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Harnessing Generative AI for Sustainable Supply Chains: Lean, Circular and Green Perspectives

Ashutosh Singh[1] | Rsha Alghafes[2] | Judit Petra Koltai[3] | Sushant Kumar Vishnoi[4]

[1]Leeds University Business School, University of Leeds, Leeds, UK | [2]Department of Management, College of Business Administration, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia | [3]Department of Statistics, Finance and Controlling, Széchenyi István University, Győr, Hungary | [4]Institute of Management Studies (IMS) Ghaziabad, Ghaziabad, Uttar Pradesh, India

Correspondence: Ashutosh Singh (a.singh1@leeds.ac.uk)

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ABSTRACT

Generative artificial intelligence is playing a significant role in the transformation of digital ecosystems by reinventing the processes of content generation, process automation, product innovation and customer experience. At the same time that these technologies are becoming more integrated into routine operations, the focus has shifted to the ethical and environmental consequences associated with their widespread application. An investigation of the operational sustainability associated with the generative artificial intelligence systems would be crucial, as it would provide information about how these systems match ideals such as efficiency, circularity and environmental responsibility. We explore how users understand and engage with sustainability principles, specifically lean, circular and green operational frameworks within generative artificial intelligence environments. We collect user reviews of 72 recently launched generative AI platforms from 2022 to 2024 and utilise advanced machine learning methods, including Word2Vec modelling, sentiment and regression analysis, to reveal how text datasets reflect customer perceptions. We find that the lean theme is the most prominent feature of operational sustainability, with the highest sentiment score, followed by the green and circular themes. Our findings show that there is a growing respect among the general public for artificial intelligence systems that exhibit responsible and efficient design.

1 | Introduction

The emergence of generative artificial intelligence (AI) has initiated a major change in the methods through which users and enterprises generate content, automate communication processes and accelerate decision-making (Ooi et al. 2025). A wide range of professional tools is advancing exponentially due to AI's capabilities, as it enables high speed, creativity and personalization. Hence, firms started adopting these technologies in routine workflows, causing a fundamental shift in the manner in which tasks are carried out in several industries (Budhwar et al. 2023). However, the usage of energy consumption and data storage grows due to the extensive use of generative AI technologies, which may create challenges to digital sustainability. Additionally, with generative AI systems gaining greater independence, questions related to transparency and embedded algorithmic bias are surfacing more frequently (Rai et al. 2019). As a result, the implementation of generative AI is not only a technological advancement; rather, it is a sociotechnical transformation that necessitates an in-depth analysis of the wider societal, environmental and organizational repercussions that it will have (Broccardo et al. 2025).

Within discussions on digital transformation, the notion of *operational excellence*, originally grounded in manufacturing and supply chain optimisation, has progressed to include considerations of digital-technology performance, ecological sustainability and moral consequences of digital systems, including generative AI. With generative AI becoming further integrated into business operations, researchers and practitioners are increasingly applying sustainability-oriented operational frameworks to determine the extended worth and implications of generative AI tools. More specifically, there are three principles under operational sustainability: lean, green and circular. The lean theme emphasises maximising efficiency and minimising waste (Knol et al. 2022). The green theme centres on reducing environmental harm and promoting responsible resource use (Khanra et al. 2022). The circular theme encourages designing products in ways that allow for reuse and long-lasting product cycles (Mangla et al. 2024). These principles provide a multifaceted lens for evaluating gen AI systems in terms of technical performance and user value with respect to broader aims such as digital sustainability, ethical innovation and social accountability (Awan et al. 2021). It is possible for organisations to ensure that the deployment of generative AI leads to long-term systemic resilience rather than short-term gains if they integrate approaches such as lean, circular and green thinking.

Currently, the majority of firms discuss their plans associated with operational efficiency and sustainability in their daily activities, but users' perceptions of these priorities are not well understood. Hence, it is crucial to investigate customer sentiments because people increasingly incorporate this advanced technology into daily workflows and decision-making processes. The growing popularity of user-generated content, which includes online reviews, feedback and ratings, provides a significant data source that may be utilised for the purpose of analysing these perceptions on a larger scale. Recent developments in natural language processing (NLP) have made it possible to conduct a more efficient analysis of this unstructured text (Bhandari et al. 2022; Trappey et al. 2021). Correlating language-based indicators with platform behaviour enables exploring the association between operational value perceptions and user engagement, which can provide actionable implications.

While prior studies shed light on user-centred dimensions of generative AI and operational sustainability (Singh et al. 2025; Zhou et al. 2025), they have largely overlooked how these perspectives integrate with real-world user discussions. Contemporary research recognises that generative AI can promote lean, circular and environmentally friendly practices (Maghroor et al. 2025); however, it predominantly emphasises organisational applications and technical outcomes (Prasad Agrawal 2025), rather than user perceptions, expressions and assessments of these sustainability-oriented attributes. Research on user-generated content has shown that it is useful for looking at patterns of sentiment and engagement, but it does not often look at how themes of operational sustainability show up in user language or how these themes connect to how users see the value of a platform. Consequently, the relationship between sustainability-focused operational signals in user reviews and the perceived value of generative AI systems is still inadequately examined. No current research amalgamates lean, circular and green principles within a linguistic analysis framework to forecast perceived value, nor does it examine the role of sustainability-related terminology as indicators of value co-creation in generative AI platforms. This gap is important because generative AI is being adopted quickly, and people are expecting digital technologies to be responsible for both their performance and their impact on society and the environment. Addressing this gap offers a timely opportunity to enhance both sustainability-focused operations research and user behaviour literature by empirically examining how users incorporate sustainability cues into their evaluations of generative AI tools. We focus on the research question below:

> *Research Question:* To what extent do operational sustainability themes in user language predict perceived value of generative AI platforms?

We use comprehensive data of user reviews from 72 generative AI platforms launched since 2022. The study leveraged Trustpilot reviews, using both rating metrics and the accompanying textual narratives to analyse users' feelings and evaluations of value. We employ the Word2Vec machine learning method to identify terms for the three themes related to operational sustainability. We also perform sentiment and regression analyses to identify the sentiments with respect to the terms obtained in the three themes. The analysis reveals that lean-related themes are the most frequently mentioned and carry the highest average sentiment (0.77). This is closely followed by the green values with a sentiment of 0.75, and circular values with a slightly lower sentiment of 0.64 from the general public. Taking into consideration these data, it appears that consumers not only recognise but also positively respond to elements in generative AI platforms that are focused on sustainability. This study enhances theory, methodology and practice by illustrating how sustainability-oriented user language influences value perceptions of generative AI platforms. From a theoretical perspective, our research suggests that users help build the value of AI platforms through co-creation with more emphasis on operational sustainability in the realm of digital services. Methodologically, the study enhances research on user-generated content by incorporating machine learning, natural language processing and econometric modelling to extract and quantify sustainability themes from extensive unstructured text, providing a scalable and rigorous framework for analysing socio-technical interactions. The findings provide useful guidance for platform designers, managers, business leaders and regulators, demonstrating that users appreciate lean and green elements, but circular characteristics are limited in visibility. Providing clear insight into energy usage and incorporating sustainability into product creation can help build user confidence and encourage responsible AI progress.

The rest of the manuscript is structured as follows: We provide the literature review in Section 2. The methodology, which contains the sample description and analysis, is reported in Section 3. Section 4 provides the interpretation of the results. We provide a discussion of the results in Section 5. Section 6 contains the conclusion, where we also explain implications and research limitations.

2 | Literature Review

The growing presence of generative AI in both industrial and service sectors led to a reassessment of how novel digital technologies align with socially and environmentally conscious innovation frameworks. The impact of generative AI surpasses simple efficiency gains as it is now positioned as a central functioning tool for idea generation, design thinking and task execution, and demands reflection on its broader impact on society and the environment (Bag et al. 2021, 2024). There is a growing scholarly consensus that the adoption of AI technologies with sustainable methodologies like lean production, environmental technologies and circular economies can ensure long-term benefits (Bashynska and Prokopenko 2024; Lin 2024). Generative AI is emerging as a transformative force in sustainable supply chains by enabling technologies that forecast demand, optimise stock levels and mitigate supplier risk, resulting in lower carbon footprints and minimised waste (Rane et al. 2025). Prior studies also suggest that advanced intelligent technologies are enhancing closed-loop supply chains, fostering traceability and openness while ensuring alignment with environmental and social governance frameworks (Hao and Demir 2024). This integrative perspective reflects a transition from perceiving generative AI as merely a technical tool to recognising it as a socio-technical force that influences user conduct, transforms institutional practices and balances between operational gains and sustainability goals. The research also suggests the importance of governance mechanisms and sustainable innovation ecosystems in shaping AI design and implementation, which can align generative AI's trajectory with the imperatives of responsible innovation and global sustainability (Secundo et al. 2024). Within this scholarly conversation, researchers also emphasise the importance of operational sustainability models, offering critical insights into the societal value and risks associated with intelligent technologies (Costa et al. 2024).

2.1 | Generative AI and Operational Sustainability

Adopting generative AI in business processes creates new pathways for advancing operational sustainability. Recent research indicates the efficiency of AI in streamlining digital workflows to strengthen sustainable practices. For instance, AI systems support lean methodologies like reducing complexity, automation and limiting errors because they learn from real-time behaviour (Luqman et al. 2024; Shahin et al. 2024). AI technology provides seamless and user-friendly services to consumers and supports sustainability by reducing resource usage. The AI platforms leverage ongoing feedback cycles for training and support the circular economy strategies by prioritising the renewal of digital assets and alignment across industries (Magas and Kiritsis 2022; Wang and Zhang 2025). Generative AI enables the reuse of digital resources across different contexts, minimising repetitive work and amplifying their value. In parallel, there is increasing awareness of the environmental costs associated with the ecological footprint of the digital infrastructure required for AI systems (Battisti et al. 2025; Wu et al. 2022). Large-scale machine learning models' training and testing process requires major energy usage, leading to carbon emissions, which draw attention to green AI (Alzoubi and Mishra 2024). Although sustainable AI design is gaining attention, awareness among users about its ecological effects remains low. The computational load of recent generative AI-powered tools like resume builders and writing assistants is often invisible to users, making it difficult to factor in their ecological impact. As a result, users rarely factor sustainability into their decisions, pointing to the need for research into how clearer sustainability indicators could influence behaviour and encourage sustainable generative AI development.

