautiful (0.0150), excellent (0.0121), value (0.0096), comfortable (0.0091), well (0.0091), loved (0.0089)

Table 18 Class-based clean token summary for BERT model in artificial fibre

Rating	Most distinctive clean tokens
1	quality (0.0471), poor (0.0296), waste (0.0251), worst (0.0174), return (0.0114), cheap (0.0107), image (0.0099), even (0.0096)
2	quality (0.0258), image (0.0173), side (0.0148), size (0.0128), cost (0.0121), misrepresentation (0.0103), coloured (0.0103), available (0.0103)
3	colour (0.0363), average (0.0247), price (0.0147), shown (0.0139), ordered (0.0133), glamocracy (0.0120), feet (0.0114), received (0.0086)
4	color (0.0204), decent (0.0193), enough (0.0186), size (0.0179), thickness (0.0125), material (0.0124), choice (0.0120), okay (0.0106)
5	nice (0.0543), value (0.0276), money (0.0160), worth (0.0121), satisfied (0.0118), super (0.0114), beautiful (0.0097), superb (0.0097)

indicators ("durable", "quality" and "value"), and material indicators ("material", "long" and "thin"), these indicators reflect the need for awareness of the essential role of material education. On the other hand, in Table 18, for artificial fibre, the lower ratings are driven by quality indicators ("quality", "poor", "cheap", "Worst") and misinformation indicators ("image", "coloured", "misrepresentation"). These indicators need to be considered while designing the education curriculum.

In contrast, Dataset 1 exhibits stronger experiential language and more sentiment polarisation, while Dataset 2 exhibits more dispersion and ambiguity in mid-range ratings, as indicated by lower macro-level metrics. These findings suggest that consumer assessments are influenced by material-specific usage practices, with natural fibre products being judged on experiential alignment and plastic products on functional dependability.

4.1 Educational implications

It is necessary to identify the practice-based insights while developing the educational implications; in this context, negative reviews of natural fibres are used to show the practice breakdown. Conversely, favourable evaluations show that the practice is aligned. According to Table 14, ratings 1 and 2 are considered negative, and ratings 4 and 5 are considered positive. Now, the tokens associated with ratings 1 and 2, such as "damaged", "thin", "sticks", and "poor", indicate a breakdown in practice due to material dissatisfaction and an expectation mismatch. On the other hand, words associated with high rating, "beautiful", "durable", "nice", "long", "great", "excellent" and "comfortable" reflect successful practice alignment. These observed tokens serve as empirical evidence for PBT by demonstrating the three constructs: material, consumer competencies, and meaning interaction in daily consumption practices.

The discussion above suggests that elements such as material comprehension, practical application, data interpretation, lifecycle comprehension, and expectation alignment should form the foundation of education for young minds. Now, words like "thin," "damaged," and "cheap" indicate that the consumer has a poor understanding of natural material variability, life, and trade-offs in green products. This shows the need for material-level literacy among young minds. The next point in this regard is competence-based usage training. The tokens like "break",

