Empowering AI with experiential learning: Implications from analysing user-generated content

ABSTRACT

Artificial intelligence (AI) has evolved into generative artificial intelligence, offering users even greater benefits. The AI platforms provide generative AI-related services to support users' professional development and gather feedback to enhance the service through experiential learning. However, comprehending large volumes of unstructured datasets in the form of customer reviews presents an increasingly serious challenge as the number of users on AI platforms grows over time. We employ advanced machine learning techniques—topic modeling and word2vec- to extract more accurate insights from unstructured data. We collect customer reviews from AI content-creation platforms from 2022 to 2024. By combining topic modeling and word2vec, we uncover valuable insights. Our analysis identifies eight key topics: Playground, Support Hub, Content Lab, Productivity, User Experience, Access, Business Assistant, and Remix. The topic of regression analysis reveals that Content Lab, User Experience, Business Assistant, and Remix are more favourable in terms of customer satisfaction scores. The word2vec analysis with negative sampling indicates that Access and Playground demonstrate better cohesion scores compared to other themes. Conversely, themes such as Content Lab, Productivity, and Business Assistant have lower cohesion scores, indicating weak clustering among words within these themes. Our research offers several valuable insights for AI platform managers, which can further enhance services through experiential learning.

Keywords: Experiential learning, generative AI, machine learning, user-generated content

1. Introduction

The rapid advancement of artificial intelligence (AI) technologies has led to significant changes across various industries (Davenport, 2018). Enhancing computing capabilities is no longer enough for firms, and they have shifted their focus to improving user experiences (Nguyen, 2024). The evolution of generative artificial intelligence is one of the crucial elements fuelling this transition. This type of artificial intelligence leverages patterns in data to create unique and engaging content (Kumar et al., 2024). This content can contain almost anything from text and pictures to music and video. Several digital platforms, including ChatGPT, GeminiAI, and Quill Bot, demonstrate the impact of generative artificial intelligence on the content creation industry. These digital platforms enable non-native speakers, individuals with disabilities, or those with non-specialized skill sets to create refined, smooth, and personalized content in a resourceful and affordable manner (Mahmoudi-Dehaki & Nasr-Esfahani, 2025; Miranda & Vegliante, 2025).

Experiential learning is a crucial component that can enhance the efficiency of generative artificial intelligence. Experiential learning involves the careful examination of customer feedback to continuously improve the AI systems (Murtaza et al., 2022). User-generated content (UGC) encompasses customers' ratings and feedback, providing a crucial understanding of the digital generative AI platforms used by many customers. Digital AI platforms can enhance their services and tailor them to meet user needs. There are significant challenges associated with experiential learning within artificial intelligence systems due to the large volume of unstructured user-generated content (UGC) present. Hence, it is crucial to comprehend the influence of experiential learning within the generative artificial intelligence framework. Recent research conducted by Gartner reveals that approximately 80–90% of company data is unstructured, and this type of data is growing at a rate three times faster than structured data (Heeg, 2023). Therefore, advanced-level methods are required to obtain contextual insights from complex UGC datasets. The utilisation of advanced machine learning methods for analysing the UGC may unlock new paths for experiential learning by shedding light on intricate details, connections, and contextual awareness within the AI environment. This process will enable AI-related businesses to meet the needs of users.

A significant portion of the existing body of literature has focused on conventional statistical and individual machine-learning approaches for analyzing unstructured text data (Adnan & Akbar, 2019). On the other hand, there remains a considerable lack of research that directly addresses experiential learning through the analysis of user-generated content within the framework of generative artificial intelligence platforms. This study aims to bridge this gap by adopting an integrated methodological approach that combines topic modeling and Word2Vec to conduct a comprehensive analysis of customer feedback data collected from various AI content-generation platforms between 2022 and 2024. In particular, the combination of topic modelling and Word2Vec fills in these gaps by locating underlying themes and extracting semantic relationships within user-generated content. This enables a deeper understanding of user experiences, enhances the adaptability of artificial intelligence, and significantly improves contextual awareness in generative artificial intelligence technologies. To be more specific, this study seeks to answer the following questions:

RQ1: How can the integration of topic modelling and Word2Vec methods improve the interpretation of user-generated content to encourage experiential learning in generative artificial intelligence systems?

RQ2: What is the impact of the integration of topic modelling and Word2Vec methods on the enhancement of adaptability in AI models?

By using topic modelling, our analytical approach is able to identify eight major topics, which are as follows: ‘Playground’, ‘Support hub’, Content lab’, ‘Productivity’, ‘User experience’, ‘Access’, ‘Business assistant’, and ‘Remix. The results of a subsequent topic regression analysis show that themes like ‘content lab’, ‘User experience’, ‘Business assistant’, and ‘Remix’ are highly associated with experiential learning from the customer reviews dataset. Additionally, the use of Word2Vec analysis demonstrates various degrees of word cohesion within these topics. This is demonstrated by the manifestation of more cohesive clustering in themes such as ‘Access’ in contrast to themes that are less cohesive, such as ‘productivity’.

Our findings have several theoretical and managerial contributions. The different themes of topic modelling align closely with the fundamental components of Kolb’s Experiential Learning Theory, which include active creation, reflective evaluation, and iterative experimentation. ‘Content Lab,’ ‘Remix,’ and ‘Business Assistant’ are examples of themes that have high regression coefficients, which indicates that they have stronger links with experiential learning. The empirical findings suggest that consumers exhibit varying levels of experiential learning based on their interactions with generative AI platforms. The different themes obtained from the topic modelling help platforms foster learning dynamics. The word2vec approach provides semantic cohesion scores for each topic, obtained from topic modeling, and offers additional information about user experiences. For instance, high-coherence themes are appropriate for elementary learning because they are connected to more organised and minimal cognitive load-related activities. Conversely, low-coherence themes such as ‘Content lab’ and ‘Business assistant’ are tied to activities that support more complicated and exploratory learning. These semantic cohesion scores suggest how various learning phases can be fostered, ranging from simple to complex experiences, and focus on the adaptive and cyclical nature of experiential learning. Considering these findings, it is advisable that platforms for generative artificial intelligence prioritize features that support content creation, remixing, and reflective feedback to enhance experiential engagement. High-cohesion themes highlight the importance of onboarding tools and automated support through which novice users can achieve their goals. Lower cohesion scores suggest more open-ended interactions, which can help experts in problem-solving and experimentation. Therefore, generative AI platforms can balance organised support and creative flexibility, personalising the interfaces according to users' needs to promote distinct positive learning experiences.

The rest of the manuscript is structured as follows. Section 2 presents an in-depth literature review on experiential learning and machine learning (ML) methods for analyzing the consumer reviews dataset. We discuss topic modelling and the word2vec framework, analysis, and results in Section 3. Section 4 concludes the manuscript where we discuss the summary, theoretical, and managerial implications of our research. Additionally, we also address research limitations and future research directions at the end of this section.

2. Literature review

The need for more intuitive and adaptable systems has led to a recent surge in interest in merging AI with experiential learning paradigms. Iterative feedback and adaptive nature are essential components of experiential learning, which has its roots in the research of academics such as Kolb (Kolb, 2014). Kolb's experiential learning paradigm and its extensions offer a potent prism for viewing AI systems' capacity for dynamic adaptation and iterative learning. By incorporating experiential learning concepts, AI systems can transcend static algorithms and become more intuitive, user-centred, and adaptable to the actual world (Gruetzemacher et al., 2021). This paradigm shift will significantly impact the processing and learning of unstructured data, particularly in fields such as customer reviews, where flexibility and contextual awareness are essential (Lee, 2021). Future studies in this multidisciplinary field are expected to yield revolutionary improvements in AI's capacity to relate to human experiences.

2.1 User-generated content's relevance in AI

One of the rich and varied sources of experienced data is user-generated content (UGC) obtained from social media entries, product evaluations, online journals, and community forums (Alberth, 2008; Sykora et al., 2022). Studies have emphasised the use of UGC as a source of data for consumer behaviour research (Jun et al., 2014), forecasting firm performance (Lin et al., 2022; Shan et al., 2020), and sentiment analysis (Gozuacik et al., 2023). However, sophisticated techniques are needed to manage UGC's high dimensionality, unpredictability, and noise in order to derive valuable insights. The study of UCG has been the subject of numerous scholarly publications and investigations in various fields, which we discussed. Although there is a large body of current literature, this article offers a succinct overview of the most relevant and recent works coupled with critical analysis specific to the goals and scope of this journal.

2.2 Topic modelling for user-generated content

Finding latent themes in text data has been made possible by topic modeling techniques, such as Latent Dirichlet Allocation (LDA) (Blei et al., 2003). The LDA technique provides a probabilistic framework for theme analysis by grouping words into subjects based on co-occurrence patterns. Recent developments have enhanced the capacity to model dynamic and context-sensitive topics, such as neural topic modelling (Wu et al., 2024) and dynamic topic modelling (Hospedales et al., 2012). Several researchers have effectively applied topic modelling. (Gozuacik et al., 2023) perform topic modelling analysis on the bibliometric database and suggest advanced deep learning frameworks to improve the prediction accuracy of text analysis. (Li et al., 2024) use topic modelling to analyze UGC extracted from the Kaggle competition associated with the discussion to improve team performance. They found that most topics derived from topic modelling are positively related to team performance, and this could help categorize the types of teams. They highlight how forum conversations impact team success in data science competitions and offer implications for maximizing community engagement. (Lin et al., 2022) suggest a user-idea processing framework to process large amounts of UGC. They use a semantic clustering method, such as LDA, to perform topic modeling and simplify the analysis to identify relevant topics related to innovative directions. They provide the framework that indicates potential for product enhancement by highlighting clusters with poor adoption rates. Kim et al. (2017) (Kim et al., 2017) use an LDA similar approach to perform the thematic analysis of UGC from a virtual tourist platform. They address gaps in conventional sentiment analysis and utilize an advanced hybrid model to provide customers with insights into their tourism experience. Although there is extensive research on the use of topic modelling in UGC, this section focuses on recent TFSC contributions, aiming to cover key issues and approaches. From bibliometric analysis to community participation, creativity frameworks, and customer satisfaction improvement, the studies show how versatile topic modelling is. These publications jointly highlight the revolutionary potential of topic modelling in extracting meaningful actionable insights from unstructured text data by utilizing LDA and its contemporary extensions.

2.3 Word2vec for user-generated content

Another innovative method in natural language processing is the word2vec algorithm. Unlike conventional topic modeling methods, it converts each word in the UGC dataset into a vector form to capture contextual similarities and semantic linkages (Mikolov et al., 2013). Woo et al. (2021) use word2vec analysis to review the literature on technology development in Autonomous Vehicles comprehensively. Using the analysis, they prepared a historical trajectory of autonomous vehicle technologies from 1991 to 2018 and suggested the significance of integrating developing technology with commercial dynamics for R&D managers. Chen et al. (2022) employ the word2vec method to investigate the structural dynamics of academic-industry collaborations in digitalization research, utilizing bibliometric data. They emphasize how industry and academia address related subjects but often have different priorities. They pinpoint areas where industry and academia might more effectively coordinate their efforts to tackle technological and societal issues. (Chung & Sohn, 2020) use semiconductor patent documents and text data to assess patent quality in advance in the semiconductor sector. Word2vec analysis vectorises each word and performs an advanced-level analysis of its research objective. They suggest a novel methodology for evaluating patents and confirm that multimodal learning improves the ability to predict patent quality. (Puccetti et al., 2023) utilize an advanced NLP model, such as word2vec, to enhance the extraction of relevant portions from high-technology patent documents, aiming to improve technical domain mapping and analysis for innovation management and forecasting. They introduce a new framework for identifying technologies while removing phrases that are not relevant and are frequently mistaken for technologies. They demonstrate that advanced machine learning methods can be integrated into the patent analysis workflows of academic and business practitioners. Although TFSC covers a wide range of subjects, other publications also utilize word2vec and similar techniques to address specific research areas. Applications in digital transformation, medicinal research, and industry-specific innovation studies are a few examples. Nonetheless, the breadth of subjects and uses covered in TFSC ensures that it offers a thorough resource for comprehending the potential and effects of sophisticated NLP approaches in machine learning-related research.