2.2 | User-Centred Views on AI Utility

Scholars now frequently analyse user-created content to gauge how AI is adopted and trusted and its overall influence. Online reviews have emerged as a valuable resource for detecting underlying sentiments related to satisfaction and value judgments (Chen et al. 2024; Ullah et al. 2016). Prior literature uses NLP techniques, such as Word2Vec, to determine the impact of semantic relationships on consumers' engagement levels (Zhang et al. 2024). Sentiment analysis has primarily centred on emotional cues, but less focus has been on how operationally themed language can predict user satisfaction with AI tools. Hence, it is more beneficial to move beyond sentiment analysis and use advanced-level NLP methods to explore the trends that are overlooked in customer reviews. Analysing terms from users' reviews associated with operational sustainability allows us to assess the gap between what users expect and what AI delivers.

Our study is based on the understanding that user expression is not limited to emotional or experiential dimensions and is deeply connected to operational dynamics. By creating a bag of words associated with lean, circular and green themes and relating them to customer ratings, we address a significant yet underexplored area in the literature: the link between how users articulate sustainability and overall value judgments. While previous research on AI systems has primarily focused on technical dimensions, it talks a little about how users articulate their assessments of broader values, particularly sustainability, through their own words. As per our review of the literature, no prior study has thoroughly investigated how machine learning methods reveal embedded views of sustainability-oriented operational quality or how these perceptions correlate with value evaluations.

We select the lean, green and circular themes of operational sustainability due to their increasing dominance in the operations management and sustainability literature. These themes are considered central pillars to achieve operational sustainability (Alkaraan et al. 2024). The lean paradigm focuses on continual improvement, waste reduction and efficient processes, whereas the green paradigm signals enhancing eco-efficiency and minimising the negative environmental impact (de Oliveira Rezende et al. 2022). As a rapidly emerging paradigm, the circular economy goes beyond efficiency and compliance by fostering regenerative practices, closed-loop systems and life cycle thinking (Khan 2024). Recent research studies integrate these three themes to show that they encompass much of the discourse on sustainable operations and supply chains (Benabdellah et al. 2024). The convergence of these themes encompasses a large portion of the sustainable operations and supply chain discourse, forming a robust yet succinct basis for empirical research. We apply this reasoning to generative AI, as these systems increasingly undertake operational roles, such as workflow optimisation, resource allocation, task automation and digital asset reutilization, rendering lean, green and circular particularly adept at encapsulating how users implicitly assess the efficiency, environmental stewardship and regenerative value of AI-driven services (Salih et al. 2025). Alternative sustainability frameworks (e.g., Triple Bottom Line or Sustainable Development Goals) are broader or institutional-level constructs. Lean, green and circular, on the other hand, directly relate to how generative AI systems work in practice, so they can be seen in how users interact with them and what they say. This makes them conceptually similar and easy to see in user-generated reviews.

Our conceptualisation is based on *value co-creation theory* (Galvagno and Dalli 2014), which emphasises that value is jointly created through dynamic exchanges between users and systems. Thus, users leverage their engagements and insights to shape value from the AI platforms. The user-generated content serves as one of the clearest and most accessible mediums through which the co-creation process unfolds (Koivisto and Mattila 2020). When users describe the AI system as efficient and eco-friendly, they contribute to the context-driven construction of value. The investigation of users' reviews on lean, circular and green concepts reveals how users engage in co-creating sustainability value. The linguistic cues for the textual datasets show how users assess operational characteristics along with the technical functionality. This process provides new avenues to the value co-creation model by showing that perceived value stems from both operational usefulness and sustainable business practices. Thus, in the context of generative AI platforms, lean, green and circular themes are clear signs of value co-creation that is focused on sustainability. The investigation of the user-generated content serves as a critical conduit for assessing the functional performance of the platform and sustainability-oriented expectations.

The prior value co-creation literature suggests its capability to explain value generation through digital and AI ecosystems. Previous researchers suggest that users' feedback is crucial for enhancing the value of platforms through experiential learning (Zhu et al. 2024). Digital platforms exhibit co-creation when users share experiential input, identify enhancement opportunities and voice expectations regarding system outcomes (Lei et al. 2022; Rubio et al. 2021). Studies also show that co-creative participation makes people trust intelligent systems more, want to use them more, and think that they are more useful (Rezwana and Maher 2023). When users convert themselves from passive receivers of service value to active architects of the system, the co-creation in AI environments started getting materialised (Babar et al. 2025). The existing literature indicates that co-creation is beyond a functional construct and also contains sustainability concerns, consistent with users' expectations for socially accountable AI systems (Lemke and Monett 2024). The prior research findings indicate that value is continuously formed through users' evaluative perceptions and participatory behaviours. This underscores that generative AI platforms will succeed in the long run only if they incorporate user-driven expectations into system design and outcomes. To translate the theoretical discussion into empirical investigation, the next section presents the methodological framework applied to analyse the relationship between sustainability-laden user language and value perceptions of generative AI platforms.

3 | Methodology

We use a mixed-methods quantitative text mining strategy to examine the impact of operational sustainability narratives, specifically lean, green and circular, present in user-generated language, on the perceived benefits of generative AI platforms (Singh et al. 2022). The study integrates methods from natural language processing, unsupervised machine learning, sentiment analysis and statistical inference to detect underlying trends and assess predictive relationships in sustainability and tech adoption frameworks. The research design is structured into four interconnected stages.

3.1 | Data Collection and Preprocessing

We collect the customer reviews of 72 generative AI platforms (Table 1), which have been launched from 2022 onwards. These platforms cover a broad spectrum of cases from content creation (e.g., Copy.ai, Jasper AI) and resume development (e.g., Resume.co, Kickresume) to visual media (e.g., Midjourney, Leonardo AI), synthetic voice/video (e.g., ElevenLabs, Heygen) and business tools (e.g., Reply IO, Zocket). Each platform is classified according to its primary function, including content generation, creative design, automated marketing and intelligent productivity solutions.

These generative AI platforms are selected for their ability to integrate operational sustainability goals, particularly those centred on lean (efficiency, waste minimisation), green (environmental and digital resource efficiency) and circular (reuse, regeneration and lifecycle optimisation) frameworks. By promoting digital reuse, automating redundant workflows and decreasing environmental costs, many of these tools embody core sustainability values. Hence, these generative AI platforms offer a meaningful lens for analysing how sustainability is woven into system capabilities and user-authored content. To gather user insights, user perspectives were captured through reviews collected on Trustpilot, a widely used site for collecting user-generated evaluations. Trustpilot offers both numerical star ratings and qualitative written reviews, making it an ideal source for combining numerical data with rich, user-generated narratives. Importantly, user feedback often touches on practical concerns such as time efficiency, resource optimisation, reusability and environmentally conscious use, all of which align with lean, green and circular values. The resulting dataset covers an extensive set of customer reviews, which is capable of providing meaningful insights that align closely with the objectives of this study. It establishes a strong basis for analysing the role of sustainability narratives in shaping user sentiment and value perception. This approach lays an empirical groundwork for analysing the relationship between generative AI and sustainability in evolving technological contexts.

The final dataset of user-generated reviews from all the generative AI service-providing platforms consists of 35,449 observations from 2022 to 2024. However, there could be some reviews that are different from normal patterns, such as spam, excessively short/long, repeated, or syntactically incoherent reviews. These deviated reviews may lead to biased outcomes. Hence, we use an unsupervised machine learning algorithm,

TABLE 1 | List of AI platforms.

Generative AI platforms				
Adcreative	B2 AI	Hix AI	Miro	Smodin
AI Apply	Beautiful AI	Home Designs AI	Netus AI	Speechify
AI Camp	ChatGPT	Imagen	Open AI	StealthGPT
AI Invideo	Claude AI	Instantly	Optionsalgo	Undetectable AI
AI Nero	Copy.ai	Jasper AI	Originality	Videoproc
AI Pro	Coursiv	Junia	Outlier AI	WordTune
AI Signals	Debutify	Kickresume	Pareto AI	Write Sonic
AI4chat	Deepl	Leonardo AI	PFPMaker	Zocket
AISEO	Deepswap	Leya AI	Phrasely AI	
Akool	Designs AI	Logome	Pictory	
Aminos AI	Docus AI	Madgicx	QuillBot	
Anyword	Dovly AI	Magic Fit AI Trainer	Reply IO	
Appen	ElevenLabs Voice	Micro1	Resume.co	
Assignment gpt	Fliki AI	Midjourney	Scribba	
Authority AI	Glitching AI	Miko	SEO Writing	
Autowriter	Heygen	Minea AI Dropshipper	Sintra AI	

Isolation Forest, for anomaly detection and isolating those anomalies through random partitioning (Cui et al. 2024). The Isolation Forest method calculates an anomaly score using the average path length and filters the unusual entries from the customer reviews dataset. The method is quite efficient with high-dimensional and unstructured datasets like customer reviews because it does not follow any specific distribution to scale large datasets. We use the contamination parameter to draw the line between normal and anomalous cases (Luan et al. 2021). The adjusted n_estimators parameter gives stable and consistent results but not so many as to slow computation unnecessarily (Al-Shehari et al. 2023). Finally, the max_samples parameter is utilized to limit the size of the subsample used for each tree by locating sparse or extreme values in our customer reviews dataset (Kumar et al. 2025). The selection of these crucial parameters ensures that we replicate our approach and make it more suitable for the characteristics of the review data.

Figures 1 and 2 show the visualisation of spotting and removing irregularities from the dataset. Figure 1 displays a t-SNE plot that simplifies the high-dimensional data into a two-dimensional space. The grey-coloured dots show normal data, and the green-coloured dots show the outliers. The visualisation plot helps in verifying anomaly detection, which is distributed in the space along with the normal data. The distribution of outliers lies on the edges or in sparsely populated areas, confirming the effectiveness of the detection approach in identifying unusual cases. In Figure 2, the x-axis shows the anomaly score, and the y-axis shows the density of observations. The plot shows a noticeable gap near the anomaly score of 0.60, which helps in splitting the distinct boundary between normal and outlier data. This clear separation justifies the use of a cut-off score to separate the normal and anomalous observations. The dataset is reduced to 24,378 observations after removing the outliers from the original dataset. We use these observations for further analysis.