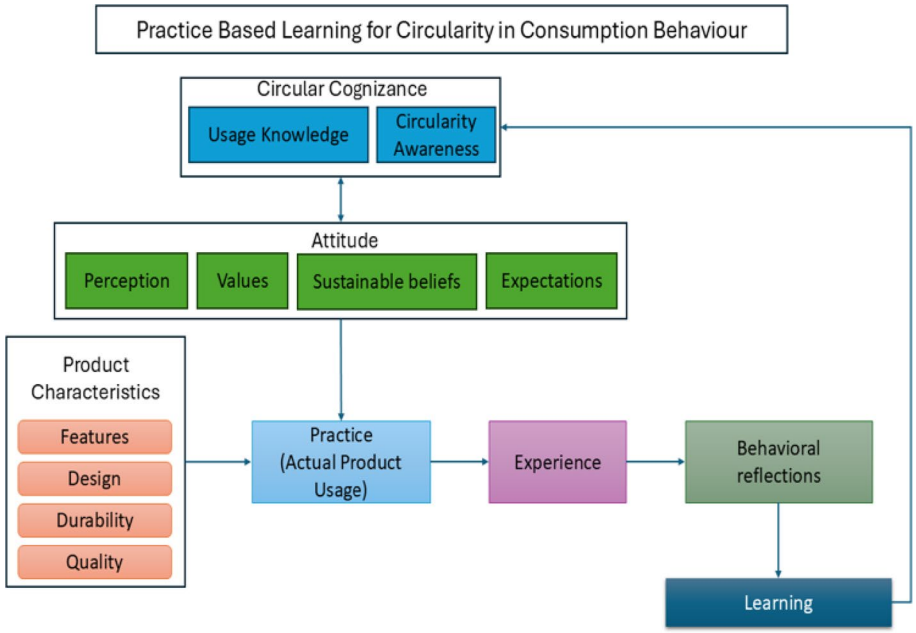

Fig. 8 Conceptual model for practice-based learning for circularity in consumption behaviour

"useless," and "mismatch" indicate improper usage, knowledge, and unrealistic expectations from the green products. The third point is meaning reconstruction, indicated by tokens such as "cheap" and "waste". Often, consumers associate inferiority with sustainability. Hence, there is a need to shift the educational approach from awareness-based lectures to practice-oriented approaches.

Particularly in consumer behaviour, applied analytics, and sustainability education, the data analytics results from the review datasets have significant implications for curriculum design at the undergraduate (UG) and school levels. Knowledge plays a fundamental role in motivating consumers to choose green or eco-friendly products. Hence, this knowledge drives the purchase intention, which serves as the bridge between awareness and sustainable consumption behaviour [27]. The analysis shows that consumer dissatisfaction is primarily driven by mismatches between product characteristics and real-world usage contexts, suggesting that students' comprehension of circular economy concepts must go beyond theoretical awareness to practice-oriented learning.

This means that environmental studies curricula at the school level should incorporate usage-based learning and material literacy. The differences between natural and synthetic materials, including their lifecycle effects, durability, and usability, should be explained to students. Students can learn why natural fibre products may fail due to their fragility and why plastic products may fail due to a mismatch in expectations through practical exercises, such as comparing product performance under various conditions. This practice of experimentation is consistent with the patterns observed in the review data, where low scores are linked to a breakdown in the use practices rather than a lack of environmental concern.

The results emphasise the significance of implementing data-driven sustainability education at the undergraduate level. Students can develop models such as TF-IDF and BERT-based classifiers by analysing real-world datasets, as in this study. As a result, they can develop their analytical and critical thinking skills by connecting behavioural patterns to textual insights [20]. Additionally, because ambiguity in mid-range ratings is reflected in confusion in classification models, the curriculum should include modules on product communication and consumer expectation management.

Figure 8 represents the overall outcome and lessons learned from the present research as a conceptual diagram of practice-based learning for circularity in consumption behaviour. The image summarises the key findings from the data analysis. Product characteristics, such as features, design, durability, and quality, impact product use and shape the experience, which is reflected in user behaviour. These behavioural reflections need to be considered when designing learning stimuli for young minds. A favorable attitude toward the use of sustainable products

may result from the stimuli being applied correctly, indicating knowledge and sufficient awareness of their use. The next section discusses the study's educational implications based on these insights.

5 Limitation

The majour limitation of the research is the timeline of data collection and the number of samples used in the research. The authors understood as the data related to a specific green product is very less in a specific ecommerce website, hence, it need to be included multiple website and multiple products. The timeline should be longer, let's say for 2 to 3 years, to observe the temporal and seasonal variation. Another limitation is that the data is only India-specific, which again bounds the result for a specific group of people. However, this study can be considered general for the Indian subcontinent. The methodological limitation is the consideration of only English reviews and only BERT base model. The model can be extended to more specific RoBERT a or language-specific IndicBERT models. The possible extension based on these limitations is mentioned in the future score under the conclusion and Future work section.

