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The implication of user-generated content in new product development process: A systematic literature review and future research agenda

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ABSTRACT

This study aims to provide a comprehensive overview of the current state of user-generated content (UGC) research within the context of new product development (NPD). A systematic literature review (SLR) was conducted across three prominent databases, namely Web of Science, Scopus, and Science Direct, using keywords to identify relevant articles. 5585 of 13,381 articles were deemed relevant following the application of inclusion and exclusion criteria. These articles were then thoroughly analyzed to create a comprehensive review of the topic. The selection process involved evaluating the titles and abstracts of all publications that were discovered, and carefully choosing 136 articles for full-text review. From these, 58 articles were ultimately selected for detailed analysis in this study. The study highlights the role of UGC in augmenting NPD process and identifies potential areas for future research based on evidence derived from an SLR of articles published between 2012 and 2023. The research methodologies adopted in this paper involve descriptive analysis and TCM framework (T-themes, C-contexts, and M-methodologies). Finally, the article concludes by shedding light on its potential applications by providing four themes and highlighting the importance of future research in the field with five propositions.

1. Introduction

Achieving innovation success depends on initially understanding customer requirements and subsequently creating products that fulfill these needs (Hauser et al., 2006). One approach that can help accomplish this is integrating customers into NPD process, which is an essential component for ensuring a company's prosperity in the context of the current socio-economic transitions (Prahalad and Ramaswamy, 2004; Vargo and Lusch, 2014). To foster innovation and enhance the diversity of products, some studies suggest that businesses should rely more on customer reviews (Al-Zu'Bi and Tsinopoulos, 2012; Nishikawa et al., 2013). Involving customers in NPD process represents a shift from their traditional roles as mere information providers to co-developers, helping businesses reduce cost, accelerate time-to-market, improve product quality, and enhance performance in creating new products. (Chang and Taylor, 2016; Nambisan, 2002). This collaboration is defined as a co-creation program (Bartl et al., 2010).

Co-creation is a strategic approach that involves customers in NPD process, fostering active, innovative, and social cooperation between producers and customers (Piller, 2012; Prahalad and Ramaswamy, 2004). Users are encouraged to actively participate in generating new ideas, refining concepts, selecting or customizing prototypes, and experimenting with new products to enhance development outcomes (Prahalad and Ramaswamy, 2004; Sawhney et al., 2005). Building on this foundation, advanced internet technology plays a crucial role in expanding the reach and efficacy of co-creation. It enables businesses to establish forums for collaboration and interactive content creation, significantly enhancing the spread of co-creation (Bartl et al., 2010).

At the same time, a similar change in the information and communication paradigm has taken place, shifting from distribution to social media systems (Kietzmann et al., 2011). As a result of the proliferation of social media platforms, UGC has developed into a significant new information resource that is published independently by users of digital systems, resulting in expressive or communicative effects (Santos, 2022; Timoshenko and Hauser, 2018). UGC is not only a valuable asset for product development, but the insights gained from it can also significantly facilitate NPD activities (Ho-Dac, 2020). By mining UGC, companies can compile customer opinions about their products without any

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requests for user input (Nambisan, 2002). UGC provides a continuous content stream on various topics for product development, unlike crowdsourcing and lead user research, solving the challenges of ensuring a steady stream of high-quality suggestions from the general population over time (Ho-Dac, 2020).

The existing literature has extensively explored UGC through systematic reviews, focusing on its definitions and various forms (Naab and Sehl, 2017; Santos, 2022), techniques for its analysis (Li et al., 2022; Manchanda, 2019), and its utilization in other contexts of research (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi and Karjaluoto, 2018). However, this study is the first systematic literature review to examine UGC's impact on NPD process, addressing three critical questions: (RQ1) what are the key themes, context, and methodologies utilized in studying UGC's implications for NPD process?; (RQ2) what is the potential gap in each theme?; (RQ3) what future research directions could further elucidate UGC's role in NPD?. By addressing these questions, the study aims to highlight the primary opportunities presented by UGC in NPD process, detail UGC's contributions to NPD, and demonstrate how customer insights can be derived from UGC. This study employs a multifaceted analytical approach, incorporating descriptive analysis, keyword co-occurrence, bibliographic coupling, and T-text, C-context, and M-methodology (TCM) framework. A thorough literature search was conducted across Web of Science, Scopus, and Science Direct, utilizing key terms such as "user-generated content," "customer review," "consumer review," "product development," "new product development," and "product innovation". This review offers substantial contributions to scholarly works by: (1) Being the first systematic literature review study to explore the influence of UGC on NPD process. (2) Providing four major themes extracted from literature concerning the implication of UGC in NPD process. (3) Beyond identifying potential gaps within each theme, it also puts forward innovative research propositions to encourage scholars and academics across various disciplines to pursue further investigation. The paper is organized as follows. Section 2 describes the methodology and research design. Section 3 presents our findings using the descriptive analysis. Section 4 describes keyword occurrence. Section 5 details the bibliographic coupling analysis. In Section 6, we delve into the findings of our study, which were derived from a TCM framework. Section 7 focuses on the potential directions for future research, and Section 8 provides a summary of the study's concluding observations.