The next task is to perform the clustering analysis with the final dataset obtained after the isolation forest method. Clustering is a core unsupervised machine learning technique that arranges related data points without requiring prior class assignments. There are several techniques of clustering, and they have distinct advantages. Techniques such as k-means, lower intracluster variance Partition, etc., are partition-based methods, which assign points to the closest centroid and offer scalable solutions (Karapiperis and Verykios 2025). Hierarchical clustering forms a dendrogram resembling a tree of nested clusters, which can be divided at different granularity levels, making it great for exploratory analysis (Karna and Gibert 2022). Methods based on probability distributions like Gaussian Mixture Models (GMMs) calculate cluster membership probabilistically, enabling soft cluster assignments (Scrucca 2025). Density-based methods like DBSCAN are noise-tolerant and detect clusters of various shapes by pinpointing regions of high point concentration (Hanafi and Saadatfar 2022). Researchers can detect multiple topics based on word co-occurrences using the topic modelling method like Latent Dirichlet Allocation (LDA), which combines text datasets into meaningful topics (Benita and Srinivasan 2024; Singh et al. 2025; Yang et al. 2024). However, LDA and bag-of-words techniques focus primarily on frequency counts, ignoring the meaning-based relationships between words. This is where Word2Vec provides a significant edge by generating low-dimensional word embeddings to predict nearby words from a target, revealing robust semantic ties (Shrivastav and Bag 2024; Wang and Li 2024). The positioned words of similar contexts in the embedding space are clustered together using k-means based on meaning rather than just co-occurrence. Focusing on

FIGURE 1 | Visualisation of outlier detection.

our framework of operational sustainability themes like lean, green and circular, we are certain that Word2Vec is more efficient in providing semantically consistent clusters based on the context. This semantic sensitivity produces more insightful clusters, reduces sparsity and boosts interpretability compared to LDA or TF-IDF techniques, establishing Word2Vec as the most effective tool for analysing unstructured review data and uncovering latent sustainability-oriented themes in user conversations. Hence, we employ the Word2Vec method to perform our analysis.

3.2 | Semantic Embedding and Clustering

After removing outliers, we preprocess the text data and generate a document-term matrix representing a tokenized dataset (Crocco et al. 2024; Kilimci and Akyokus 2018). We use a skip-gram model of the Word2Vec method, which uses the following objective function (Akbar et al. 2022):

$$\delta_{\text{skipgram}} = \frac{1}{L} \sum_{t=1}^{L} \sum_{-c \leq k \leq c, j \neq 0} \log P\left(\frac{S_{t+k}}{S_k}\right) \tag{1}$$

Equation (1) shows the log-likelihood of the skip-gram objective function, where c is the context window size, and the objective is to maximize the context words (S_{t+k}) for a given focal word (S_k). The function on the right-hand side in Equation (1) is called the softmax probability function, shown in Equation (2). This equation expresses the probability of a context word conditioned on a target word, which is influenced by the dot product of their vectors.

$$P\left(\frac{S_{t+k}}{S_k}\right) = \frac{\exp(y_{n0} \times y_{n1})}{\sum_{n=1}^{T} \exp(y_{n0} \times y_{n1})} \tag{2}$$

We configure the Word2Vec model for a 100-dimensional embedding space and provide a context window of five words. This setting generates 100-dimensional embeddings for each corpus, reflecting the semantics of its neighbouring words. Following the embedding process, we perform K-means clustering to group semantically similar words. K-means clustering is an unsupervised machine learning method, which uses centroid distance to partition the words into specific clusters (Xi et al. 2023). After performing the clustering, we conduct a manual keyword anchoring to examine the most indicative terms in each cluster and assign meaningful thematic labels. We find three dominant operational sustainability themes: lean—reflecting streamlined and performance-focused processes, green—emphasizing environmentally conscious digital practices, and circular—indicating flexibility and resource recirculation. We categorize all words under one of the three themes for the deeper exploration of language patterns related to operational sustainability in

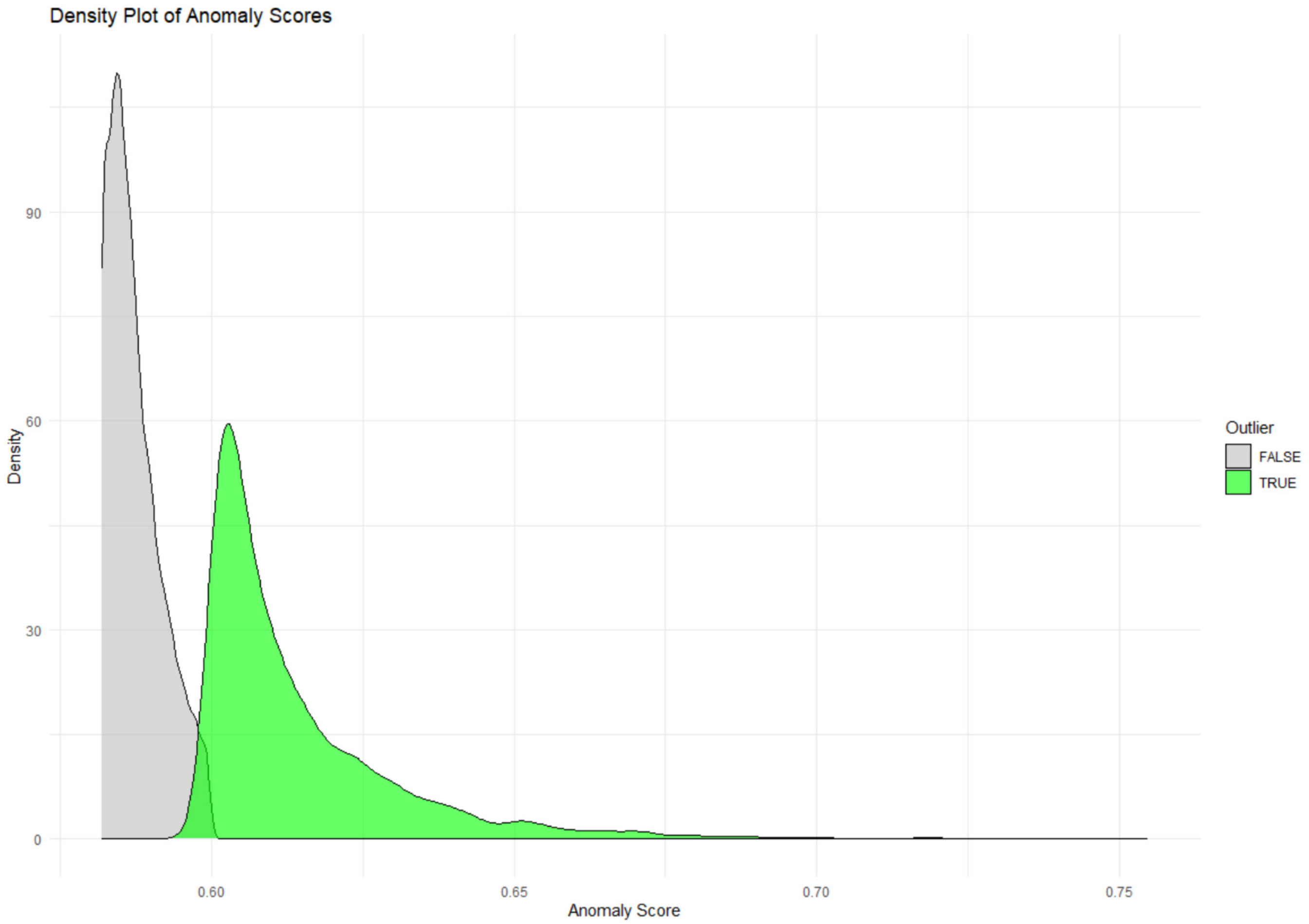

FIGURE 2 | Density plots of anomaly scores.

user-generated content. Figure 3 shows the Word2Vec clustering results, categorizing terms into operational sustainability themes through unsupervised algorithms and dimensionality reduction.

It is crucial to clarify that the clustering approach applied here is a theoretically informed procedure, which is not associated with exploratory topic modelling. Based on existing literature, lean, green and circular are set as a priori themes, and Word2Vec is used to embed words in a semantic space to cluster contextually similar terms. The clusters are then matched with the three pre-established themes to ensure consistency with the theoretical framework. This method focuses on computational similarity measures for clustering, which avoids the need for subjective judgment to form clusters, additional manual coding or inter-rater validation. Word2Vec helps capture semantically meaningful word associations and provides a solid representation of themes within the dataset.

3.3 | Sentiment Analysis

The goal of the sentiment analysis is to explore the emotional sentiments linked to each sustainability theme—lean, green and circular—as expressed in users' feedback. We use the *sentimentr* package of R-Studio, which offers fine-grained scoring by considering context, modifiers and negations (Majumdar 2021). After creating clusters of words for the three themes, we use the built-in lexicon of R-Studio to classify the sentiment associated with each word. These insights are essential for evaluating how generative AI is perceived in supply chains, which can bridge the gap between technical functions and user sentiments.

3.4 | Ordinal Regression Analysis

Following the computation of sentiment scores for each theme, we explore the impact of these perceived sentiments on customer satisfaction. We estimate proportional-odds ordered logit models considering customer ratings as our dependent variable, which is a proxy for customer satisfaction. We utilise the average sentiment score associated with each theme and volume of words as our independent variables for this analysis. We also use some additional control variables for robustness. The comparison of log-odds estimates from the analysis signals the effectiveness of perceived sentiments of themes on customer satisfaction. The approach helps identify and compare the impact of operational sustainability themes on user feedback. All the results of the analysis are reported in the next section.

FIGURE 3 | Thematic clustering.