6 Conclusion and future work

This study used machine learning and text analytics techniques to investigate how consumers evaluate products through textual reviews and how these evaluations vary across materially distinct products, such as natural fibre mats and plastic mats. The results offer a complex understanding of consumption behaviour that goes beyond conventional attitudinal or sentiment-based explanations when viewed through the prism of PBT. The findings show that consumer ratings are embedded in situated consumption practices rather than simple statements of satisfaction or discontent. The experiential and aesthetic aspects had a significant impact on the evaluation of natural fibers, with favorable assessments indicating sensory and symbolic value (e.g., "beautiful," "nice") and unfavorable assessments indicating a breakdown of the anticipated durability (e.g., "damaged," "thin"). On the contrary, plastic mats were assessed primarily on functional and utility aspects, with higher ratings for durability and value for money, and lower ratings due to perceived mismatches between expectations and the product's actual performance. The review comments indicate that consumers first consider the utility of the purchased product, and only if it meets the first utility criteria, do they consider sustainability. This clearly reflects the consumer's utilitarian mindset. It indicates that consumers' mindsets need to be familiarized with sustainable products. The observed dataset reflects this biased sentiment distribution for the sustainable products, i.e., natural mat.

The machine learning findings further support this interpretation. The concentration of incorrect classifications around nearby rating categories (e.g. 4–5 and 3–4) shows that rather than at clear categorical boundaries, consumer judgments fall along a continuum of practice alignment. This implies that classification errors reflect the inherent ambiguity in how consumers perceive and describe product use in everyday contexts rather than being solely due to algorithmic limitations.

One significant finding from this research is that consumers' lack of awareness of environmental issues is less of a barrier to the adoption of circular products than the discrepancy between product features and real usage habits. While consumers are sceptical of plastic products' authenticity and consistency of quality, natural fibre products face primarily perceived fragility-related difficulties. The manufacturers of natural fibre mats may carefully apply the analytical results of this study to develop appropriate strategies and obtain a competitive edge over manufacturers of synthetic mats. However, the use of machines in the production of synthetic goods makes the competition difficult. Because they use machines, their products are less expensive than hand-made products. Manufacturers of machine-made goods can easily reduce costs by quickly achieving scale. However, the issue of achieving scale for natural products may also be largely resolved as awareness of the benefits of natural products over artificial, environmentally harmful plastic or synthetic goods grows. In essence, raising consumer awareness

or potential consumers about natural and artificial fibres, sustainable products, and related issues will gradually create an ecosystem for the production and use of natural handmade goods in place of artificial, environmentally harmful ones.

In conclusion, the present study advances theory and practice by showing how well products fit into lived practices has a fundamental impact on consumer assessments and, consequently, sustainable product adoption. Therefore, rather than relying solely on normative sustainability appeals, it is crucial to design and communicate products that align with users' everyday routines, expectations, and experiential realities to advance circular economy transitions.

As mentioned in the limitations section, this study can be extended over a broader timeline, as per data collection, enabling the same model to capture temporal or seasonal variation in usage behavior. Also, multiple sustainable green products need to be considered to detect the exact sentiment variation across product variety and usage requirements. As India is a country of various languages the model, so, IndicBERT or any other transformer architecture need to be considered for refined result. Another scope is considering demographic information within the same model to improve sentiment prediction. These considerations will open up new avenues for more possible insights related to the sustainable product usage behavior and circular practices.

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Author contributions P.B. supervised entire study and helped in preparing the manuscript. D.B. and H.M. designed the methodology and performed the data analysis. A.G. and D.P. collected the data and helped in data analysis. All authors contributed in manuscript writing and revising for its' quality improvement.

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Data availability The data were confidential, and the authors chose not to share them. However, it will be shared on the basis of requests.

Declarations

Conflict of interest The authors declare no conflicts of interest regarding this research.

Uses of AI We confirm that we have used AI tools for enhancing and proofreading, including grammar checking. These tools have not been used to generate original academic content, research outlines, perform analysis, or interpret research findings.

Ethics, Consent to Participate, and Consent to Publish declarations not applicable.

Competing interest The authors declare no competing interests.