2.4 Literature gaps

Topic modelling and Word2Vec analysis are commonly used methods in NLP research; however, prior research has utilised these methods independently, failing to exploit their complementary strengths. Word2Vec embeddings are designed to capture contextual and semantic relationships between words by representing them as vectors in a continuous space. Conversely, topic modelling techniques are widely used to uncover hidden thematic structures in large textual datasets. Prior studies have demonstrated the power of topic modelling in fields ranging from customer experience to innovation forecasting (Kim et al., 2017; Lin et al., 2022; Li et al., 2024) However, despite their respective strengths, limited research has explored the integrated application of Word2Vec and topic modelling, especially within user-generated content from generative AI platforms. Most existing literature (e.g., Woo et al., 2017; Gozuacik et al., 2023) applies one technique or the other, often missing the richer insights that emerge from analysing both topic structure and semantic relationships simultaneously. This siloed approach constrains the potential to capture the dynamic, user-centred learning processes involved in interacting with generative AI tools. Moreover, although experiential learning theory (Kolb, 2014) has been proposed as a conceptual framework for AI adaptability (Gruetzemacher et al., 2021; Lee, 2021), very few empirical studies operationalize this theory through real-world user data, particularly in the form of user-generated content (UGC). Existing research on UGC focuses on consumer sentiment, team performance, or innovation outcomes but not on mapping learning cycles or adaptive user behaviour across generative AI platforms.

This study addresses these interconnected gaps by combining topic modeling and Word2Vec in a unified framework, which enables both macro-level thematic discovery and micro-level semantic interpretation. We apply this framework to UGC from generative AI platforms, a novel and underexplored domain that presents complex, high-dimensional learning interactions. We interpret findings through the lens of experiential learning theory, thus offering new insights into how users engage with, learn from, and adapt to generative AI systems over time. By doing so, our study contributes both methodologically, through the innovative integration of NLP techniques, and theoretically, by extending experiential learning into AI-user interaction analysis. These contributions help bridge the disconnect between computational methods and behavioural understanding, offering a more holistic view of AI's evolving role in user-centred digital environments.

3. Methodology

We use a UGC dataset from the Trustpilot website for the generative AI platforms. Trustpilot is a consumer review website where consumers can provide their experiences and evaluations of various businesses, products, and services. Most businesses have started placing a significant amount of importance on their internet reputation because trust plays a crucial role in consumer decision-making (Kim et al., 2008). Hence, the Trustpilot website serves as a bridge of trust between consumers and firms, providing consumers with sufficient information to make informed choices. The total number of reviews on Trustpilot exceeds 250 million, with 64 million active users in 2023, indicating a large and diverse dataset that highlights the uniqueness of the Trustpilot website compared to its competitors[1]. Hence, Trustpilot is one of the best sources for consumer reviews of AI platforms, particularly for studies on experiential learning in AI systems, as it provides valuable insights into how AI

[1] https://www.statista.com/statistics/1488415/trustpilot-reviews/

technologies function in practical settings by compiling user reviews. Trustpilot's platform promotes transparency and continuously scrutinises reviews to check their validity. These policies encourage the precise and ethical data collection required for responsible AI research. Prior researchers also used Trustpilot to support their hypotheses (Beker et al., 2024; Mariani & Nambisan, 2021).

By working directly with tools and technology, experiential learning discloses the AI functions in our daily lives. The hands-on experience provides the advantages and weaknesses of AI platforms. As generative artificial intelligence continues to revolutionize organisations, there are two fields where these tools make significant contributions: content generation and writing support (Khalifa & Albadawy, 2024; Tom, 2024). Our objective is to understand how experiential learning in AI systems can enhance output quality, personalization, and adaptability by focusing on these areas. Table 1 provides information on the generative artificial intelligence content provider platforms, the number of observations, and website links. Customers get help from these copywriting support platforms for performing various tasks, such as assignments, blog posts, and marketing copy. We collect user evaluations for content-generating and writing support platforms from Trustpilot based on their experiences. Customers can post candid reviews on Trustpilot, helping others make informed choices based on real customer experiences. We can learn about the different experiences of consumers from Trustpilot and provide insights into the AI content provider platforms.

Table 1

AI platforms providing content creation and writing assistance

Firm Categories	Data Points	Firm URLs
AI4chat	180	https://www.ai4chat.co/
AISEO	1174	https://aiseo.ai/
Anyword	2000	https://www.anyword.com/

Assignment gpt	1555	https://assignmentgpt.ai/
Autowriter	220	https://www.autowriter.ai/
Copy.ai	180	https://www.copy.ai/
Jasper Ai	1999	https://www.jasper.ai/
Junia	184	https://www.junia.ai/
Phrasely AI	579	https://phrasly.ai/
Scribba	139	https://scribba.online/
SEO Writing	160	https://seowriting.ai/
Smodin	398	https://smodin.io/
StealthGPT	153	https://www.stealthgpt.ai/
QuillBot	259	https://quillbot.com/
WordTune	472	https://www.wordtune.com/
Write Sonic	1966	https://writesonic.com/

3.1 Fake review detection

After the data collection, we start with text preprocessing. First, we remove different language texts, emoji signs, numeric and non-alphabetic characters, and additional whitespaces, retaining only those reviews that exist in the English language. We convert the review text into lowercase. We also eliminate special characters and punctuation. We also convert contraction words like 'wouldn't' to 'would not' to ensure each English word is read clearly. After cleaning the dataset, we look for any fake reviews that may still exist within it. There may be fake reviews on the website because firms have incentives to influence public opinion. Businesses can write overly optimistic evaluations in order to artificially inflate their ratings and appear more appealing to potential customers, investors, or job seekers (Banerjee et al., 2017). However, competitors can provide negative reviews to tarnish the firm's reputation. The validity of UGC may be distorted due to fake reviews on the website, which don't provide accurate information for our analysis. Hence, we identify and remove those fake reviews from our analysis to provide accurate results.

We use the cleaned dataset to detect fake reviews. We concatenate the titles and reviews of users because they can provide crucial cues for consumers' views. A Document-Term Matrix (DTM) is created based on frequencies of each observation. We implement a Principal Component Analysis (PCA) dimension reduction process using this DTM matrix dataset to eliminate repeated words or phrases to get unique reviews (Maurya et al., 2024). We use the isolation forest unsupervised anomaly detection to identify dubious reviews (Liu et al., 2019). The isolation forest method identifies and tags the fake reviews as outliers. The outliers can be visualised with a PCA scatter plot. The review data points are coloured based on their regular or suspicious nature. This scatter plot shown in Figure 1 represents the results of a fake review detection model using PCA and Isolation Forest algorithm for anomaly detection. The green dots are normal reviews (Outlier = FALSE), and the red dots are the suspicious reviews (Outlier = TRUE) in Figure 1. The green dots are clustered together in one region, and the red dots are departed from the normal trends. We removed the suspicious reviews shown in Table 2 and worked on the remaining cleaned dataset.

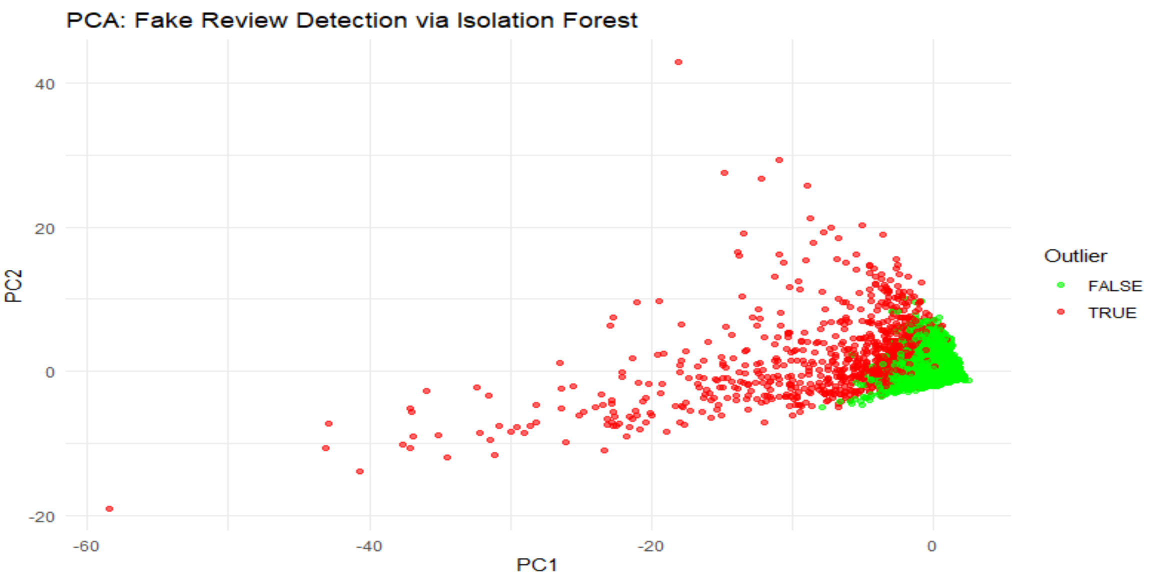


Fig. 1. PCA visualization of fake review detection using Isolation Forest

Table 2

List of suspicious or outlier reviews

Firms	% of Outliers
AI4chat	0.01
AISEO	0.08
Anyword	0.03
Assignment gpt	0.04
Autowriter	0.09
Copy.ai	0.13
Jasper Ai	0.16
Junia	0.03
Phrasely AI	0.09
SEO Writing	0.15
Smodin	0.08
StealthGPT	0.03
WordTune	0.07
Write Sonic	0.12

3.2 Topic modelling

Topic modelling is a machine learning method to find topics or themes within a group of text data. Organizing words and phrases into topics helps reveal hidden structures within extensive collections of raw text content, such as articles, feedback, or social media updates. Using topic modeling, it is possible to acquire experiential learning from reviews of generative AI platforms effectively. This is because topic modelling enables learners to extract important themes and insights from significantly larger amounts of user-generated content (UGC). The process of topic modeling reveals how people interact with and experience the platform in real-world scenarios by identifying recurring themes. We can gain insight into real-world usage patterns and varied perspectives across domains using topic modelling**.** Rather than depending solely on theoretical knowledge, topic modelling facilitates hands-on learning by organising unstructured data into themes that are both explicit and reflective. Because it promotes more in-depth involvement, critical thinking, and data-driven decision-making, it is an invaluable resource for researchers interested in investigating the impact of generative AI technologies in the real world and their evolution over time. We use the following steps to clean the initial database for topic modelling after merging titles and reviews in a single column of the dataset:

Step 1: We use *tokenization* to split text into discrete words or phrases (*tokens*). We divide the text according to whitespace between words. We use word-level tokenization to convert each word into a token.

Step 2: We eliminate stop words using the standard lexicon of stop words present in R Studio. Following prior literature, we also removed rare words that occur in fewer than 1% of our dataset (Büschken & Allenby, 2016). The stop and rare words contribute less to identifying co-occurring topics, and their elimination confirms the consistency of the topic modelling analysis.