4 | Results

4.1 | Word2Vec Analysis Results

Table 2 provides a portion of words with high cohesion scores according to each theme. As a key component of sustainable operations, the lean theme prioritises *fast*, *efficient* and simplified systems that contribute to overall value *generation* and *effectiveness*. Users look for platforms that *apply* lean principles, serving as a productive *companion, coach* and digital *helper* to enhance *operations* and limit wasted effort. The inclusion of *efficiency, productivity, resource, solution, selection* and *save* highlights user expectations for platforms that remove inefficiencies, simplify tasks and support smarter decision processes. The use of words such as *customization, functionality, experiment* and *incorporate* points to user expectations for systems that foster creative interaction and allow them to modify processes according to individual needs. Action-focused terms such as *engage, enhance, endeavor, impress* and *recommend* reflect users' desire for platforms that elevate their workflow to a higher *notch* rather than simply supporting it. Mentions of *professional, potential, specialist, boss* and *recruitment* indicate that users anticipate platforms performing at an elevated level and providing complementary or substitute expertise when necessary. Looking more broadly, references to *land, scene, form, piece* and *gesture* show that users regard these platforms as polished components, which align naturally with ongoing processes and operate smoothly. In the context of supply chains, these terms emphasise user preference for platforms that streamline tasks, minimise effort and eliminate inefficiencies. The clustering of words related to the lean theme provides an empirical insight into how users apply lean principles in assessing generative AI platforms.

The green theme of operational sustainability emphasises maintaining an *environment* that feels secure, supportive and balanced to encourage long-term user engagement. The presence of terms like *balance, community, safety, secure, responsive, guidance, helper* and *hand* suggests that users seek platforms, which offer confidence and emotional support in addition to technical functionality. This theme highlights operations that allow users to *enjoy* their experience and *learn*, opening space for *opportunity, originality* and *expertise* to thrive. Confidence decreases when users cannot *fix* technical *defaults*, find an *assignment* or *homework* challenging, or do not receive proper *advice* or *guidance*, as the platform does not create the supportive *environment* they look for. Conversely, when platforms *accelerate* useful actions, *organize* tasks seamlessly and respond with empathy to all users, whether a *child, kid, daughter* or adult, they cultivate confidence and show enduring value. The green theme indicates that users prefer systems that function as a *helper*, ready to *bring balance* and provide a *hand* and ensure a safe experience,

TABLE 2 | Representative sample of words per theme.

Lean	Green	Circular
apply, boss, coach, companion, creative, customization, detection, effectiveness, efficiency, endeavor, engage, enhance, experiment, fast, form, functionality, generation, gesture, helper, impress, incorporate, land, notch, operation, perspective, piece, polished, potential, productivity, professional, recommend, recruitment, replace, resource, save, scene, selection, solution, specialist, standout	accelerate, advice, assignment, balance, bring, camp, career, child, community, daughter, defaults, enjoy, environment, expertise, fix, game, gift, guidance, hand, helper, homework, hope, introduction, join, kid, last, learn, love, machine, math, opportunity, organize, originality, reading, responsive, safety, school, screen, secure, shout	agent, answer, care, con, confirm, converter, credit, customer, deal, decide, disappoint, discount, end, exist, file, follow, have, let, mention, mode, offer, order, page, phone, platinum, polite, pop, rate, realize, reason, refund, remove, request, send, service, show, situation, solve, spend, subscribe

whether used for *school*, *career*, *camp* and *home* purposes. When platforms allow users to *join* seamlessly, *learn* freely and *love* interacting without concerns about *safety*, it becomes more than a technical tool and transforms into a *gift* that nurtures lasting engagement. The green theme of operational sustainability is essentially a reflection of the demand that users have for a platform that not only provides novel AI outputs but also does so through procedures that are transparent, dependable and ethically grounded.

The circular theme of operational sustainability centres on a cycle of repeated actions that *exist* over time and provide value as long as the platform and the *customer* remain connected. The appearance of terms like *agent, answer, care, confirm, offer, service, show, solve, rate, request, refund, remove, order, page, phone* and *subscribe* highlights that users prioritise platforms, which oversee the whole support cycle smoothly and reliably. Circularity is reinforced when the platform manages to *answer* queries, *solve* challenges, *confirm* user decisions and *show* results, encouraging individuals to *follow* up, *spend* more time inside the system or *subscribe* for continued access. When platforms *offer* smooth workflows, respond with *care* and address *service* issues *politely* rather than making them *disappointed*, the cycle becomes stronger. When platforms manage a *request* properly, a transparent *reason* for a decision or an efficient *refund*, effortlessly strengthens trust and minimises frustration. Loyalty can grow even through routine interactions involving a *file, page, mode*, or *order* that are completed without confusion or delay. The cycle weakens and can ultimately *end* if users *have* to *deal* with unresolved issues or nonsupporting *agents*. Moments such as discovering unexpected *credit* deductions during a *subscription and being* unable to *realize* the reason behind an action, the experience is disrupted and repeat engagement becomes less likely. Consistent value provided through *phone* or online *service* interactions, the cycle tends to *pop* back into flow, leading users to *follow*, return and *mention* the platform across their social circles. Users in this circular dynamic *request* and evaluate rather than acting as passive receivers. The platform supports this cycle by offering reliable *answers* and personalised *care*, which ensures an active relationship between the system and the user. The generative AI platforms reciprocate users' responses by providing insightful content and advancing circular economy goals.

4.2 | Sentiment Analysis Results

Table 3 and Figure 4 provide a representation of the manner in which users are interacting with the three primary sustainability themes—lean, green and circular—in the context of their evaluations of generative AI platforms. Among these, the lean theme has the highest volume of mentions at 22707. This indicates that there is a significant amount of user interest in the effectiveness and streamlined performance that these platforms are thought to provide. The average word count per review for lean (6.6 words) is also the highest, which could be an indication that consumers feel more motivated to explain when mentioning certain features that enhance productivity. Supporting this idea is the theme's high sentiment score of 0.77, reflecting an overall positive user perception that is likely tied to the time-saving and outcome-driven benefits associated with lean-oriented tools.

The green theme has been mentioned in 21,265 reviews, and the sentiment score (0.75) is slightly lower than the lean theme sentiment score. The average review length (5.0 words) is moderate, but users show high enthusiasm in the tone. Users support the green theme and consider it a meaningful enhancement to the platform once the platform clearly expresses its environmental values. Many users appreciate sustainability-focused messaging, as it indicates that platforms prioritise more than performance alone. Users perceive the green theme works in harmony with the lean and circular themes, and together these themes provide efficient service and environmental awareness. Users tend to prefer themes that offer direct benefits and measurable operational value, like lean and circular. However, the green theme is still important because it builds trust, responsibility and a positive brand image. The presence of the green theme indicates that platforms prioritise sustainable use of resources and designing with long-term impact in mind. The users' reviews suggest that they feel more confident when platforms' goals align with environmental sustainability. It gives an opportunity to platforms by designing their activities with high performance and environmental responsibility to improve the user experience.

The circular theme has a lower sentiment score (0.64) and fewer mentions overall (13,567) than the green and lean themes, but users are still very interested in it. The shorter average review length (4.6 words) suggests that interactions related to the circular theme may be more direct and transactional, focusing on specific support experiences instead of more general thoughts. The trend shows that users express quick and short reviews under the circular theme as they deal with customer support, subscriptions or service workflows. Thus, the theme is less about expressing feelings and more about how the platform works and how quickly it responds. Even if the sentiment is not as high, the feedback shows that users just want quick, steady support and results they can trust. If these interactions are handled well, the feedback will strengthen trust instead of being a complaint. The circular theme shows how a practical way of getting involved can affect satisfaction by making it easier to meet user requests.

TABLE 3 | Descriptive statistics of review engagement and sentiment per theme.

Theme	Average word count	Review mentions	Average sentiment
Lean	6.6	22,707	0.77
Green	5.0	21,265	0.75
Circular	4.6	13,567	0.64

4.3 | Ordinal Regression Analysis Results

Our dependent variable is customer ratings for the generative AI platforms. Therefore, we use ordered logit regression to reflect the ordered structure of the dependent variable. The primary independent variable is the average sentiments associated with each theme. Additionally, we add some control variables in the analysis for robustness. We add the counts of the number of financial-related terms (e.g., refund, payment issue,

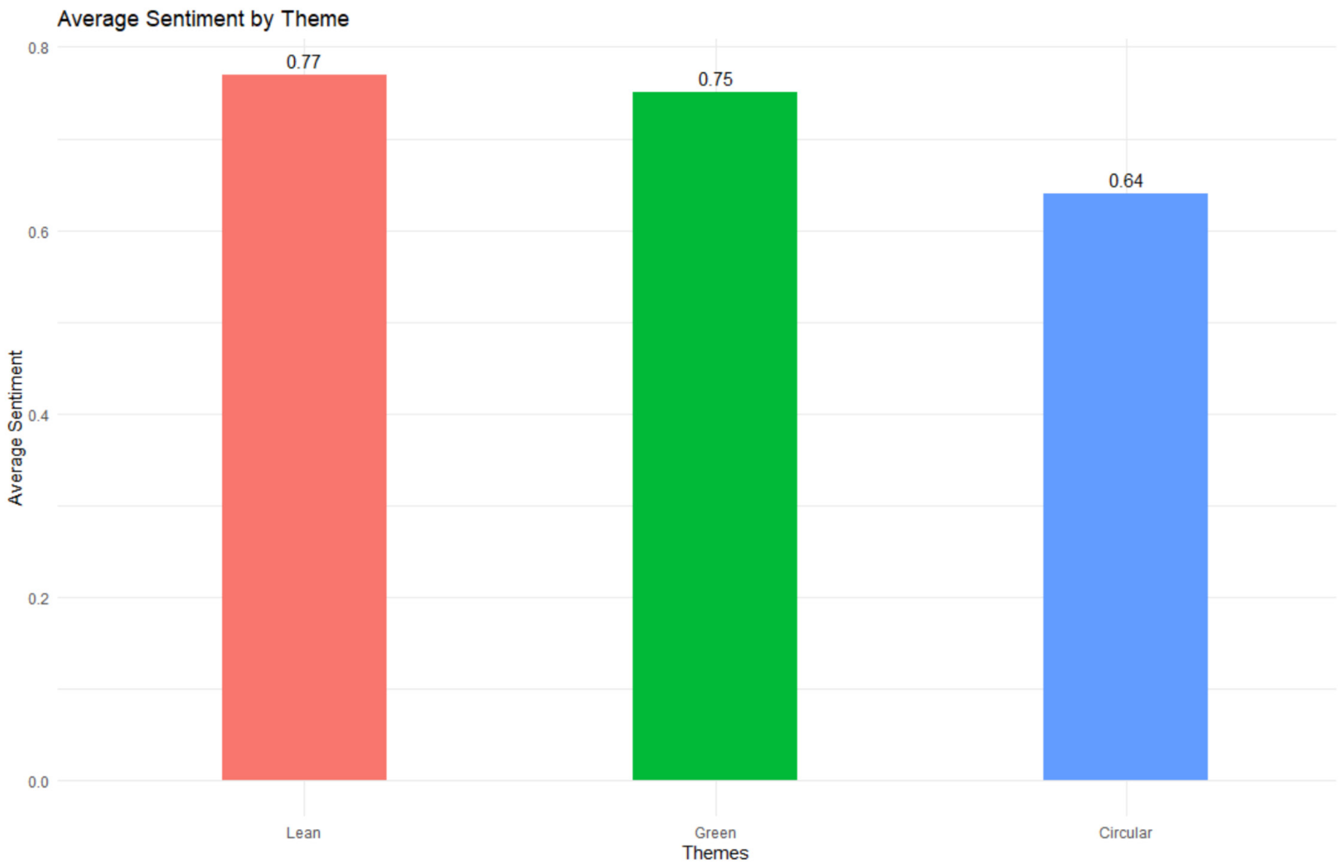

FIGURE 4 | Average sentiment by sustainability-oriented operational theme.