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References

1. Anas M, Sultan MU, Arzoo A, Nasir UA, Amin JHJ. Environmental sustainability awareness, attitude and practices in dental education and clinical practices in Pakistan. Discover Sustain. 2026;7(472). https://doi.org/10.1007/s43621-026-02872-z.
2. Banerjee SB, Morley C. Professional doctorates in management: Toward a practice-based approach to doctoral education. Acad Manage Learn Educ. 2013;12(2):173–93. https://doi.org/10.5465/amle.2012.0159.
3. Barbosa MW, Gomes A. Themes and sentiments in conversations about food waste on Twitter: Proposal of a framework using neural topic modeling. Food Qual Prefer. 2025;122:105311. https://doi.org/10.1016/j.foodqual.2024.105311.
4. Bespalyy S, Alnazarova G, Scalcione VN, Vitliemov P, Sichinava A, Petrenko A, Kaptsov A. Sustainable development awareness and integration in higher education: A comparative analysis of universities in Central Asia, South Caucasus and the EU. Discover Sustain. 2024;5(346). https://doi.org/10.1007/s43621-024-00562-2.
5. Bhavikatta NB. The impact of predictive and prescriptive big data analytics on sustainable product development through technological innovation in manufacturing SMEs. Prod Manuf Res. 2026;14(1). https://doi.org/10.1080/21693277.2026.2618335.
6. Burger M, Stavropoulos S, Ramkumar S, Dufourmont J, van Oort F. The heterogeneous skill-base of circular economy employment. Res Policy. 2019;48(1):248–61. https://doi.org/10.1016/j.respol.2018.08.015.
7. Buyukyazici D, Quatraro F. The skill requirements of the circular economy. Ecol Econ. 2025;232:108559. https://doi.org/10.1016/j.ecolecon.2025.108559.
8. Castro-Lopez A, Iglesias V, Santos-Vijande ML. Organizational capabilities and institutional pressures in the adoption of circular economy. J Bus Res. 2023;161:113823. https://doi.org/10.1016/j.jbusres.2023.113823.
9. Catelli R, Pelosi S, Esposito M. Lexicon-based vs. BERT-based sentiment analysis: A comparative study. Electronics. 2022;11(3):374. https://doi.org/10.3390/electronics11030374.
10. Devlin J, Chang MW, Lee K, Toutanova K. BERT: Pre-training of deep bidirectional transformers for language understanding. NAACL. 2019. https://doi.org/10.18653/v1/N19-1423.
11. Feldman M, Worline M. The practicality of practice theory. Acad Manage Learn Educ. 2016;15(2):304–24. https://doi.org/10.5465/amle.2014.0356.
12. Gardazi NM, Daud A, Malik MK, et al. BERT applications in natural language processing: a review. Artif Intell Rev. 2025;58:166. https://doi.org/10.1007/s10462-025-11162-5.
13. Ghosh A, Pathak D, Bhola P, Bhattacharjee D, Sivarajah U. Analysing product attributes of refurbished laptops based on customer reviews and ratings: machine learning approach to circular consumption. Ann Oper Res. 2025;355(2):1727–49. https://doi.org/10.1007/s10479-023-05758-9.
14. Gisev N, Bell JS, Chen TF. Interrater agreement and interrater reliability: key concepts, approaches, and applications. Res Social Administrative Pharm. 2013;9(3):330–8. https://doi.org/10.1016/j.sapharm.2012.04.004.
15. Hibbert P, Siedlok F, Beech N. The role of interpretation in learning practices in the context of collaboration. Acad Manage Learn Educ. 2016;15(1):26–44. https://doi.org/10.5465/amle.2014.0004.
16. Huang P, Wright AL, Middleton S. How material objects shape student team learning processes. Acad Manage Learn Educ. 2022;21(1):35–60. https://doi.org/10.5465/amle.2020.0025.
17. Jim JR, Talukder MAR, Malakar P, Kabir MM, Nur K, Mridha MF. Recent advancements and challenges of NLP-based sentiment analysis: A state-of-the-art review. Nat Lang Process J. 2024;6:100059. https://doi.org/10.1016/j.nlp.2024.100059.
18. Kamal MM, et al. Immediate return in circular economy. J Bus Res. 2022;151:379–96. https://doi.org/10.1016/j.jbusres.2022.06.021.
19. Karaca F, Tleuken A, Pineda-Martos R, Ros Cardoso S, Orel D, Askar R, Agibayeva A, Güemez EG, Salles A, Varol HA, Bragança L. Cultivating sustainable construction: Stakeholder insights driving circular economy innovation for inclusive resource equity. Buildings. 2024;14(4):935. https://doi.org/10.3390/buildings14040935.
20. Khare VK, Verma P, Tewari M, Hasan A. Scale Development for Assessing Awareness, Attitudes, and Practices of Indian Knowledge Systems. Res J Translation Literature Linguistics Educ. 2026;2(1):20–33. https://doi.org/10.64120/tpxgxy32.
21. Kvasnička R, Kvasničková Stanislavská L, Balsalobre-Lorente D, Huseynova R, Pilař L. A systematic analysis of twelve years of circular economy communication. Cogent Bus Manage. 2026;13(1):2609931. https://doi.org/10.1080/23311975.2025.2609931.
22. Leung XY, Yang Y. Are all five points equal? Scaling heterogeneity in hotel online ratings. Int J Hospitality Manage. 2020;88:102539. https://doi.org/10.1016/j.ijhm.2020.102539.
23. Loon M. Practices for learning in early careers. Acad Manage Learn Educ. 2021;20(2):182–202. https://doi.org/10.5465/amle.2019.0019.
24. Lundberg SM, Lee S-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765–4774. https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html