2. Methodology

We conducted a systematic literature review (SLR) based on Tranfield et al. (2003) to create an up-to-date review of current research on UGC in NPD process, identifying relevant themes and future research avenues (Fig. 1). To fulfill the goal of this study, a structured literature review (SLR) was conducted using VOSviewer and Rayan QCRI software, aiming to analyze and synthesize existing research to identify research trends and future possibilities. SLR articles summarize pertinent material to compare results of earlier research, give readers a current grasp of the study issue, identify critical research gaps, and provide future study directions with fresh ideas, theories, metrics, methodologies, and research questions (Massaro et al., 2016; Paul and

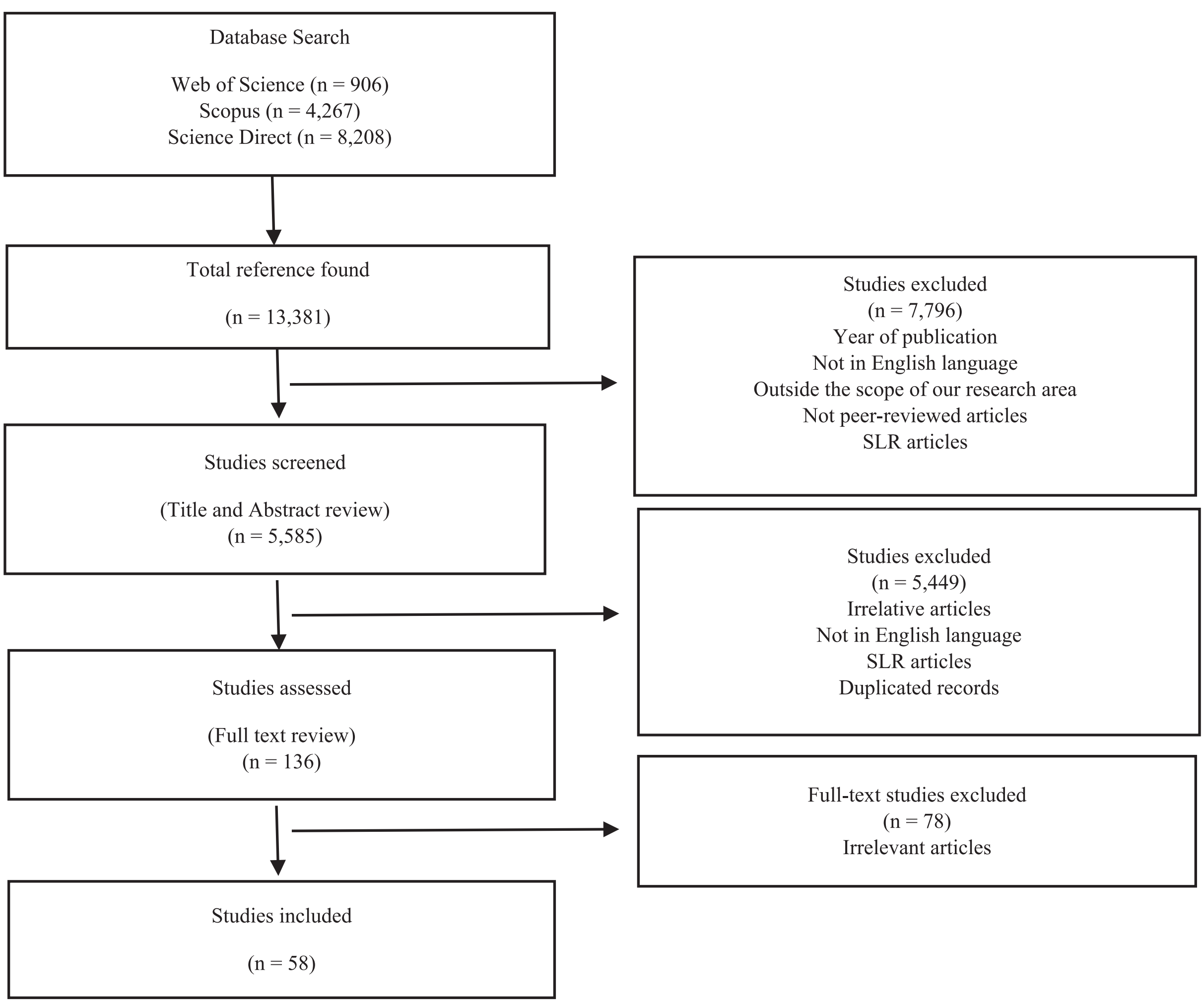

Fig. 1. Search strategy.

Criado, 2020; Tranfield et al., 2003).

Elsevier Scopus, Clarivate's Web of Science, and Science Direct were chosen to search articles. Scopus and Web of Science are two of the most popular academic databases, and we looked through their indexed papers. These datasets were selected because of their widespread use in previous academic studies (Caputo and Kargina, 2022; Liñán and Fayolle, 2015; Mongeon and Paul-Hus, 2016; Zupic and Čater, 2015).

2.1. Data extraction

This article utilizes the following classification system: the names of authors, titles, countries, total number of publications, citation counts, journal sources, keyword combinations, and author-level metrics.

2.2. Review protocol

Before beginning searching articles in databases, we developed a list of keywords related to UGC in the context of NPD. The identified keywords are: "user-generated content," "customer review," "consumer review," "user review," "product development," "new product development," and "product Innovation". We searched for articles using these keywords in conjunction with one another, employing the Boolean operators "OR" and "AND", in the fields that were designed for "title," "abstract," and "keywords." All works published from January first of 2012, until January the end of 2023, were considered.

One of the criteria followed for excluding papers was limiting them to peer-reviewed research publications in English and excluding conference papers and proceedings, and book chapters (Kushwah et al., 2019; Schneider and Spieth, 2013; Shree et al., 2021). The research was further narrowed down to the research areas of "Business, Management and Accounting," "Business, Economics" and "Engineering". In addition, SLR or review articles, and those clearly outside the scope of