overcharged) because the financial transactions may affect the customer satisfaction ratings. Similarly, subscription-related issues may also be tied to the dissatisfaction, and thus, we add the subscription-related word counts (e.g., renewal, cancellation, trial ended) in the analysis. We also add positive and negative brand personality-related words associated with AI services because these words may affect the ratings (Bruce 2020). For instance, positive descriptors of the AI services (e.g., friendly, helpful, trustworthy) are closely linked with higher satisfaction, and negative descriptors (e.g., rude, unhelpful, dishonest) may signal strong dissatisfaction. We use a standard lexicon-based approach to identify common synonyms and morphological variants of the key terms (Barbaglia et al. 2025). This approach helps in capturing the consistent words associated with our control variables. We use exact term matching with enriched dictionaries and compute the count of matches for each review. The counts of each control variable are used in the ordinal regression model. Furthermore, we add the word count of each review as another control variable because review length often correlates with extremity and emotional engagement (Noguti 2016). We perform the analysis by including all these variables, and the results are reported in Table 4.

The coefficients of the ordinal logit are in log-odds, and we interpret them in terms of positive or negative effects on the odds of being in higher customer ratings to aid readability. For the lean theme, the coefficient of average sentiment is positive and significant ($\beta = 1.24$, $p < 0.01$). The positive and significant results suggest that customers have higher odds of rating their experiences with positive sentiments around lean-related concepts. For the green theme, the coefficient of average sentiment is positive and significant ($\beta = 1.61$, $p < 0.01$). The positive and significant results suggest that customers evaluate their experiences more favourably (i.e., have higher odds of higher ratings) when their positive sentiments are tied to green-related aspects. For the circular theme, the coefficient of average sentiment is positive and significant ($\beta = 2.33$, $p < 0.01$), suggesting that when customers highlight circular-related approaches, their overall evaluations are associated with higher odds of being more positive. The coefficient of financial-transaction–related terms is negative and significant for lean ($\beta = -1.81$, $p < 0.01$) and green ($\beta = -1.26$, $p < 0.01$) themes, while not significant for the circular theme ($\beta = -0.12$, $p > 0.1$). The coefficient of subscription-related concerns is negative and significant for all themes. The negative effect is particularly strong for lean ($\beta = -1.23$, $p < 0.01$) and green ($\beta = -1.03$, $p < 0.01$) models compared to circular ($\beta = -0.19$, $p < 0.01$). For perceived positive AI personality (friendly, helpful, trustworthy, etc.), the coefficients are positive and significant for circular ($\beta = 0.20$, $p < 0.01$) theme, but not statistically significant for the lean ($\beta = 0.01$, $p > 0.1$) and green ($\beta = 0.06$, $p > 0.1$) themes. These results suggest that the description of AI services as positive brand personality has a modest association in the circular theme and is not statistically significant for lean or green themes of operational sustainability. The coefficients of lean and green themes are negative and significant for perceived negative AI personality (β [lean] $= -5.35$, $p < 0.05$; β [green] $= -3.07$, $p < 0.05$). However, the coefficient of the circular theme is negative but not significant ($\beta = -1.37$, $p > 0.1$). Hence, negative descriptors present in AI brand personality are associated with substantially lower odds of higher ratings, with the strongest effects in lean and green themes, but not statistically significant in the circular theme. The word count variable is negative and significant for all themes, with a large negative effect shown by the circular theme ($\beta = -0.24$, $p < 0.01$) and relatively low negative effects shown by lean and green themes (β [lean] $= -0.02$, $p < 0.01$; β [green] $= -0.04$, $p < 0.01$). Thus, customers' longer reviews towards AI services for all themes are associated with lower odds of higher ratings. We also report McKelvey and Zavoina's R^2 for each theme in Table 4 (Saeed and Riaz 2021). The higher value of McKelvey and Zavoina's R^2 for the circular theme suggests that it explains the highest percentage of variance in the latent propensity to give higher ratings. The other two themes explain a moderate amount of variance. We also report the mean variance inflation

TABLE 4 | Regression results, DV-Customer ratings.

Variables	Model 1: Lean	Model 2: Green	Model 3: Circular
Average sentiment	1.24***	1.61***	2.33***
	(0.04)	(0.05)	(0.05)
Financial transactions	−1.81***	−1.26***	−0.12
	(0.15)	(0.13)	(0.10)
Subscription propensity	−1.23***	−1.03***	−0.19***
	(0.07)	(0.06)	(0.05)
Perceived positive AI personality	0.01	0.06	0.20***
	(0.04)	(0.04)	(0.05)
Perceived negative AI personality	−5.35**	−3.07**	−1.37
	(1.72)	(1.37)	(1.31)
Word count	−0.02***	−0.04***	−0.24***
	(0.004)	(0.01)	(0.01)
McKelvey and Zavoina's R^2	0.20	0.26	0.56
VIF (mean)	1.07	1.09	1.25

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

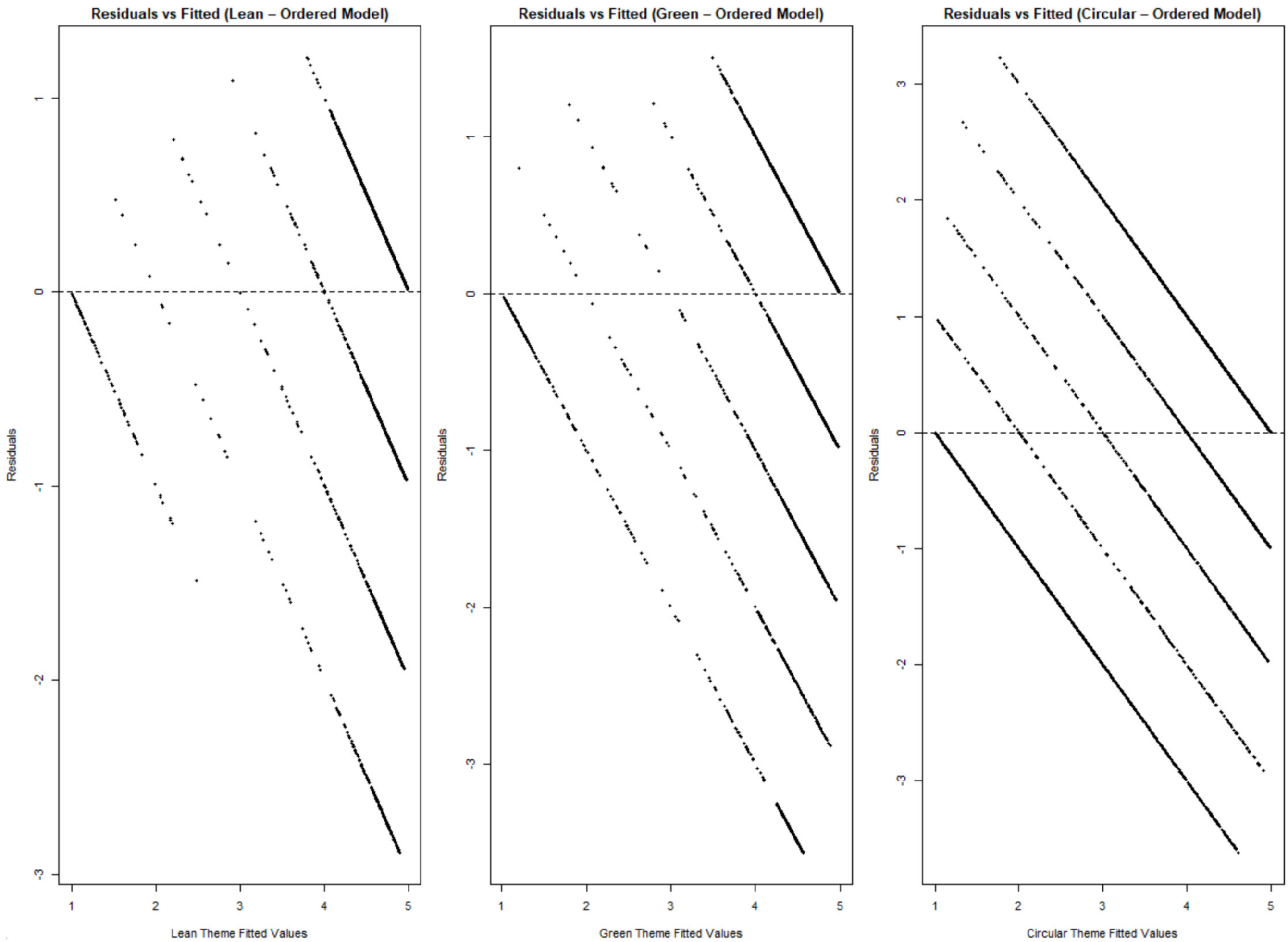

FIGURE 5 | Residuals versus fitted plots for lean, green and circular themes.

factor (VIF) for the three themes. The mean values of VIF for the three themes are less than the conventional thresholds (Rahman et al. 2024). Therefore, multicollinearity is not a concern in our analysis, and the estimates are stable. We also use robust standard errors for all ordinal logit models to address heteroskedasticity (Corrente et al. 2016).