Step 3: We also identify that users often use the platforms' names while giving their reviews. We remove the platforms' names from user reviews using an additional word-to-remove function containing all platforms' names. We also use only root words to avoid repetition in topic modelling analysis.

The above steps are the primary data-cleaning process required for topic modelling analysis. As the next step in topic modelling, we proceed with data description.

3.2.1 Data

Table 1 shows the list of AI platforms from which we collect customer reviews. The second column of Table 1 displays observations extracted from various platforms. The number of data points on the provided platforms varies significantly, ranging from a minimum of 139 to a maximum of 2,000. There are 11,618 observations across all platforms, spread across 172 unique countries. The dataset spans a duration of 2 years, from 2022 to 2024. After the detection and exclusion of fake reviews, as reported in Table 2, we have the final observation of 8,253 across 158 countries. Notwithstanding these variations, the data is adequate for topic modelling, as it allows for discovering important trends and topics among AI platforms that support writing and content creation and are cantered on experience learning. The diversity and size of the data pieces ensure the effective extraction of relevant insights. After completing all data processing phases, we get 2,63,227 words, averaging 31.89 words per observation. Reviews are typically brief, as evidenced by the mean of 2.78 sentences per review. Users give more than two sentences on average, indicating that they usually give succinct feedback. Users appear to provide sufficient depth in their evaluations, effectively communicating their perspectives, with an average of 31.89 words per review. Some evaluations are far longer, though, as indicated by the low median value, which raises the average. A high degree of customer satisfaction is indicated by an average rating of 4.62 out of 5, suggesting that most users are satisfied with the platform. This figure indicates that the platform is operating at an extraordinarily high level, with little opportunity for development to reach a perfect score, as the scale only goes up to 5. Most people offer minimal reviews, typically just one, as evidenced by the average of 1.29 reviews per person. Nonetheless, the fact that the mean is marginally higher than one indicates that certain individuals are more active and provide more evaluations, which in turn raises the average. However, almost 77% of users provide reviews only once. Hence, multiple user posts regarding AI platforms do not affect our analysis. Table 3 shows the summary statistics of the user reviews dataset.

Table 3

Summary statistics

	Mean	Median	Standard Deviation	Range
Number of sentences per review	2.78	2	1.42	1 to 6
Number of words per review	31.89	24	29.80	1 to 76
Rating	4.62	5.0	1.01	1 to 5
User reviews count	1.29	1.0	0.66	1 to 4

Table 4 lists frequently used words based on consumer ratings ranging from low (1-2) to high (4-5). A discernible pattern emerges across all these evaluations, manifesting as an increase in positive language associated with experiential learning as ratings improve. In the lower ratings (1-2), the words emphasise unsatisfactory encounters for customers (e.g., scam, refund, money, charged, cancel, trial, etc.). The middle-range ratings (2-3 and 3-4) show an improved awareness of the user experience, where the words evolve towards terms that are neutral or moderately favorable (e.g., good, use, support, experience, free, make, using). The high ratings (4-5) suggest words in a distinct, optimistic, and joyful voice as they become more experiential (e.g., amazing, best, easy, love, great, helpful). This unequivocally demonstrates a high level of experiential learning, characterized by positive emotional involvement with the service of content generation platforms. Hence, when customer ratings shift from low to high, there is a noticeable increase in the amount of experiential learning reflected in user language throughout the process.

Table 4

Most frequently used words arranged with ratings

Rank	Rating 1 to 2	Rating 2 to 3	Rating 3 to 4	Rating 4 to 5
1	service	good	good	tool

2	subscription	use	like	great
3	scam	free	words	love
4	customer	words	app	use
5	refund	subscription	great	best
6	trial	support	use	good
7	money	tool	free	easy
8	charged	service	really	amazing
9	get	customer	tool	really
10	use	experience	service	time
11	account	make	product	write
12	even	need	help	app
13	cancel	pay	using	helpful
14	support	really	time	using
15	card	using	nice	work

3.2.2 Topic modelling analysis

The Latent Dirichlet Allocation (LDA) is a frequently used method of topic modelling in natural language processing (NLP)(Chen et al., 2017; Zhang et al., 2016). It assumes that the distribution of words describes every topic. Customer reviews are not restricted to a single topic but are characterized by combining different topics according to their contribution. LDA finds the recurring topics within the customer reviews. It connects customers' sentiments associated with topics and creates a bag of words for topics associated with a similar theme based on customer sentiments. We describe the process of model fit to show how well the model performs in the context of AI platforms' customer reviews.

After loading and preprocessing the data using the above four steps, we create a document term matrix (DTM), where rows show the number of documents and columns show the frequency of the words used for reviews. We fit the LDA model by assuming that each document is a combination of topics, where a distribution over words characterizes each topic. We explain the process using relevant equations.

A topic distribution is drawn using the Dirichlet distribution with a parameter for the hyperparameter controlling the density of the topic distribution. (Blei et al., 2003). The equation below represents the process:

$$\theta_d \sim Dirichlet(\alpha) \quad \text{...}(1)$$

where,

θ_d= Topic distribution for a specific document d

α= Hyperparameter controlling topic sparsity

A topic is selected for each word in the document using a multinomial distribution, and the word is drawn from the word distribution of the chosen topic. The equations associated with this process are given below:

$$z \sim Multinomial(\theta_d) \quad \text{...}(2)$$

$$w \sim Multinomial(\phi_z) \quad \text{...}(3)$$

where,

z= Topic selected from a multinomial distribution

w= Word taken out from the word distribution

ϕ_z= Parameter to control the concentration of selected words

The parameters θ and ϕ play crucial roles in the topic modelling, which follows the probabilistic model (Blei *et al.,* 2016). These parameters are used to define topic distribution per document and word distribution per topic, as explained in the equations below:

$$\theta_d = [P(z_1 \mid d), P(z_2 \mid d) \ldots\ldots, P(z_k \mid d)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

$$\phi_k = [P(w_1 \mid z_k), P(w_2 \mid z_k) \ldots\ldots, P(w_n \mid z_k)] \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(5)$$

where,

$P(z_k \mid d)$ = Probability of topic *k* in document *d*

$P(w_n \mid z_k)$= Probability of the *n*th word given the topic

Equations (4) and (5) explain how topics are made up of words and how documents are made up of topics, allowing the LDA model to reveal hidden patterns in the data. We calculate the perplexity measure, which can predict the accuracy of the LDA model and be used for generalization (Seo & Afifuddin, 2024; Xu et al., 2021). The equation below obtains the perplexity measure:

$$Perplexity\ of\ Documents\ =\ \exp\left(-\sum_{\{d\in D\}} logP(w_d) \,/\, \sum_{\{d\in D\}} N_d]\right)\ldots\ldots\ldots(6)$$

where,

$P(w_d)$ = Probability of the sequence of words in the document

N_d= Total number of words in the document

3.2.3 Topic modelling results

We divide the dataset into training and testing sets to assess the model's performance and generalisability. We train the model using the training dataset to classify patterns of term frequencies and latent themes. Alternatively, the testing data offers an unbiased assessment of the model's capacity to generalise to the new dataset of customer reviews. Both training and testing sets are used to compute perplexity. Out-of-sample (testing set) perplexity evaluates the model's predictive performance on unknown data, guaranteeing robustness and preventing overfitting, whereas in-sample (training set) perplexity gauges how well the model fits the data it was trained on. Splitting and analysing the data on training and testing samples provides better results that are closer to real-world performance. For consistent comparisons across experiments, the split is guaranteed to be reproducible by using a random seed. We divided the data, allocating 20% to the testing set and 80% to the training set following prior literature (Gozuacik et al., 2023). The metric values of the analysis are reported in Table 5.

Table 5

Model fit metric values

Metric	**Value**
In-Sample Perplexity	957.89
Out-of-Sample Perplexity	970.69
Number of Training Observations	6602
Number of Testing Observations	1651
Number of Topics	8

Table 4 uses the customers' review database to assess the topic model's functionality and effectiveness. The in-sample perplexity value is 957.89, suggesting the model's capacity to learn from the training data. The value of the out-of-sample perplexity is 970.69, which is slightly greater than the in-sample perplexity. This significant value suggests a moderate probability of accuracy in the model prediction when handling unseen datasets (Amami et al., 2016). The dataset is divided into 1,651 testing observations and 6,602 training observations, providing a strong basis for model evaluation and training. Eight latent topics, or distinct themes or word clusters that regularly occur together in the dataset, are set up for the model to detect. Table 4 suggests that the model is well-equipped to draw important conclusions from the review database.

Figure 2 illustrates the distribution of words according to the mean posterior probabilities (ϕ) that are derived from an LDA topic model concerning those terms. The graph on the left displays the top fifty terms ranked according to their average importance across all topics. It shows a sharp decline, suggesting that a few words have a greater influence on topic modeling compared to other words. Words numbered 51 to 200 are displayed on the right graph. The line begins to flatten out after this point, which suggests that words between 51 and 200 have low probabilities and are less comparable to one another. The overall pattern from Figure 2 indicates that topic modelling generates a few dominant topics along with the tails of less relevant terms. This is a valuable insight when picking keywords for topic interpretation or filtering noise in text analysis. Figure 2 suggests that selecting fewer topics for topic modelling would provide better interpretation, as more topics may bring noise or redundancy.

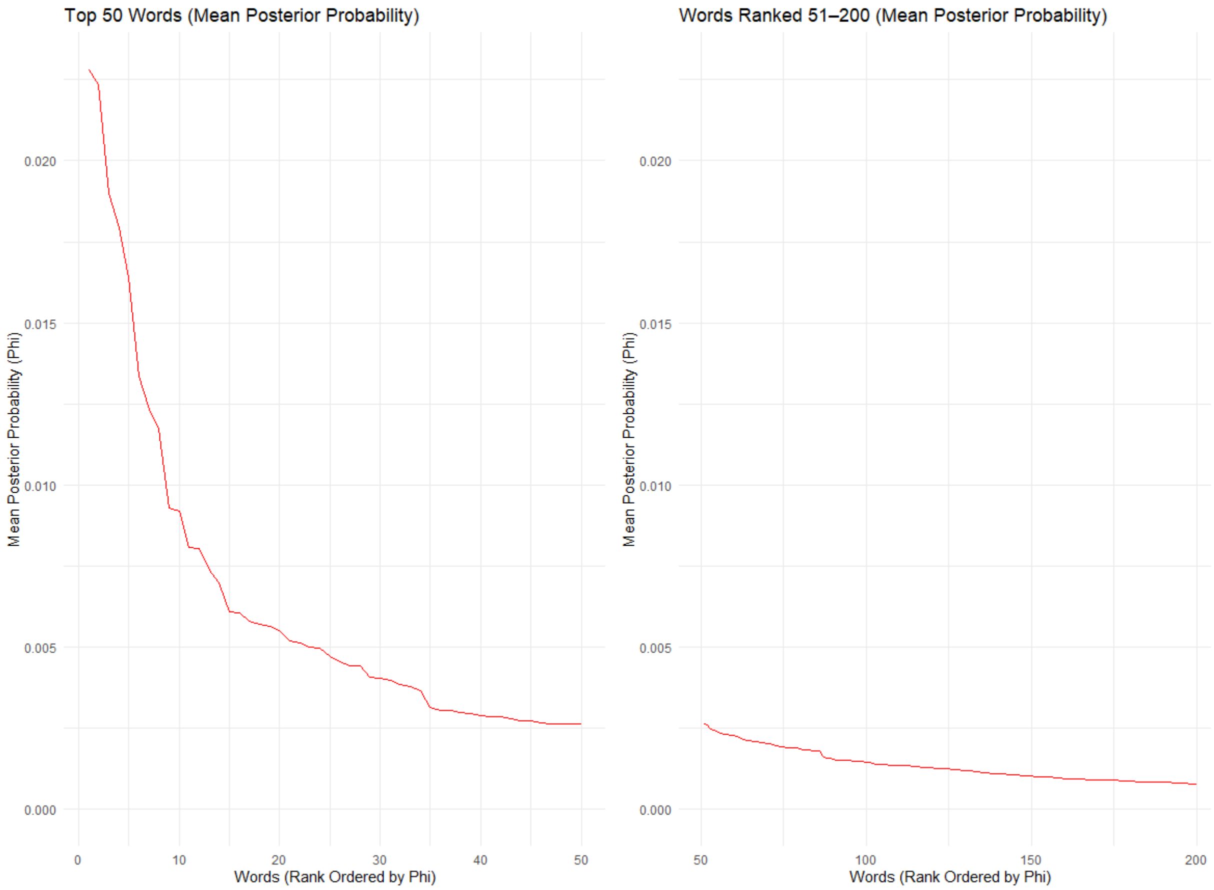


Fig. 2. Ranked word probabilities from the LDA model.