our research, were excluded. All excluded SLR or review articles focused on UGC's definitions and its various forms (Naab and Sehl, 2017; Santos, 2022), techniques for its analysis (Li et al., 2022; Manchanda, 2019), and its utilization in other research contexts (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi and Karjaluoto, 2018). Certain studies suggest that SLR or review articles can be omitted from the current SLR study, as noted by Kushwah et al. (2019), Schneider and Spieth (2013), and Shree et al. (2021).

2.3. Data screening

After using keywords across all three databases to locate and choose relevant articles, the search criteria were applied to a total of 13,381 articles. Following the application of inclusion and exclusion criteria, 5585 items were identified. Documents were screened with the help of Rayan QCRI software, designed specifically for use in systematic reviews. Duplicated papers (368), SLR or review articles (223), and articles that were not written in English (10) were excluded. In addition, the titles and abstracts of all the publications discovered through this procedure were carefully evaluated by the authors, and any unrelated articles that were obviously out of the scope of review were excluded (5449). When the decision on whether to include a publication was uncertain, the entire text was analyzed. To avoid bias, two authors independently reviewed and selected relevant publications (Zupic and Čater, 2015). We identified 136 articles that could be relevant to our research. For the remaining articles, we carried out full-text screening. Following this screening, 78 studies were determined to be disqualified for detailed consideration.

3. Descriptive analysis

Descriptive analysis is conducted to map the existing literature on UGC in the process of NPD. This allows for the identification of patterns, as well as the strengths and limitations of the existing work (Tranfield et al., 2003). In this part, our findings represent the year of publication, country, and publication outlets.

3.1. Publications by year

The growth of publications on the subject of UGC in NPD was mapped out over time, starting in 2012 and continuing up to January 2023. Fig. 2 illustrates this progression, indicating that the majority of research has been conducted over the past five years, reflecting increasing scholarly interest in the subject matter. More than half of the articles pertaining to this object (51.66 % of the total 58) cover the years 2019 to December 2021. Therefore, it appears reasonable to predict that further studies will be released before the end of 2023.