We also demonstrate the residual plots of the three ordinal logit models in Figure 5. The diagonal stripes are expected due to customer ratings from 1 to 5. Hence, these stripes do not signal a misfit. Residuals sit close to zero and keep a consistent spread, indicating stable variance and unbiased means. A small tail of residuals at the margins indicates isolated underprediction or overpredictions rather than a generalised error. The residual patterns for the three themes are comparable, with the green theme exhibiting marginally less dispersion, consistent with its best-fitting model. Because these plots do not diagnose proportional odds, we supplement them with formal tests and robustness analyses.

5 | Discussion

We explore the critical insights into how generative AI platforms are evaluated by users through the lens of lean, green and circular themes of operational sustainability and contribute to customer satisfaction. We utilise customer reviews of generative AI platforms and perform Word2Vec, sentiment and regression analyses to get empirical support for this exploration. The sentiment analysis and regression models suggest that technical performance is necessary but not a sufficient attribute of these platforms. Users value the principles of sustainability, which are provided by different actions on different platforms. Existing research indicates that customer satisfaction in digital services is increasingly shaped by sustainability-oriented perceptions rather than solely technical attributes (Luo et al. 2024). The lean theme has the highest volume of user mentions and a positive predictive impact on customer ratings. Users value generative AI platforms that provide effectiveness, user-friendliness and productivity gains. The high sentiment score and significant positive coefficient reinforce the performance-centric solution delivered by platforms. Previous marketplace analytics indicate that productivity-enhancing features are significant predictors of sustained usage and loyalty towards AI-enabled services (Rezaei and Ansary 2024). However, the significant negative coefficient for word count indicates that excessive elaboration when discussing lean-related attributes may diminish customer satisfaction. The green theme has the second-highest mentions and sentiment score. This signals that users discuss environmental sustainability explicitly in the reviews. The sentiment score and negative impact of word count suggest that users have clarity regarding environmental claims provided by platforms, but do not feel the need to provide details in their feedback. The circular theme has relatively lower mentions and sentiment score than other themes, demonstrating a limited enthusiasm toward platforms that emphasise reusability and consistent performance. The positive coefficient for sentiment in the regression analysis underscores the appreciation offered by customers. The negative and significant coefficient of the volume of words suggests that users associate lengthy elaboration with lower perceived value. The reduced sentiment reflects gaps in how support and subscription processes are communicated. This result indicates a need for platforms to improve service workflows and improve customer confidence. This aligns with the co-creation literature, which shows the importance of customer narratives on shaping the sustainable digital ecosystems (Chandra and Rahman 2024). The results highlight that customer reviews deliver meaningful observations for the operational values with generative AI platforms. The users' language employs a more integrated approach to mutual value creation, which aligns with the co-creation theory. Customers are the key agents in shaping the perception of sustainable features provided by platforms. The significant sentiment scores of the three themes show that operational sustainability is a key dimension of customer satisfaction.

6 | Conclusions

Our results show that users appreciate generative AI platforms, which have strong technical performance and are sustainable enough to keep supporting them over time. The lean theme has the highest sentiment score, which shows that users like platforms that help them be more efficient, faster and more productive in their daily tasks. Users like the green theme when platforms show more transparency towards this theme. The circular theme, on the other hand, has lower sentiment and fewer mentions. This shows that users do not care as much about support-related interactions and transactional processes. The pattern indicates that service situations are handled in a straightforward manner, leading users to leave shorter and more neutral feedback. Customer reviews give us a lot of information about how users work together to create value with generative AI platforms. The integration of sustainability, usability, and performance is crucial to improving user experience. The best and most long-lasting user experience will come from platforms that combine lean efficiency, green responsibility and circular service consistency.

6.1 | Theoretical Implications

We contribute to the existing literature on user-centred artificial intelligence operational sustainability through our findings. First, our findings extend co-creation theory by revealing that users move beyond passive use and actively contribute to how generative AI platforms are interpreted and valued based on their feedback. We show that users started paying close attention to sustainability in addition to the technical performance of the generative AI platforms. Our conceptualisation and findings enhance socio-technical systems theory by illustrating that social norms, values and sustainability expectations affect perceived utility and trust on digital platforms. Second, we broaden the scope of operational sustainability to encompass digital environments, which have historically been linked solely to physical supply chains. This new way of thinking shows that using digital resources in a smart, efficient and reusable way increases the value of a platform. Third, we demonstrate that the vocabulary users select in their reviews indicates perceived value, suggesting that authentic user comments provide a significant framework for examining socio-technical interactions. This link connects the theory of responsible innovation with the theory of technology acceptance by showing how features that are good for the environment affect how users see and trust technology. Our work shows that sustainability is a key factor in creating value for users in the digital age. This adds to larger discussions about how to design and use AI responsibly.

6.2 | Methodological Implications

We also contribute to methodological approaches for analysing what users post online, especially in relation to operational sustainability. The integration of advanced-level machine learning methods (like Isolation Forest, Word2Vec embeddings, K-Means clustering and thematic labelling) presents a scalable, semiguided method to dig up sustainability-related topics from the unstructured review data. This methodological combination helps researchers quickly spot unusual data, uncover important patterns and analyse large-scale text data with both computational efficiency and thoughtful depth. Importantly, our approach, combining theme-focused sentiment regression with an ordered logit model, reliably shows how users tie their emotions and evaluations to sustainability areas like lean, circular and green. The ordinal logit model is appropriate for handling the ordinal nature of customer ratings, and we further enhance analytical robustness by reporting McKelvey and Zavoina's R^2, conducting variance inflation factor (VIF) checks for multicollinearity, and using robust standard errors to account for heteroskedasticity. The inclusion of these additional robustness checks brings something new to the table in business and management research methods, where mixing high-level text analytics with rigorous econometric methods remains unusual. Furthermore, by testing these methods on genuine user reviews, we can highlight how fuzzy concepts like efficiency, reuse and being resource-conscious can be made concrete for effective analysis using natural language processing, machine learning and econometric methods. These breakthroughs expand the options for sustainability researchers and heighten the empirical accuracy of socio-technical studies, which are built on unstructured digital traces, paving the path for integrating computational and statistical tools to investigate the intersection of sustainability and technology in digital platforms.

6.3 | Practical Implications

Our findings suggest several recommendations to professionals in the digital AI sector, especially those involved in platform management and strategic development. Customer reviews show that people do not just judge generative AI platforms by how fast they work or how accurate they are. The users support sustainable business practices as suggested by the high sentiment scores of lean and green themes. This suggests that sustainability is becoming a more important factor in deciding whether or not to use a digital service. The suggestions help managers align their goals with users' expectations. The lean-oriented improvements should be at the top of the list of priorities for managers because users value applications that make processes smoother and boost efficiency. They can implement low-latency processing and energy-efficient computation. The functionality would be enhanced by using these features, and customer loyalty will also increase because they correspond to customers' wants. The use of lean practices by managers saves the time and effort of users without wasting energy and computational power of platforms.

The second managerial recommendation is the use of green initiatives by managers of generative AI platforms. Managers can initiate transparent communication to show that they utilise renewable cloud servers or carbon-aware computing. These activities will close the gap between consumers and generative AI platforms, which will increase consumers' satisfaction due to the platforms' visible and sustainable business activities. Several activities, like an optimisation dashboard to show low energy usage, Environmental Management System certifications, or transparent ESG reporting, can be performed by the platforms to signal responsible innovation. Users can trust platforms more once they receive this kind of transparent communication. They are more likely to develop emotional connections and trust a service over time when platforms find meaningful ways to talk about their green practices.

Third, users' sentiments towards circularity are relatively lower, as indicated by our findings. Our analysis shows that users focus on circular features when they think of support workflows. Users' pattern of providing short and neutral comments suggests that the interactions of users with the circular theme are transactional. Users expect support to work quickly, and when it does, there is not much need for more explanation. The professionals should not ignore circularity and enforce reliable customer services to keep users happy. Speedy refunds, easy subscription process and attentive customer support can improve the user experience, even if they do not directly raise sentiment scores.

The high sentiment score of lean and green themes suggests to managers to integrate lean efficiency with green responsibility to attain sustainable competitive advantage. Platforms that build features with sustainability in mind, both in terms of how well they work and how they use resources, are more likely to keep and satisfy users who care about the environment. As rules around carbon use, digital resource use and ethical AI become stricter around the world, platforms that put sustainability first will have less risk of breaking the rules and a better brand reputation. This model turns sustainability from a marketing slogan into a long-term business strategy.

Our research provides implications for platforms' new offerings. Marketing and innovation managers can reinforce sustainability by integrating with activities associated with customer acquisition and retention. UX designers can add eco-friendly prompts that help users find more efficient ways to work. Managers of platforms can teach customer service teams to talk about the benefits of sustainability when helping users. Regulatory authorities and policymakers can provide incentives to these generative AI platforms to encourage the creation of energy-efficient and sustainable products and services. Basically, our findings suggest that lean and green principles may provide more satisfaction to customers. Additionally, circularity is crucial for logistics, but it does not set people apart emotionally. The platforms will receive more engagement and subscriptions if they follow efficient and environmentally responsible activities.

6.4 | Limitations and Future Research Directions

This study uses a large dataset of Trustpilot user reviews to investigate consumer sentiment and patterns in lean, green and circular domains. We acknowledge the methodological and interpretive limits of using a single platform. As a dedicated consumer review platform, Trustpilot's user community and rating tendencies may differ from other platforms like Google Reviews or Bazaarvoice. Users on Trustpilot may have a polarized sentiment pattern for some specific websites compared to a more balanced review for other platforms. Hence, the dataset may disproportionately include consumers with firm opinions, amplifying one-sided sentiment scores and increasing variance across themes. Hence, researchers can combine the datasets of various platforms and perform the analysis as an extension to this research. Secondly, the geographical reach of platforms differs. For instance, Trustpilot coverage is strong in Europe and North America, but may not be efficient in some emerging markets. The uneven geographical spread may lead to a dataset that predominantly captures Western consumer expectations and values. The platform-level differences may influence the emphasis and sentiment of each theme, restricting the generalizability of conclusions to global contexts. Hence, researchers can collect the data from those platforms, which are more familiar in emerging markets and perform a comparison study to provide additional insights to our findings. We mitigated some of these constraints by leveraging a broad dataset spanning multiple firms and using unsupervised machine learning to capture semantically linked terms contextually, rather than relying entirely on frequency-based techniques. Additionally, we applied robust regression models and incorporated word-count controls to mitigate bias stemming from excessively brief or extended reviews. However, we recommend that researchers explore other platforms, which can provide new avenues to this field.