We have plenty of unstructured data in the consumer reviews of AI content authoring platforms. We use LDA to group the most talked-about features of the platforms. By doing this, we can identify the features, pricing, and convenience of use that people value most and highlight both our strengths and areas for improvement. By determining user priorities and experiences, the procedure allows AI platforms to learn from experience data. They can enhance AI training and refine services based on this learning, ultimately providing a better user experience for consumers. By using these phrases, businesses can track the varying perspectives of their consumers over time. The LDA analysis helps identify a bag of words from the consumer reviews, which will reflect logical topics related to experiential learning.

Based on their context, the generated words are grouped into relevant topic names and ranked as the top 20 words for each topic. The list of 8 topics, ranked in order of 20 words concerning each topic, is reported in Table 6.

The theme of Topic 1 is Playground, where consumers *love* experiential learning through exploration. The generative AI platforms provide a *fun* and easy environment equipped with appropriate *tools* to facilitate experiential learning. The platforms support consumers from *marketing* or content design backgrounds in *creating* in real-time. Consumers can *generate* ideas and *copy* or adapt them based on their needs. The platform is a place where *writers* can play with words and also *review* their content. The platform *makes* learning enjoyable with *numerous options, enabling users to create effective and high-quality* content. The platform *fosters a stronger connection between learning and doing, enabling users to enjoy the journey truly*. The theme of Topic 2 is the Support Hub, which is designed for consumers, including writers, customers, or academics, who seek help to succeed. The generative AI platforms have a committed *team* to *offer reliable support* that thoroughly perceives user needs. The platforms *provide* an *incredibly valuable product* that helps consumers in their journey. They craft a *top*-standard *service* that meets the demands of consumers. The theme of Topic 3 is Content Lab, which demonstrates that the generative AI platform is an innovative space designed to support experiential learning for consumers by offering the opportunity to write, explore diverse *tools*, and generate purposeful *output*. The platform encourages consumers to *begin their activities with the correct information, such as a blog, an assignment, or a post, and helps them improve their tasks more efficiently*. The platform's resources are excellent, and consumers can dive into the world of creative writing content with every type of tool, all without *plagiarism*. The theme of Topic 4 is Productivity, which assists the users' experiential learning by providing *software* and *programs* to make learning more efficient. The generative AI platform features a user-friendly interface that helps consumers manage their ideas and complete tasks efficiently by optimizing their *time*. Consumers *save* hours of struggle and effort, simplifying complex *process* steps. They transform jobs into growth prospects by drafting sentences or refining text, making life and learning easier, and ensuring successful outcomes**.** The platform has *fantastic* tools to *block* distractions and keep the *job* focused.

The topic 5 theme is User Experience, which supports students' experiential learning in an amazing and friendly atmosphere that enhances their learning and creative process. The platform is available *online* and with the *app*, focusing on a *fast* and *accurate assignment experience*. Users are motivated to *create* and explore *helpful* content. Users have *loved* how the tools *helped* them find *answers***,** and they are *happy* that turning learning into a game makes it easy to *recommend* to anyone. The theme of Topic 6 is Access, supporting experiential learning through adaptable choices such as trial periods, subscriptions, and personalized plans. Consumers can use the generative AI platforms through an *account* on the *site* **and** utilize email support to cancel or request a refund for the monthly *plan*. They can use a *credit card***,** and the fee will be charged monthly. The platform has a clear *response* system to support the consumers. Topic 7: Business Assistant theme enables experiential learning by providing an efficient platform that functions like a real *assistant*, with *simple, quick,* and highly *professional applications.* Many users have *found* it to be a *nice* platform that can improve their *business*. The consumers are *impressed* with the platform for improving *grammar* and managing tasks multiple *times* a *day*. The theme of Topic 8, Remix, encourages experiential learning by allowing consumers to utilize powerful tools such as *paraphrasing, chat*, and content *generator* features. The platforms offer *free human* or intelligent content, which can be used for *blogs, articles*, or *social media posts*. Consumers can easily learn how *unique* content is *generated* and convert raw *articles* into polished ones using the *recommended* content. Each *bit* of content can be converted into perfect writing, and the tool usage is *worth* the consumers' time.

Table 6: Top 20 words from the LDA rating model (T = 8)

Rank	Topic 1: Playground	Topic 2: Support hub	Topic 3: Content lab	Topic 4: Productivity	Topic 5: User experience	Topic 6: Access	Topic 7: Business assistant	Topic 8: Remix
1	tool	product	write	helps	amazing	site	lot	blog
2	love	customer	tools	time	app	trial	platform	highly
3	easy	writer	awesome	software	experience	subscription	nice	articles
4	copy	service	blogs	life	helpful	money	found	free
5	words	support	assignment	text	helped	refund	business	article
6	makes	team	information	easier	wow	account	absolutely	perfect
7	generate	top	post	fantastic	recommend	plan	impressed	posts
8	creating	reliable	feature	program	create	cancel	simple	worth
9	marketing	offers	extremely	saves	user	charged	quick	generated
10	review	provide	wonderful	results	friendly	days	helping	social
11	pretty	valuable	started	job	fast	credit	efficient	media
12	effective	understand	complete	saved	accurate	card	professional	human
13	writers	incredibly	plagiarism	block	game	bad	assistant	recommended
14	enjoy	academic	improve	save	happy	month	application	chat
15	quality	level	start	quickly	assignments	emails	day	generator
16	fun	impressive	faster	process	students	email	feel	generating
17	lots	recently	learning	hours	answers	charge	writes	bit
18	market	services	output	interface	school	pour	cool	unique
19	forward	users	type	idea	loved	paid	grammar	powerful
20	creates	skills	world	sentences	online	response	times	paraphrasing

We also examine how various topics contribute to the experiential learning process. For this purpose, we generate a synthetic dependent variable called Experiential Learning based on the conceptual alignment between topics and foundations of experiential learning. We give more weight to topics that are also related to hands-on learning, creativity, content creation, and user interaction. These topics include Topic 3 (Content Lab), Topic 5 (User Experience), Topic 7 (Business Assistant), and Topic 8 (Remix). Words like 'write', 'assignment', 'create', 'assistant', 'generator', etc., are examples of active and practical learning. We assign moderate weights to Topic 1 (Playground) and Topic 4 (Productivity) because they contain relatively fewer experiential learning words. In contrast, Topic 6 (Access) has the lowest weight, as it is more administrative in nature. We calculate the probabilities of each topic used for maintaining a data frame using the posterior function. The contribution of each topic to Experiential Learning is also calculated using these topic probabilities. The regression equation is given below:

$$Experiential\ Learning = \beta 0 + \beta 1 * Topic\ 1 + \beta 2 * Topic\ 2 + \beta 3 * Topic\ 3 + \beta 4 * Topic\ 4 + \beta 5 * Topic\ 5 + \beta 6 * Topic\ 7 + \beta 8 * Topic\ 8 + \varepsilon \ldots\ldots..(7)$$

The results of the topic regression are reported in Table 7. The coefficient for Topic 1 is positive and significant ($\beta = 0.79$, $p < 0.05$), indicating that creativity and exploration support consumers' experiential learning. Topic 2 has the lowest coefficient ($\beta = 0.30$, $p<0.05$), suggesting a relatively weaker contribution to experiential learning than other topics. The coefficient of Topic 3 shows a strong positive effect ($\beta = 2.01$, $p<0.05$), emphasising that writing and creation tools are essential to experiential learning. The coefficient for Topic 4 is positive ($\beta = 1.31$, $p < 0.05$) and contributes to experiential learning, indicating that efficiency and task completion are crucial for hands-on learning. Topic 5's positive and significant coefficient ($\beta = 1.79$, $p<0.05$) suggests amazing interfaces support experiential learning through experience. The positive and significant coefficient ($\beta = 1.88$, $p < 0.05$) of Topic 7 indicates the intelligent assistance applied to consumers' experiential learning. Topic 8 has the highest positive and significant coefficient ($\beta = 2.19$, $p < 0.05$), highlighting the impact of creative remixing on experiential engagement. The topic regression analysis signals the relative importance of each topic in the experiential learning of consumers with generative AI platforms.

Table 7: Topic regression results, DV- Experiential learning

Topics	Coefficient	S.E.	t-Value	p-Value
Topic 1: Playground	0.79	0.01	73.42	<0.05
Topic 2: Support hub	0.30	0.01	29.15	<0.05
Topic 3: Content lab	2.01	0.01	186.84	<0.05
Topic 4: Productivity	1.31	0.01	129.55	<0.05
Topic 5: User experience	1.79	0.01	177.04	<0.05
Topic 7: Business assistant	1.88	0.01	173.97	<0.05
Topic 8: Remix	2.19	0.01	201.66	<0.05
(Intercept)	0.20	0.01	32.18	<0.05

Topic modelling analysis and topic regression provide information on distinct topics related to experiential learning. However, a traditional drawback of topic modelling analysis is that it selects words based on frequency and does not focus on the context in which words are used (Doogan, 2022). Therefore, we employ an alternative machine-learning method to address this limitation.

3.3 Word2vec analysis

We employ the LDA technique for topic modeling to identify topics in consumer review data for AI content writing platforms. This technique is based on the bag-of-words method, which extracts semantically similar words across different topics based on their co-occurrence. For instance, words like ‘love’, ‘fun’, 'amazing, ‘wow’, ‘happy’, etc., have similar positive semantic meaning, but they are placed in different topics because of their high co-occurrence. However, these words could be grouped based on their sentiments and contexts. Therefore, we utilize the Word2Vec method to bridge this gap by understanding the semantic properties of each word and providing an enhanced understanding of customer reviews (San Kim & Sohn, 2020). Word2Vec is an NLP technique that expresses words in numerical vectors across multiple dimensions. It is frequently used for tasks involving natural language processing (NLP), such as examining and evaluating textual material (Trappey et al., 2021). We utilize the Word2Vec approach to analyze customer review data for AI content creation platforms.

We use the cleaned dataset obtained from step 3 of section 3.2. We use R's word2vec and text2vec libraries for preprocessing and vectorized operations. Converting sentences into tokens is the first step in the process of tokenizing the textual data using the text2vec package. The whole consumer reviews dataset is converted into manageable components through the process of tokenization. A list of all distinct terms contained inside the corpus is created after tokenization. All unique words are considered in this vocabulary list and prepared for vectorization. The word2vec model uses this tokenized vocabulary list and generates word embeddings where a numerical vector represents each word. The matrix of this numerical vector captures the semantic links that exist between words. Hence, we utilize these semantic links to gain a clearer understanding of the text data.