3.2. Publications by country

According to the number of papers and citations gathered from Scopus, Table 1 displays the geographic distribution of articles for each country. Even if an article may have been created in partnership with another country, each country is assigned a point for its unique contribution to its authorship (Del Vecchio et al., 2022). This analysis aims to reveal which nations have shown interest in researching the subject of creating new products using UGC. Out of 58 articles, those from China ($n = 31$), the United States ($n = 18$) had the greatest impact. Each of the other countries contributed to between one to five publications. The Netherlands has 348 citations despite having just two publications, Belgium has 116 citations despite having only one, and Australia has 118 citations despite having five publications.

3.3. Research fields and publication outlets

The subject categories of some of the journals were determined by using the CABS journal guide, while the subject categories of the remaining journals were determined by reading the journal's profiles on their own websites. The majority of papers belong to the fields of information management ($n = 20$; 34 %), innovation ($n = 6$; 10 %), artificial intelligence 10 % with 6 journals respectively. The complete list of 32 journals, together with the total number of articles contained in each publication, can be seen in Table 2.

3.4. Citation analysis

Scopus was used to compile article citation data to evaluate the impact of previously published work (Del Vecchio et al., 2022; Kiduk and Meho, 2006; Zhao and Strotmann, 2007). In Table 3, the top 20 articles are ranked according to the total number of citations received. Seven articles with the most citations overall accounted for 51.63 % of the total for all 58 articles: Qi et al., 2016; Timoshenko et al., 2019; Jeong et al., 2019; Dong and Wu, 2015; Rathore et al., 2016; Jian et al., 2016; Muninger et al., 2019. Studies from a wide range of academic disciplines show that this line of inquiry has the potential to provide exciting new avenues for interdisciplinary collaboration and study.

4. Common keywords

An additional type of analysis involves highlighting the keywords most frequently used and sought after by the authors. This allows for the evaluation of a significant volume of text while concentrating on a particular topic. The comprehensive overview of the scholarly work on UGC in NPD resulted from the topic analysis. In this regard, an effort was made to identify the primary research emphasis of the evaluated publications to classify the findings into broader research themes within the scope of this research. A keyword co-occurrence analysis was conducted to create a keyword co-occurrence network (Radhakrishnan et al., 2017). Keywords are used to investigate the geographical connections between various terms, and co-occurrence analysis enables a pictorial

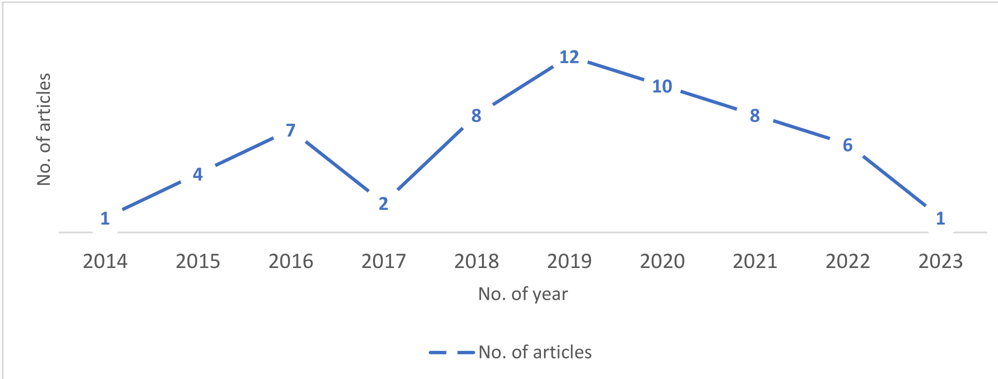

Fig. 2. Number of articles per year.

Table 1
Countries by number of documents.

Country	Documents	% Documents	Citation	% Citation
China	31	33.6 %	1599	37.8 %
USA	18	19.5 %	737	17.4 %
Australia	5	5.4 %	118	2.7 %
Taiwan	5	5.4 %	223	5.2 %
UK	4	4.3 %	231	5.4 %
South Korea	4	4.3 %	362	8.5 %
India	4	4.3 %	174	4.1 %
France	4	4.3 %	80	1.8 %
Netherlands	2	2.1 %	348	8.2 %
Canada	2	2.1 %	60	1.4 %
Russia	2	2.1 %	20	0.4 %
Turkey	2	2.1 %	20	0.4 %
Germany	1	1.08 %	12	0.2 %
Ireland	1	1.08 %	1	0.02 %
Denmark	1	1.08 %	12	0.2 %
Belgium	1	1.08 %	116	2.7 %
Italy	1	1.08 %	26	0.6 %
Morocco	1	1.08 %	4	0.09 %
Spain	1	1.08 %	12	0.2 %
Qatar	1	1.08 %	35	0.8 %
Singapore	1	1.08 %	35	0.8 %

display and comprehension of the keywords architecture of a specific scientific topic (Su and Lee, 2010). Co-occurrence analysis investigates the implicit connections that authors of research papers make between their chosen keywords and the topics of their respective articles (Su and Lee, 2010). The frequency of certain keywords in 58 different articles is shown in Fig. 3. Authors, editors, and publishers use keywords to report on the most relevant themes discussed in the articles. A minimum of 5 keyword occurrences is shown in Table 4.