We also recognise that our dataset has time limits. As generative AI technology gets better, more popular and adds new operational and environmental features, people's views and expectations about it are likely to change quickly. Thus, our results show a snapshot in time, not a stable or fixed picture of how users feel. In addition, we see that the generative AI industry is very unstable, with many platforms, especially those that are driven by startups, quickly growing and then changing direction or shutting down. Some of the platforms in our dataset may pivot their business after some time as per changing customer demands, which could affect how people feel about them in the future and how long they last. Hence, collecting and analysing the longitudinal database associated with user-generated content would be helpful to trace the temporal development of user expectations within a swiftly evolving AI environment.

Future studies should also aim to triangulate our findings by drawing on data from various review platforms. While we identify the effect of review sentiments on customer satisfaction, we recognize that researchers can also explore other factors affecting customers' underlying attitudes and experiences, along with sentiments. Future research could combine sentiment analysis with alternative measures of satisfaction (e.g., repeat purchases, churn rates) that directly link customer retention to satisfaction outcomes. Combining complementary data sources with user-generated reviews could provide a more nuanced understanding of how sentiment diverges from genuine customer satisfaction.

Our research uses the customer reviews dataset for the analysis. Researchers can conduct qualitative interviews and quantitative surveys with customers to gain additional insight into operational sustainability. Comprehensive interviews with firms' C-Suite officers can also add additional perspectives in this academic area. Researchers can also collect secondary data to explore the three themes associated with operational sustainability.

Researchers can perform the analysis with a combination of primary and secondary datasets, which would broaden conceptual understanding in this field. There could be another option of merging the user reviews with videos or images, which can give a better idea of how people feel, act and engage. Researchers can also combine text datasets with sensor or biometric data to look at how people think and feel when they interact with computers. Researchers can study organizations to see how communication patterns affect outcomes (productivity) by comparing text data with performance metrics. This multimodal approach facilitates more comprehensive interpretations and significant discoveries.

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References

Akbar, S., M. Hayat, M. Tahir, S. Khan, and F. K. Alarfaj. 2022. "cACP-DeepGram: Classification of Anticancer Peptides via Deep Neural Network and Skip-Gram-Based Word Embedding Model." *Artificial Intelligence in Medicine* 131: 102349.

Alkaraan, F., M. Elmarzouky, K. Hussainey, V. G. Venkatesh, Y. Shi, and N. Gulko. 2024. "Reinforcing Green Business Strategies With Industry 4.0 and Governance Towards Sustainability: Natural-Resource-Based View and Dynamic Capability." *Business Strategy and the Environment* 33, no. 4: 3588–3606.

Al-Shehari, T., M. Al-Razgan, T. Alfakih, R. A. Alsowail, and S. Pandiaraj. 2023. "Insider Threat Detection Model Using Anomaly-Based Isolation Forest Algorithm." *IEEE Access* 11: 118170–118185.

Alzoubi, Y. I., and A. Mishra. 2024. "Green Artificial Intelligence Initiatives: Potentials and Challenges." *Journal of Cleaner Production* 468: 143090.

Awan, U., M. G. Arnold, and I. Gölgeci. 2021. "Enhancing Green Product and Process Innovation: Towards an Integrative Framework of Knowledge Acquisition and Environmental Investment." *Business Strategy and the Environment* 30, no. 2: 1283–1295.

Babar, Z., R. Paul, M. A. Rahman, and T. Barua. 2025. "A Systematic Review of Human-AI Collaboration in IT Support Services: Enhancing User Experience and Workflow Automation." *Journal of Sustainable Development and Policy* 1, no. 01: 65–89.

Bag, S., J. H. C. Pretorius, S. Gupta, and Y. K. Dwivedi. 2021. "Role of Institutional Pressures and Resources in the Adoption of Big Data Analytics Powered Artificial Intelligence, Sustainable Manufacturing Practices and Circular Economy Capabilities." *Technological Forecasting and Social Change* 163: 120420.

Bag, S., M. S. Rahman, A. Singh, D. Bryde, and G. Graham. 2024. "Leveraging Digital Technology Capability for Circular Economy Innovation in the Food Products Supply Chain: A Mixed-Method Study." *IEEE Transactions on Engineering Management* 71: 13997–14010.

Barbaglia, L., S. Consoli, S. Manzan, L. Tiozzo Pezzoli, and E. Tosetti. 2025. "Sentiment Analysis of Economic Text: A Lexicon-Based Approach." *Economic Inquiry* 63, no. 1: 125–143.

Bashynska, I., and O. Prokopenko. 2024. "Leveraging Artificial Intelligence for Circular Economy: Transforming Resource Management, Supply Chains, and Manufacturing Practices." *Scientific Journal of Bielsko-Biala School of Finance and Law* 28, no. 2: 85–91.

Battisti, E., S. Bo, F. Petruzzella, and A. Salvi. 2025. "Greenwashing and Sustainability Disclosure in the Climate Change Context: The Influence of Third-Party Certification on Chinese Companies." *Business Strategy and the Environment* 34, no. 6: 7851–7863.

Benabdellah, A. C., K. Zekhnini, A. Cherrafi, and J. G. Reyes. 2024. "Driving Sustainable Innovation: Exploring Lean, Green, Circular, and Smart Design." *Procedia Computer Science* 232: 880–889.

Benita, F., and P. Srinivasan. 2024. "On the Circular Entrepreneurship Across Continents: An Analysis of Terms of Business Descriptors." *Business Strategy & Development* 7, no. 3: e70006.

Bhandari, K. R., M. Ranta, and J. Salo. 2022. "The Resource-Based View, Stakeholder Capitalism, ESG, and Sustainable Competitive Advantage: The Firm's Embeddedness Into Ecology, Society, and Governance." *Business Strategy and the Environment* 31, no. 4: 1525–1537.

Broccardo, L., E. Crocco, H. Alofaysan, and A. Mehrotra. 2025. "Climate Change and Business Model Innovation: A Synthesis of Review and Qualitative Exploration of the Cultural Shift in Environmental Strategies." *Business Strategy and the Environment* 34, no. 2: 1826–1846.

Bruce, K. L. 2020. *Assessing Brand-Consumer Personality Congruence on Twitter: A Computational Textual Analysis Approach*. University of Alabama.

Budhwar, P., S. Chowdhury, G. Wood, et al. 2023. "Human Resource Management in the Age of Generative Artificial Intelligence: Perspectives and Research Directions on ChatGPT." *Human Resource Management Journal* 33, no. 3: 606–659.

Chandra, B., and Z. Rahman. 2024. "Artificial Intelligence and Value Co-Creation: A Review, Conceptual Framework and Directions for Future Research." *Journal of Service Theory and Practice* 34, no. 1: 7–32.

Chen, C., C. Zhang, and Z. Xu. 2024. "Online Reviews-Driven Kano-QFD Method for Service Design." *IEEE Transactions on Engineering Management* 71: 8153–8165. https://doi.org/10.1109/TEM.2024.3387579.

Corrente, S., S. Greco, B. Matarazzo, and R. Słowiński. 2016. "Robust Ordinal Regression for Decision Under Risk and Uncertainty." *Journal of Business Economics* 86, no. 1: 55–83.

Costa, F., N. Alemsan, A. Bilancia, G. L. Tortorella, and A. P. Staudacher. 2024. "Integrating Industry 4.0 and Lean Manufacturing for a Sustainable Green Transition: A Comprehensive Model." *Journal of Cleaner Production* 465: 142728.

Crocco, E., L. Broccardo, H. Alofaysan, and R. Agarwal. 2024. "Sustainability Reporting in Carbon-Intensive Industries: Insights From a Cross-Sector Machine Learning Approach." *Business Strategy and the Environment* 33, no. 7: 7201–7215.

Cui, X., Z. Zhu, L. Liu, Q. Zhou, and Q. Liu. 2024. "Anomaly Detection in Consumer Review Analytics for Idea Generation in Product Innovation: Comparing Machine Learning and Deep Learning Techniques." *Technovation* 134: 103028.

de Oliveira Rezende, M., M. R. M. Saade, A. O. Nunes, V. G. da Silva, V. A. S. Moris, and D. A. L. Silva. 2022. "A Lean and Green Approach for the Eco-Efficiency Assessment on Construction Sites: Description and Case Study." *Clean Technologies and Environmental Policy* 24, no. 5: 1535–1552.

Galvagno, M., and D. Dalli. 2014. "Theory of Value Co-Creation: A Systematic Literature Review." *Managing Service Quality* 24, no. 6: 643–683.

Hanafi, N., and H. Saadatfar. 2022. "A fast DBSCAN Algorithm for Big Data Based on Efficient Density Calculation." *Expert Systems with Applications* 203: 117501.

Hao, X., and E. Demir. 2024. "Artificial Intelligence in Supply Chain Decision-Making: An Environmental, Social, and Governance Triggering and Technological Inhibiting Protocol." *Journal of Modelling in Management* 19, no. 2: 605–629.

Karapiperis, D., and V. S. Verykios. 2025. "Scaling Entity Resolution With K-Means: A Review of Partitioning Techniques." *Electronics* 14, no. 18: 3605.

Karna, A., and K. Gibert. 2022. "Automatic Identification of the Number of Clusters in Hierarchical Clustering." *Neural Computing and Applications* 34, no. 1: 119–134.

Khan, T. 2024. "Circular-ESG Model for Regenerative Transition." *Sustainability* 16, no. 17: 7549.