We use the Skip-gram model, which is the part of Word2Vec used after the tokenization process. The objective of the Skip-gram model is to achieve the highest possible probability of correctly predicting content words found in the context of a target word. We use the following objective function, which is derived from the softmax function (Bartunov et al., 2016):

$$J = p(Y \mid X, \theta) = \prod_{i=1..N} p(y_i \mid x_i, \theta) \quad \text{……………………..(8)}$$

where,

$p(Y \mid X, \theta)$ =Overall probability of a set of contextual words (Y) concerning target words (X)

$p(y_i \mid x_i, \theta)$= Probability of observing a specific contextual word (y_i) concerning the ith target word (x_i)

θ=Word embedding parameter

Equation (8) shows the probabilistic underpinnings of the skip-gram model, which breaks down the probability of correctly predicting every context word given its target words into smaller probabilities for each context word separately. The model is computationally feasible due to the independence condition. We further optimize the model using negative sampling. The revised objective function with negative sampling is given by (Kaji & Kobayashi, 2017):

$$J = \; log\, \sigma\left(v_{context} \cdot v_{target}\right) + \textstyle\sum_{w \epsilon N} \log \sigma \left(-v_w \cdot v_{target}\right) \ldots\ldots\ldots\ldots(9)$$

where,

$\sigma(.)$= Sigmoid function

$v_{context}/v_{target}$= Context/target word embedding

$-v_w$=Negatively chosen random samples

The first term on the right-hand side of the equation (9) includes a sigmoid function with context/target word embedding, which has a high value when the target and context words are similar. It emphasizes the fact that the model should attribute higher probabilities to correct word-context pairs. The second term on the right-hand side of the equation (9) penalises the target word's resemblance to negative samples, randomly selected words that do not fit the target word's context. We use unigram distribution to draw negative samples from the vocabulary (Davison & Austern, 2023). Equation (9) seeks to maximise the objective function (J) in order to learn the model to group words that are highly similar to one another and vice versa based on classification. Negative sampling increases the objective function's computational efficiency by separating genuine word-context combinations from unrelated words chosen at random. We load the trained embeddings into the word2vec model after the revision process.

3.3.1 Word2vec results

We start with Figure 2, which shows the process of word2vec analysis. It shows the word2vec model's skip-gram architecture, which is utilized to learn word embeddings. The input word is 'experience' in the skip-gram architecture, which is the target word. We want the word2vec model to predict contextual words close to this target word. The projection layer, labeled SUM in the skip-gram network, is comprised of dense vectors for the target word and is used to predict the context words. The projection layer uses the objective function Utilise to calculate the likelihood of each context word based on the dot product results. We focus on the context window of five neighbouring words on each side of the target word to analyse the co-occurrence of words following prior literature. (Horn, 2017). The output node shows the context words- 'pleasant', 'thumb', 'fulfill', and 'epic'. These are the words semantically related to the target word in the document. Hence, Figure 3 illustrates how a word2vec model uses the input word 'experience' to train and predict contextually related terms. This illustration distinguishes word2vec from topic modelling because word2vec mainly focuses on the semantic relationship between words, while topic modelling discovers the topic from a group of words.

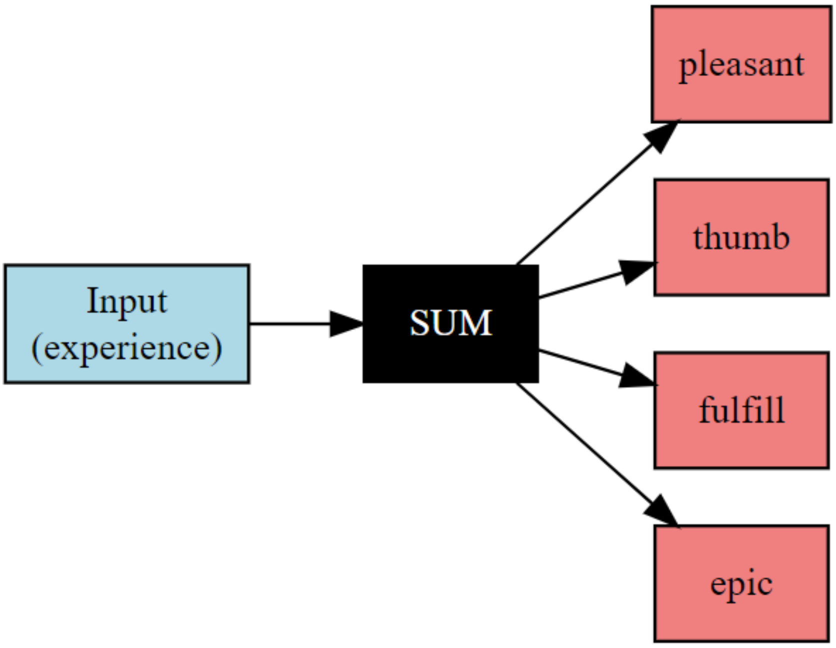


Fig. 3. Skip-gram projection

In the previous section, we discussed the topic modelling analysis of the words present in the customer reviews of AI content writing platforms. We create high-dimensional word representations that encode contextual relationships between words, utilizing Word2Vec to expand the topic modeling technique. We enhance topic modeling by accurately representing the connections between words within their context in the dataset using Word2Vec modeling. Word2vec embeddings capture word relationships using cosine similarity between words for better topic validation (Hain et al., 2022). We focus on the words reported in each topic given in Table 6. We compute the similarity of each word to other words to identify anchor (high similarity) and outlier (low similarity) words (Wang et al., 2021). We calculate the average pairwise cosine similarity for each topic, indicating its semantic cohesiveness. The results are reported in Table 8.

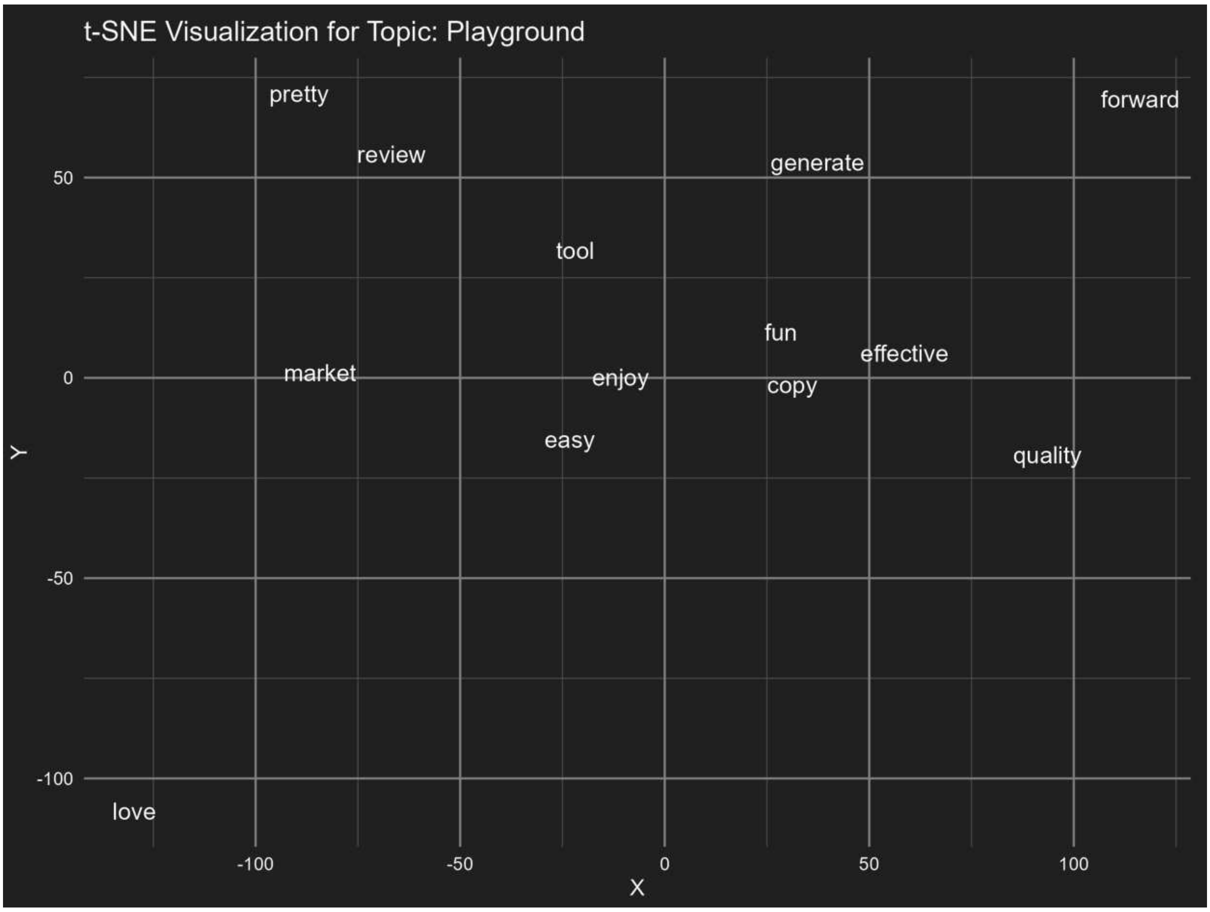
Table 8

Word2vec cohesion score of each topic

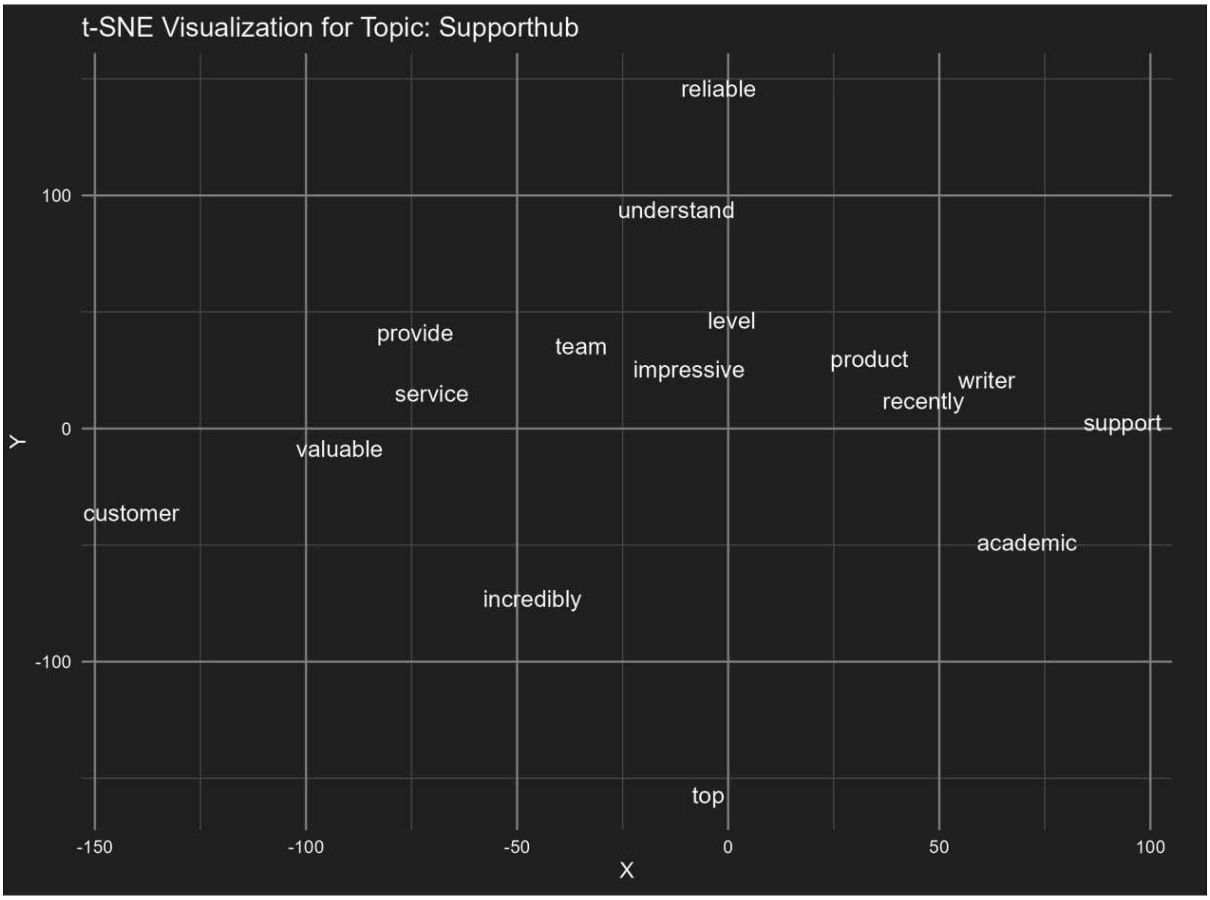
Topic	**Cohesion Score**
Topic 1: Playground	0.20
Topic 2: Support hub	0.19
Topic 3: Content lab	0.16
Topic 4: Productivity	0.16
Topic 5: User experience	0.19
Topic 6: Access	0.31
Topic 7: Business assistant	0.15
Topic 8: Remix	0.17