25. Mersha MA, Kalita J. Explainable AI: Context-aware layer-wise integrated gradients for explaining transformer models. Neurocomputing. 2026;133050. https://doi.org/10.1016/j.neucom.2026.133050.
26. Nadeau C, Bengio Y. (1999). Inference for the generalization error. Advances in neural information processing systems, 12. https://proceedings.neurips.cc/paper_files/paper/1999/hash/7d12b66d3df6af8d429c1a357d8b9e1a-Abstract.html
27. Nguyen QTK, Doan TAL. The role of green self-identity in enhancing green purchase intention and sustainable consumer behaviors. Discover Sustain. 2026;2026. https://doi.org/10.1007/s43621-026-02597-z.
28. Patwa N, et al. Towards a circular economy. J Bus Res. 2021;122:725–35. https://doi.org/10.1016/j.jbusres.2020.05.015.
29. Pookduang P, Klangbunrueang R, Chansanam W, Lunrasri T. Advancing sentiment analysis: Evaluating RoBERTa against traditional and deep learning models. Eng Technol Appl Sci Res. 2025;15(1):20167–74. https://doi.org/10.48084/etasr.9703.
30. Raelin JA. Toward an epistemology of practice. Acad Manage Learn Educ. 2007;6(4):495–519. https://doi.org/10.5465/amle.2007.27694950.
31. Reckwitz A. Toward a theory of social practices: A development in culturalist theorizing. Eur J social theory. 2002;5(2):243–63. https://doi.org/10.1177/13684310222225.
32. Shove E, Pantzar M, Watson M. The dynamics of social practice: Everyday life and how it changes. SAGE Publications Ltd; 2012. https://doi.org/10.4135/9781446250655.
33. Singh R, Sharma G, Dixit A, Hasan A. (2026). Future of MSMEs With Digitally Matured Vision. In AI, Virtualization, and the Future of Marketing (pp. 29–70). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3373-8142-8
34. Testa F, Iovino R, Iraldo F. The circular economy and consumer behaviour. Bus Strategy Environ. 2020;29(8):3435–48. https://doi.org/10.1002/bse.2587.
35. Tewari M, Hasan A, Khare VK, Suhail M. (2026). Understanding the Power of Augmented Reality in Insurance: A Survey-based Approach to Customer Engagement. https://doi.org/10.1108/978-1-80592-551-420261005
36. Tleuken A, Orel D, Iskakova A, Varol HA, Karaca F. Exploring stakeholders' opinions on circular economy in the construction sector: A natural language processing analysis of social media discourse. J Ind Ecol. 2024;28(4):853–67. https://doi.org/10.1111/jiec.13502.
37. Zdonek I, Podgórska M. Zero waste trends in consumption: Demand-side insights through social media analysis. Qual Quant. 2026;60:2939–71. https://doi.org/10.1007/s11135-025-02378-2.

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