Khanra, S., P. Kaur, R. P. Joseph, A. Malik, and A. Dhir. 2022. "A Resource-Based View of Green Innovation as a Strategic Firm Resource: Present Status and Future Directions." *Business Strategy and the Environment* 31, no. 4: 1395–1413.

Kilimci, Z. H., and S. Akyokus. 2018. "Deep Learning-and Word Embedding-Based Heterogeneous Classifier Ensembles for Text Classification." *Complexity* 2018, no. 1: 7130146.

Knol, W. H., K. Lauche, R. L. Schouteten, and J. Slomp. 2022. "Establishing the Interplay Between Lean Operating and Continuous Improvement Routines: A Process View." *International Journal of Operations & Production Management* 42, no. 13: 243–273.

Koivisto, E., and P. Mattila. 2020. "Extending the Luxury Experience to Social Media–User-Generated Content Co-Creation in a Branded Event." *Journal of Business Research* 117: 570–578.

Kumar, A., A. Kumar, R. Raja, et al. 2025. "Revolutionising Anomaly Detection: A Hybrid Framework for Anomaly Detection Integrating Isolation Forest, Autoencoder, and Conv. LSTM." *Knowledge and Information Systems* 67, no. 12: 11903–11953.

Lei, S. I., D. Wang, and R. Law. 2022. "Mobile-Based Value Co-Creation: Contextual Factors Towards Customer Experiences." *Tourism Review* 77, no. 4: 1153–1165.

Lemke, C., and D. Monett. 2024. "AI-Based Service Systems: Digital-Ethical Issues and Their Impact on Value Co-Creation." In *Handbook of Services and Artificial Intelligence*, 228–249. Edward Elgar Publishing.

Lin, K. Y. 2024. "Circular Supply Chain for Smart Production in Industry 4.0." *Computers & Industrial Engineering* 198: 110682.

Luan, S., Z. Gu, L. B. Freidovich, L. Jiang, and Q. Zhao. 2021. "Out-of-Distribution Detection for Deep Neural Networks With Isolation Forest and Local Outlier Factor." *IEEE Access* 9: 132980–132989.

Luo, X., W. Qian, M. Liu, X. Yu, and Y. Liu. 2024. "Towards Sustainability: Digital Capability, Sustainable Business Model Innovation, and Corporate Environmental Responsibility of High-Performing Enterprises in an Emerging Market." *Business Strategy and the Environment* 33, no. 6: 5606–5623.

Luqman, A., Q. Zhang, S. Talwar, M. Bhatia, and A. Dhir. 2024. "Artificial Intelligence and Corporate Carbon Neutrality: A Qualitative Exploration." *Business Strategy and the Environment* 33, no. 5: 3986–4003.

Magas, M., and D. Kiritsis. 2022. "Industry Commons: An Ecosystem Approach to Horizontal Enablers for Sustainable Cross-Domain Industrial Innovation (a Positioning Paper)." *International Journal of Production Research* 60, no. 2: 479–492.

Maghroor, H. R., F. Madanchi, and T. O'Neal. 2025. "Leveraging Generative AI for Sustainable Supply Chain: Adoption Challenges and Strategic Insights." *Production Planning & Control*: 1–20. https://doi.org/10.1080/09537287.2025.2561967.

Majumdar, P. 2021. *Learn Emotion Analysis With R: Perform Sentiment Assessments, Extract Emotions, and Learn NLP Techniques Using R and Shiny (English Edition)*. BPB Publications.

Mangla, S. K., S. Luthra, J. A. Garza-Reyes, C. J. C. Jabbour, and A. Brem. 2024. "Sustainability and Industry 4.0: The Role of Social, Environmental and Technological Factors in the Development of Digital Manufacturing." *Technological Forecasting and Social Change* 201: 123223.

Noguti, V. 2016. "Post Language and User Engagement in Online Content Communities." *European Journal of Marketing* 50, no. 5/6: 695–723.

Ooi, K. B., G. W. H. Tan, M. Al-Emran, et al. 2025. "The Potential of Generative Artificial Intelligence Across Disciplines: Perspectives and Future Directions." *Journal of Computer Information Systems* 65, no. 1: 76–107.

Prasad Agrawal, K. 2025. "Organizational Sustainability of Generative AI-Driven Optimization Intelligence." *Journal of Computer Information Systems* 65, no. 3: 265–279.

Rahman, A. U., F. Wen, and F. Amjad. 2024. "Role of Sustainable Business Model, Industry 4.0, Crowdfunding, and Stakeholders' Pressure Toward Firm's Sustainability: A SEM-ANN Approach." *Business Strategy and the Environment* 33, no. 7: 7409–7426.

Rai, A., P. Constantinides, and S. Sarker. 2019. "Next Generation Digital Platforms: Toward Human-AI Hybrids." *MIS Quarterly* 43, no. 1: iii–ix.

Rane, N. L., S. P. Choudhary, and J. Rane. 2025. "Enhancing Sustainable Construction Materials Through the Integration of Generative Artificial Intelligence, Such as ChatGPT." *Sustainable and Clean Buildings* 1, no. 1: 98–122. https://ojs.wiserpub.com/index.php/scb/article/view/5409.

Rezaei, S., and A. Ansary, eds. 2024. *Artificial Intelligence of Things (AIoT) for Productivity and Organizational Transition*. IGI Global.

Rezwana, J., and M. L. Maher. 2023. "Designing Creative AI Partners With COFI: A Framework for Modeling Interaction in Human-AI Co-Creative Systems." *ACM Transactions on Computer-Human Interaction* 30, no. 5: 1–28.

Rubio, N., N. Villaseñor, and M. J. Yagüe. 2021. "Value Co-Creation Between Consumers and Distributors: The Moderating Effect of Relationship Characteristics." *International Journal of Retail & Distribution Management* 49, no. 7: 1067–1088.

Saeed, A., and H. Riaz. 2021. "Navigating Through Firm–Environmental Groups' Relationships: The Impact of Societal Trust on Corporate Environmental Strategy." *Business Strategy and the Environment* 30, no. 8: 3552–3568.

Salih, S., O. Husain, E. A. M. Abdalla, et al. 2025. "Generative AI for Industry Transformation: A Systematic Review of ChatGPT's

Capabilities and Integration Challenges." *International Journal of Computer Science and Network Security* 25, no. 5: 221–249.

Scrucca, L. 2025. "A Model-Based Clustering Approach for Bounded Data Using Transformation-Based Gaussian Mixture Models." *Journal of Classification*. https://doi.org/10.1007/s00357-025-09511-8.

Secundo, G., C. Spilotro, J. Gast, and V. Corvello. 2024. "The Transformative Power of Artificial Intelligence Within Innovation Ecosystems: A Review and a Conceptual Framework." *Review of Managerial Science* 19: 2697–2728.

Shahin, M., M. Maghanaki, A. Hosseinzadeh, and F. F. Chen. 2024. "Improving Operations Through a Lean AI Paradigm: A View to an AI-Aided Lean Manufacturing via Versatile Convolutional Neural Network." *International Journal of Advanced Manufacturing Technology* 133, no. 11: 5343–5419.

Shrivastav, S. K., and S. Bag. 2024. "Blockchain Technology in Circular Economy: Unpacking the Potential Issues and Critical Echoes Through Data Triangulation and Natural Language Processing." *Business Strategy and the Environment* 33, no. 6: 5463–5484.

Singh, A., R. Agarwal, R. Alghafes, and A. Papa. 2025. "Empowering AI With Experiential Learning: Implications From Analysing User-Generated Content." *Technological Forecasting and Social Change* 219: 124261.

Singh, R. K., S. Kumar Mangla, M. S. Bhatia, and S. Luthra. 2022. "Integration of Green and Lean Practices for Sustainable Business Management." *Business Strategy and the Environment* 31, no. 1: 353–370.

Trappey, A., C. V. Trappey, and A. Hsieh. 2021. "An Intelligent Patent Recommender Adopting Machine Learning Approach for Natural Language Processing: A Case Study for Smart Machinery Technology Mining." *Technological Forecasting and Social Change* 164: 120511.

Ullah, R., N. Amblee, W. Kim, and H. Lee. 2016. "From Valence to Emotions: Exploring the Distribution of Emotions in Online Product Reviews." *Decision Support Systems* 81: 41–53.

Wang, L., and M. Li. 2024. "An Exploration Method for Technology Forecasting That Combines Link Prediction With Graph Embedding: A Case Study on Blockchain." *Technological Forecasting and Social Change* 208: 123736.

Wang, S., and H. Zhang. 2025. "Leveraging Generative Artificial Intelligence for Sustainable Business Model Innovation in Production Systems." *International Journal of Production Research* 63, no. 18: 6732–6757. https://doi.org/10.1080/00207543.2025.2485318.

Wu, C. J., R. Raghavendra, U. Gupta, et al. 2022. "Sustainable AI: Environmental Implications, Challenges and Opportunities." *Proceedings of Machine Learning and Systems* 4: 795–813.

Xi, X., F. Ren, L. Yu, and J. Yang. 2023. "Detecting the Technology's Evolutionary Pathway Using HiDS-Trait-Driven Tech Mining Strategy." *Technological Forecasting and Social Change* 195: 122777.

Yang, N., D. Dousios, N. Korfiatis, and K. Chalvatzis. 2024. "Mapping the Signaling Environment Between Sustainability-Focused Entrepreneurship and Investment Inputs: A Topic Modeling Approach." *Business Strategy and the Environment* 33, no. 6: 5405–5422.

Zhang, H., A. M. Kassim, N. H. Samsudin, L. Teng, and C. Y. Tang. 2024. "A Hybrid Deep Learning Framework for Hotel Rating Systems: Integrating Word2Vec, TF-IDF, and Bi-LSTM With Attention Mechanism." *IEEE Transactions on Computational Social Systems* 12, no. 5: 2371–2384.

Zhou, L., X. Shi, Z. Wang, C. Ma, and L. Gao. 2025. "Exploration of Applications With ChatGPT for Green Supply Chain Management." *Annals of Operations Research* 355: 1–34.

Zhu, K., W. Khern-am-nuai, and Y. Yu. 2024. "Negative Peer Feedback and User Content Generation: Evidence From a Restaurant Review Platform." *Production and Operations Management* 34: https://doi.org/10.1177/10591478231224941.