Table 8 presents the cohesion score, or the mean pairwise cosine similarity score, between terms within each topic. The topic ‘Access’ has the greatest score (0.31), suggesting words in this topic are highly semantically related. However, topics such as ‘Business assistant’ (0.15), ‘Content lab’ (0.16), and ‘Productivity’ (0.16) have the lowest cohesion scores, indicating fewer semantic connections and may overlap with other topics. Topics like ‘Playground’, ‘Support hub’, and the ‘User experience’ category receive almost similar scores (0.19 & 0.20), which indicates that they are moderately cohesive. The topic ‘Remix’ (0.17) falls into a comparable range, suggesting that even though their words are relatively connected, these subjects may still contain some semantic noise. The overall cohesion scores demonstrate that the topic of ‘Access’ is relatively highly cohesive as compared to other topics, such as ‘Business assistant’ and ‘Content lab’, which are less semantically consistent. The majority of the other themes exhibit somewhat satisfactory levels of coherence.

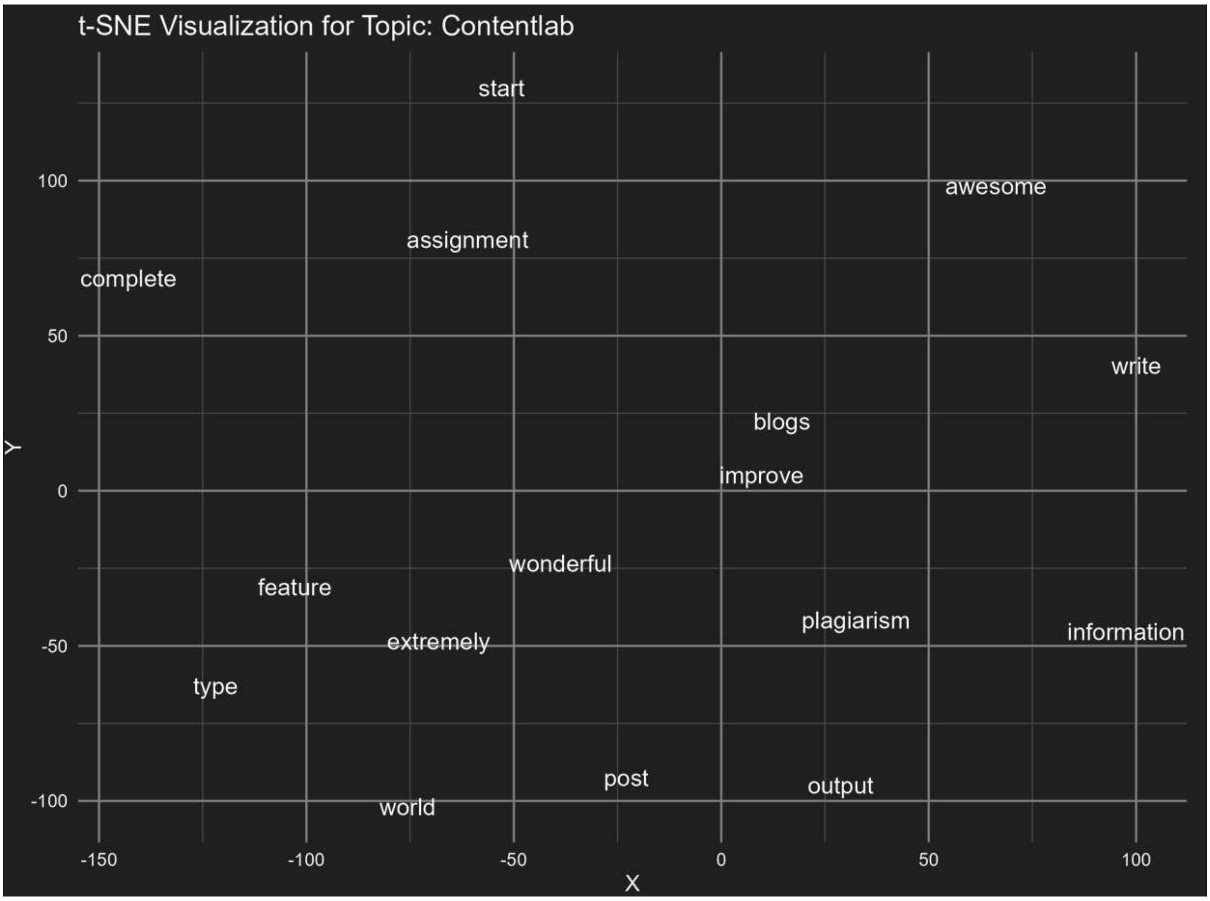
We assume each word as a vector in word2vec analysis, and that is why we have more than 100 dimensions in this process. Therefore, we use t-distributed Stochastic Neighbor Embedding (tSNE) to reduce the dimensions and visualize the group of similar contextual words in an X-Y (2D) plane (Heuer et al., 2016). Figure 4 shows tSNE plots for each topic in a 2D X-Y plane. The scales on the axis range from negative to positive values created by the tSNE algorithm to show the transformed coordinates. The separation of words in the semantic space reflects high or low cohesion scores. For instance, the tSNE visualization plots of topics ‘Content lab’, ‘Productivity’, and ‘Business assistant’ show that the words within these topics are not densely grouped. The lowest cohesion score also suggests the same insight. However, the tSNE visualization plot of the topic ‘Access’ shows that words like ‘refund’, ‘account’, and ‘money’ are closer, suggesting that the topic ‘Access’ has relatively more well-defined clusters than other topics. Similarly, we can compare or interpret the tSNE visualization plot of other themes. The cohesion score in Table 8, along with the tSNE visualization plot, makes the word2vec analysis easy to comprehend.



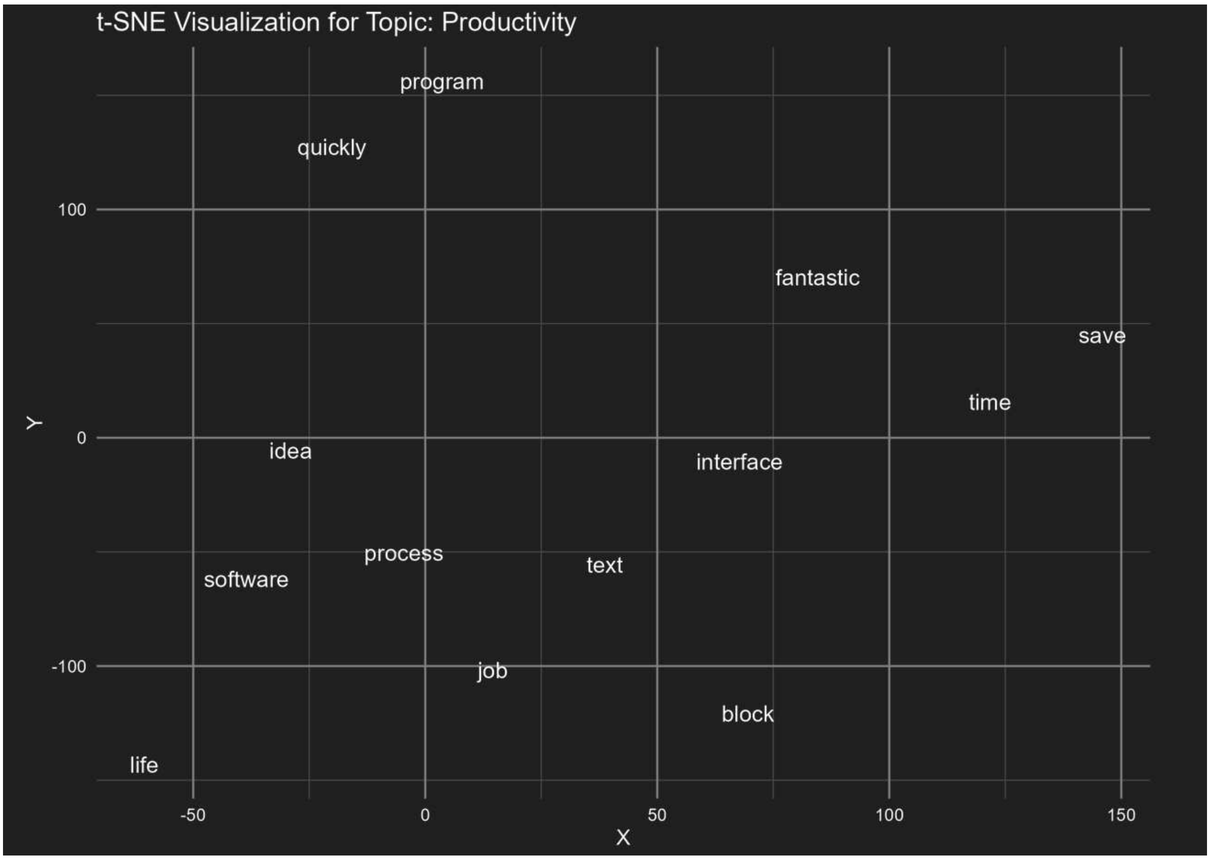
(a) Playground



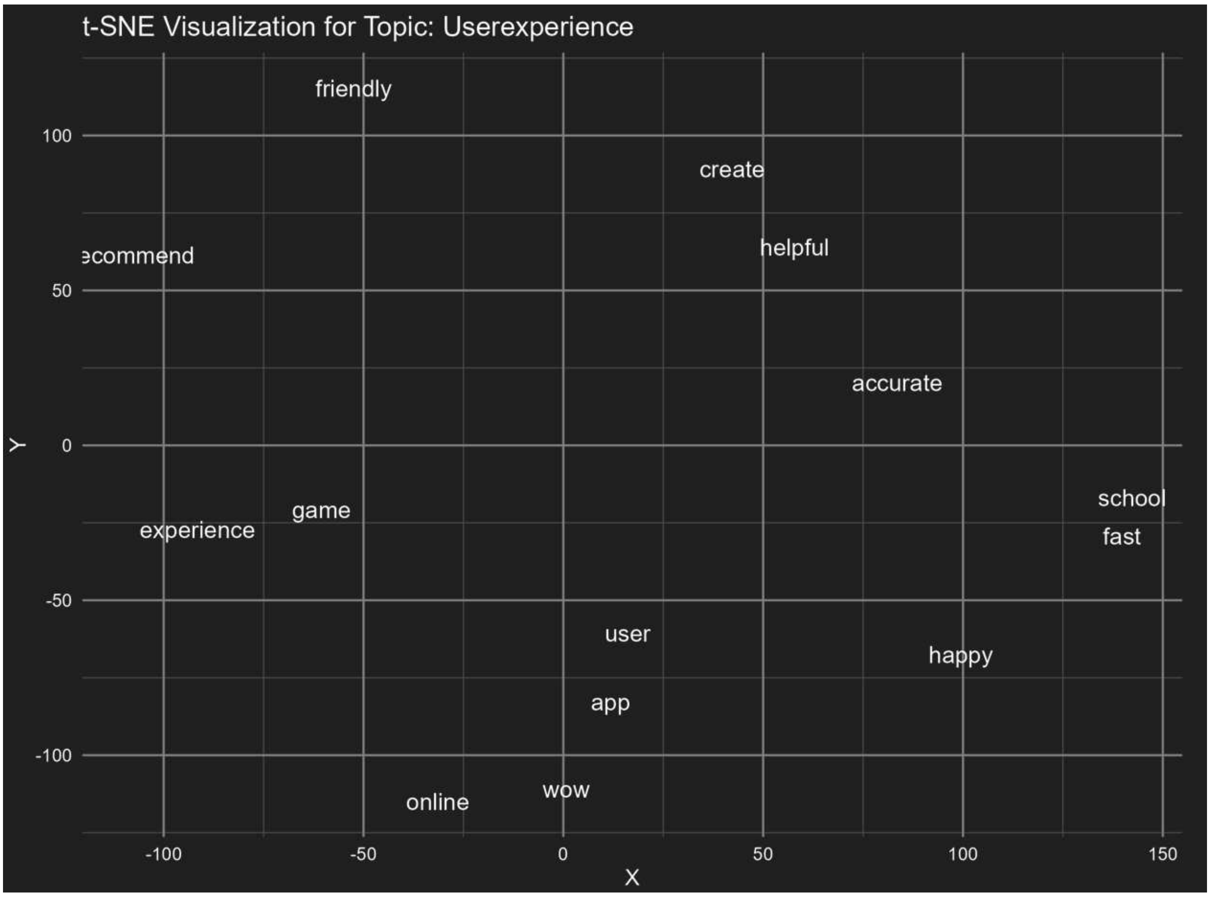
(b) Support hub



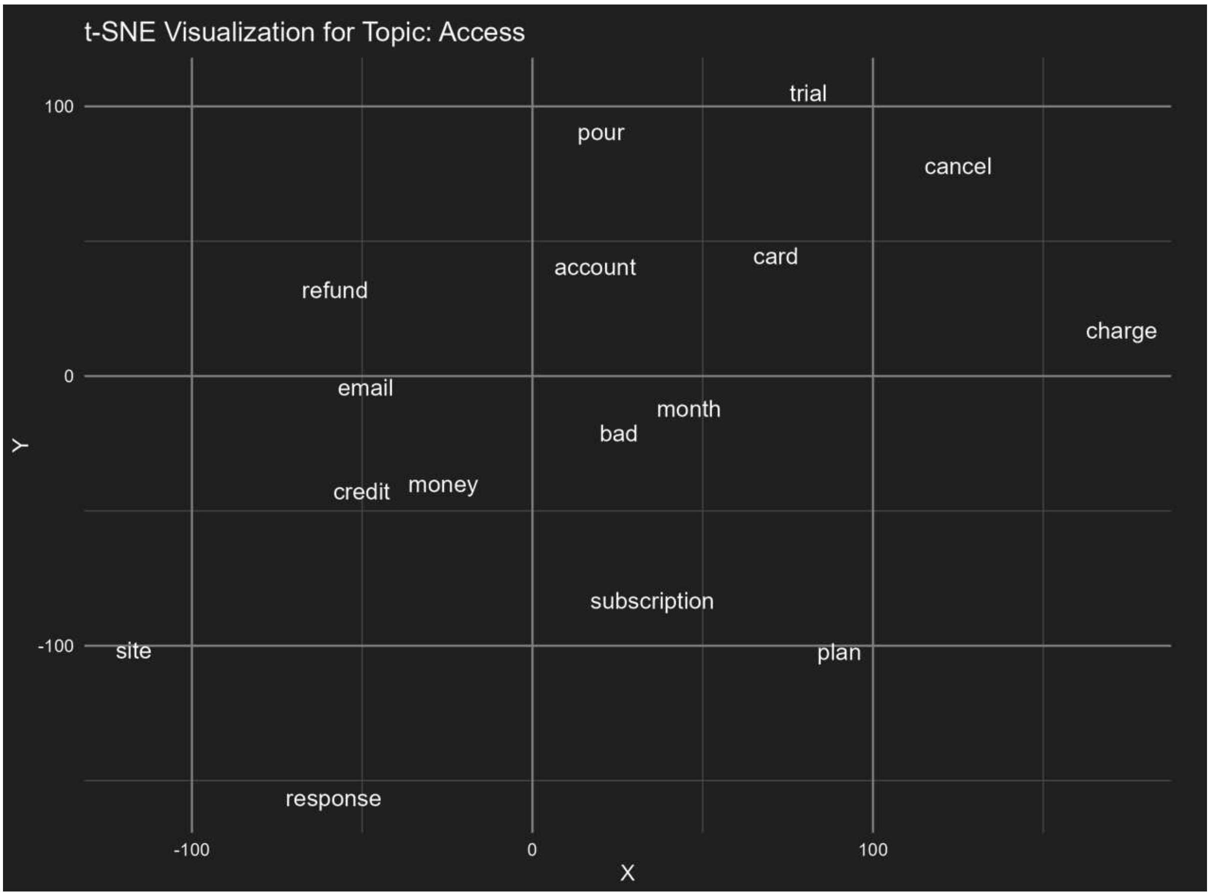
(c) Content lab



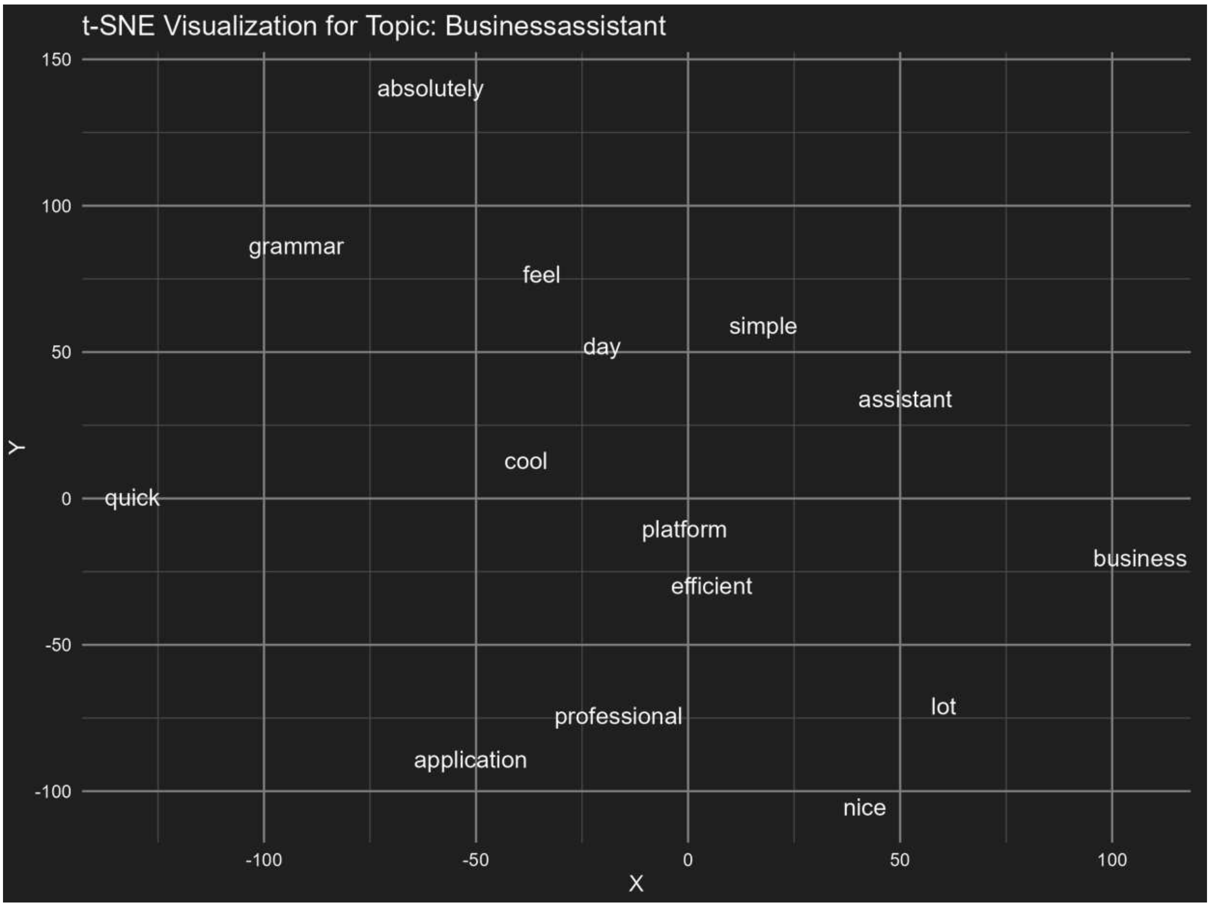
(d) Productivity



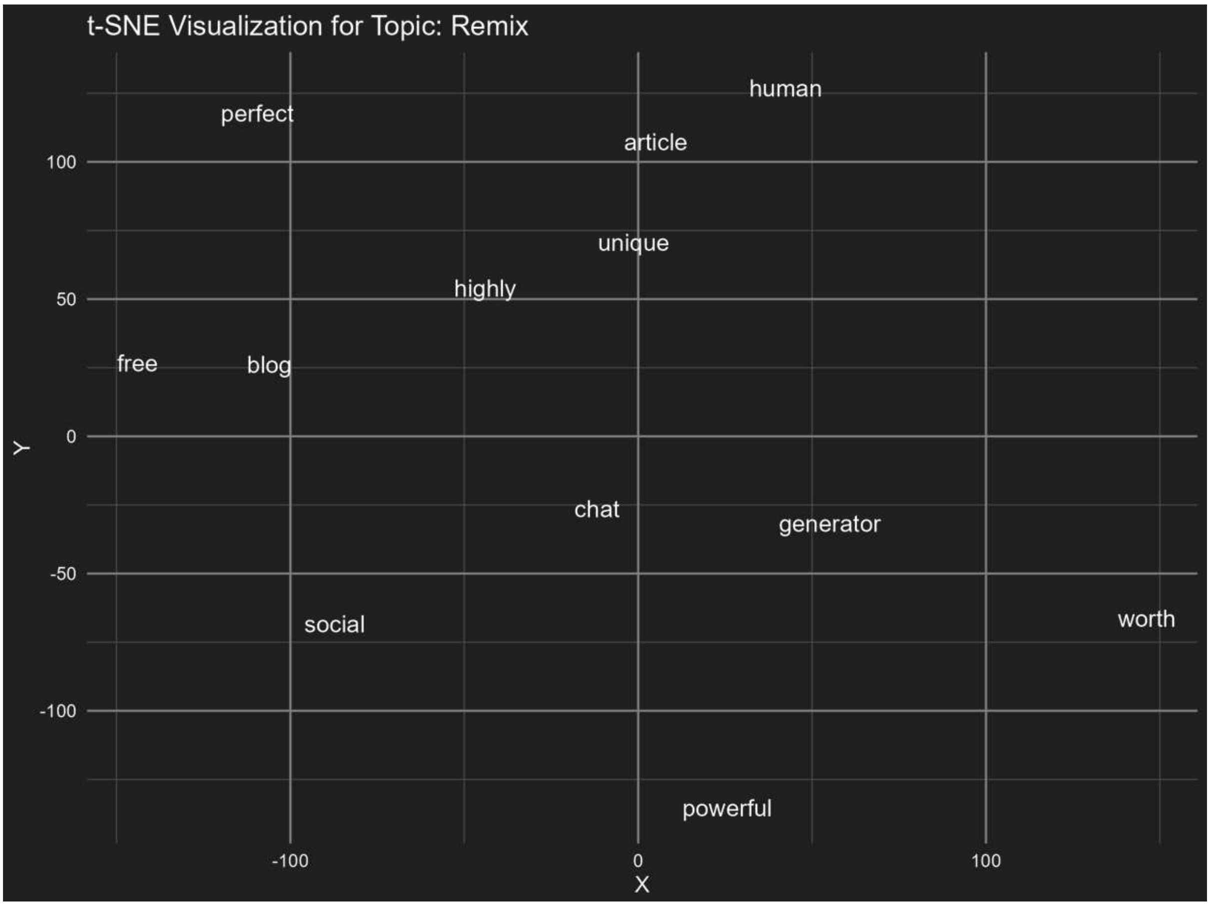
(e) User experience


t-SNE Visualization for Topic: Access
trial
pour
cancel
account
card
refund
charge
email
month
bad
credit
money
subscription
site
plan
response
100
0
-100
-100
0
100
X
Y

(f) Access



(g) Business assistant



(h) Remix

Fig. 4. tSNE visualization plot

It is interesting to note that the topic ‘Access’ received the highest cohesion score (0.31) out of all the themes. This indicates that the words contained within this theme are semantically well-clustered and internally consistent. However, we use this topic as a contrast in our topic regression analysis and assign it less weight. This illustrates a notable distinction between semantic relevance and semantic coherence. The topic ‘Access’ contains more administrative words (‘trial’, ‘account’, ‘email’, etc.), which don’t directly reflect learning processes. Hence, we consider it a contrast. However, these findings could have greater implications, which we explain in the next section.

4. Conclusion and discussion

4.1 Summary

We investigate two research questions in this study. First, how does the combination of topic modelling and word2vec techniques improve the interpretation of UGC in order to facilitate experience learning in generative artificial intelligence systems? Second, what is the impact of this integration method on the enhancement of the adaptability of AI models? To answer this research question, we collect the UGC or consumer reviews dataset for generative AI content generation platforms from the Trustpilot website. After screening the dataset with outliers using the isolation forest technique, we perform topic modelling analysis and find eight key themes- 'Playground', 'Support hub', 'Content lab', 'Productivity', 'User experience', 'Access', 'Business assistant', and 'Remix'. We also perform the topic regression and find that the themes 'Content lab', 'Business assistant', and 'Remix' are strongly associated with experiential learning as compared to other themes. We also perform word2vec analysis and discover that the theme 'Access' has the highest cohesion score as compared to other themes.

We attempt to explore possible explanations for the research questions based on our findings. Topic modelling analysis reveals latent themes, which improves the interpretability of the UGC. Specific topics like 'Content lab', 'User experience', 'Business assistant', and 'Remix' contain a plethora of action-oriented and experiential words like write, generate, assignment, assistant, post, blog, recommend, etc. These words are closely aligned with the fundamental concepts of experiential learning, which include active involvement, iterative processes, creativity, and content development (Kolb, 2014). Topic modelling provides a systematic understanding of how users describe their experiences with generative AI systems. This provides valuable insights into how such systems either help or hinder experiential learning. The Word2Vec method improves topic modelling by providing semantic cohesion scores. Though experiential themes like ‘Business assistant’, ‘Content lab’ and ‘Remix’ have relatively low coherence scores (ranging from 0.15 to 0.17), their vocabularies contain phrases relevant to experiential learning. However, the theme ‘Access’ has a relatively higher semantic cohesion score, but it contributes less to the aims of experiential learning. The two methods integrate semantic cohesion and semantic relevance from the UGC dataset. Topic modelling assists in the identification of essential experiential learning themes, and the utilisation of Word2Vec offers a profound semantic framework for evaluating the internal coherence of those themes. Not only does this dual method ensure that data drives the interpretation of issues, but it also ensures that it aligns with the conceptual foundations of knowledge gained through experiential learning. Because of this, the combined method produces insights that are meaningful, structured, and of high quality regarding how users interact with and learn from generative AI technologies. The themes must enable the system to comprehend the deeper semantic and experiential goals that lie behind user input, which goes beyond the surface-level feedback that it provides.

4.2 Theoretical contribution

The examination of topic modelling indicates different subject patterns within user-generated reviews that are in close alignment with the fundamental components of Kolb’s Experiential Learning Theory (Akella, 2010). The method reveals how people interact with generative AI platforms through active production, reflective evaluation, and iterative experimentation (Morris, 2020). We classify a few themes to achieve these insights. The high regression coefficients for these subjects provide empirical evidence that experiential learning is most effective when users develop information and transform ideas, which are hallmarks of both tangible experience and abstract conceptualization. As a result, topic modelling makes a theoretical contribution by demonstrating that not all forms of interactions with artificial intelligence are created equal. Some themes are more connected with experiential learning than others. Topic modelling provides an evidence-based viewpoint for operationalising experiential learning in online generative AI platforms. This goes beyond the traditional method of mapping user behaviour to learning phases. It facilitates a precise understanding of experiential learning in practical scenarios of AI-mediated contexts by demonstrating how distinct platform scenarios affect learning outcomes differently.

By quantifying the coherence of language within each topic, Word2Vec modelling adds a semantic layer to the notion of experiential learning. Users are likely to engage in clear, structured activities, which is expected to reduce cognitive load and improve foundational learning, particularly during the early phases of the experiencing cycle. Topics with high coherence scores, such as 'Access', show that users engage in clearly structured activities. However, themes of lower coherence scores, such as 'Business assistant' or 'Content lab', promote exploration and deeper analysis of conceptual learning. The Word2Vec approach contributes to the theory of experiential learning by bringing attention to the impact and scope of experiential learning through the utilisation of semantic coherence scores. The high and low cohesion scores associated with users' learning suggest the iterative and flexible nature of experiential learning. Word2Vec is an independent method that offers a fresh approach to evaluating the internal consistency and conceptual clarity of user interactions. This method reveals the nature of learner engagement by analyzing the semantic relationships present in interactions that occur on generative AI platforms.

While our empirical findings provide valuable insights, the fundamental theoretical contribution of this work lies in advancing experiential learning theory within the context of generative AI environments. We recognize that generative AI platforms are not just passive tools; they function more like dynamic learning spaces that can shape, reinforce, or even shift how experiential learning unfolds. We notice that some users' interactions tend to involve hands-on experimentation, whereas others reflect more introspective or evaluative behavior. These distinct forms of interactions with generative AI environments reveal that the path of experiential learning is complex and non-linear. Instead, it is adaptive and often non-sequential, challenging the traditional view of Kolb's learning cycle. We examine different learning themes and coherence structures to show that users' better understanding is associated with the quality of experiential learning in AI settings.

4.3 Practical contribution

The results of the topic modelling research indicate that generative artificial intelligence platforms have the potential to enhance experiential learning by actively supporting high-impact learning interactions. These interactions encompass the creation of content, remixing of material, and the provision of reflective feedback. The platform designers should emphasize features that promote user-generated content creation, as subjects such as 'Content lab' and 'Remix' are most closely associated with learning benefits. The introduction of features such as providing suggestions, structuring assignment formats, and creating narrative modes encourages users to follow an analytical approach and improve their content effortlessly. The platforms should offer dynamic learning opportunities to enhance consumers' learning through experimentation and feedback.

Through the application of Word2Vec cohesion analysis, practical information is provided on how platforms can effectively manage the complexity of user experiences to support various phases of learning. Examples of high-cohesion themes include 'Access', which suggests that streamlined, goal-oriented features, such as onboarding videos, refund automation, or tooltips, may lower cognitive load and scaffold initial interaction, hence making platforms more approachable for less experienced learners. However, in order to encourage more profound learning, platforms should also make room for use cases that represent a wide range of semantics and promote exploration. This suggests that open-ended activities with multiple semantic routes can promote sophisticated problem-solving and creative experimentation, as well as lower-cohesion subjects, as indicated by themes such as ‘Content lab’ and ‘Business assistant’. The generative AI platforms can balance systematic support and open-ended creative areas by guiding workflows for beginner users and exploratory environments for more experienced users within the realm of practical application. Content generation platforms can customise the interface based on the user’s learning goals to enhance the depth and diversity of experiential engagement.

Managers from the generative AI platforms should consider implementing modular learning environments that adjust to users’ skill levels. The high-level cohesion theme, such as ‘Access,’ suggests that managers can implement structured templates and guided walkthroughs for novice users. In contrast, low-level cohesion themes, such as ‘Content lab’ or ‘Business assistant’, highlight that they can implement sandbox-style environments where advanced users can explore, iterate, and reflect freely. Managers should train their employees using real-time feedback systems within generative AI platforms to provide personalized learning to users. Practitioners in the content creation field should train themselves by focusing on the attributes associated with different topics to provide a better user experience in real-world scenarios. Such targeted interventions not only enhance the user experience but also operationalise the platform’s educational potential in diverse industry contexts.

4.4 Limitations and future research directions

We utilize online customer reviews of AI platforms from Trustpilot for our analysis. Researchers can utilize alternative platforms, such as Capterra or Reddit, to gain additional insights from the analysis. This is one of the earliest types of research related to generative AI, focusing on a few key themes through semantic analysis. Researchers can gain motivation from this topic and focus on large unstructured datasets to gain comprehensive insight regarding AI platforms. In this research, we utilise cross-sectional customer review datasets. However, researchers can examine longitudinal datasets and conduct machine learning analyses to gain deeper insights into shifts in consumer perspectives over time. We focus solely on content-creating AI platforms and provide implications for those platforms. The researchers can also explore other generative AI platforms that provide services for video generation, software programming, or text-to-image generation, and investigate the various learning patterns associated with users of those platforms. Researchers can scrape the reviews of these AI platforms to extend the area of this study.

We focus on two machine learning models for the analysis. Topic modelling and word2vec do not necessarily complement one another; each offers distinct and valuable implications for understanding the concept of experiential learning. Integrating these two methods captures both macro-level patterns (themes or topics) and micro-level associations (semantic cohesion), strengthening the insights obtained from customer reviews and extending theoretical applications of experiential learning in the context of AI technologies. Researchers can consider using other advanced analytical models, depending on the specific aims they strive to achieve, which may result in the acquisition of additional insights. As a further development of this work, comparative evaluations and sentiment analysis could potentially be conducted to broaden the implications of the findings and gain a deeper understanding of the situation. Another possible extension to this study should be the inclusion of multiple language reviews in the dataset and the cross-cultural perspectives from the analysis. Researchers can also perform survey studies with AI platform users to validate the findings and get more extensive feedback. They can also interview executives from highly AI-oriented firms to get their views and provide a more comprehensive analysis, which may bring new avenues to this research area. The firm executives and customers can also provide their views regarding ethical considerations of AI platforms. This is another important area to work on because customers value transparency and privacy while using these platforms.

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