According to our findings, terms that share a keyword co-occurrence network might be conceptually related. Similarly, the closeness of one keyword co-occurrence network to another may be interpreted as a measure of the similarity between the two ideas (Mariani et al., 2022; Su and Lee, 2010). It is possible to include occurrences of the keywords "product development," and "product improvement" in searches for "new product development" because all of these keywords fall under the category of product development projects (Ulrich and S. D. E., 2018; Kruachottikul et al., 2023). In addition, when looking for "user-generated content," the terms "online product reviews," "online reviews," and "online customer reviews" can be included since they can be used interchangeably. To illustrate the results of our co-occurrence study, a graphic format was used in which the size of the circles corresponded to the frequency with which each keyword appeared.

5. Bibliographic coupling

Articles citing the same references are linked because the sources they reference help clarify the issue (Kessler, 1963; Perianes-Rodriguez et al., 2016). Bibliographic coupling confers several benefits, including the ability to generate visualization maps based on highly cited publications, provide valuable insights into contemporary research problems, and offer guidance for future studies (O. Jones and Gatrell, 2014; Mariani et al., 2022).

Bibliographic coupling was performed utilizing VOSviewer software, taking into account the 58 articles included in the data sample. The units of analysis were identified as documents, and the evaluation of the report was conducted by examining articles that share common references. The analysis yielded a total of four clusters (Appendix A, Fig. 4). The VOSviewer software, developed by van Eck and Waltman (2010), is used to build bibliometric maps, and has been frequently used in the literature (Ferreira, 2018; Ferreira et al., 2016; Merigó et al., 2015). VOSviewer software is preferable to multidimensional scaling for the construction of bibliometric maps (van Eck and Waltman, 2010; Van Eck and Waltman, 2014).

6. Key findings: themes, contexts, and methodologies identified in the implication of UGC in NPD process

The TCM framework, consisting of T-themes, C-context, and M-methodologies, was derived from previous reviews conducted by (Mishra et al., 2021; Paul et al., 2017; Paul and Rosado-Serrano, 2019). This framework was employed in this study to categorize and analyze the main outcomes. Furthermore, the TCM framework plays a crucial role in identifying the most significant UGC themes in research studies related to NPD process. It assists in defining the key themes, context, and methodologies, thereby offering valuable insights for future research endeavors in this field (Billore and Anisimova, 2021; Paul et al., 2021). The findings of this study have been organized into specific sub-sections based on this framework.

6.1. Major themes

To enhance the precision of clustering and deepen the understanding of research domains, a thorough analysis was conducted on the articles previously acquired through bibliographic coupling. The lack of thematic coherence between articles in each cluster derived from bibliographic coupling analysis has been attributed to their disparate disciplinary origins or multifaceted subject matter. Therefore, the articles were analyzed again thoroughly to identify their respective research fields. Initial steps involved a content analysis of the 58 articles in the pool, with attention paid to each article's declared goal, research questions, method, important arguments, and primary structures. This was carried out to determine the main phenomena that each article was concerned with.

After that, a descriptive statement outlining the topic of each article was allocated to it, and from these statements, the initial theme titles for

Table 2
List of journals included in our study.

Research field	Journal	No. of articles
Artificial Intelligence	Engineering Applications of Artificial Intelligence	6
Innovation	Technological Forecasting and Social Change	4
Knowledge and Engineering application	Advanced Engineering Informatics	4
Information Management	Information & Management	4
Information Management	International Journal of Information Management	3
Information Management	Electronic Commerce Research and Applications	3
Product design	Journal of Mechanical Design	3
General Management, Ethics, Gender, and Social Responsibility	Journal of Business Research	2
Information Management	Journal of Enterprise Information Management	2
Information Management	Decision Support Systems	2
Operations & Technology Management	Computers in Industry	2
Computing and Information Science	Information Processing & Management	2
Electrical - Electronics - Computing	IEEE Access	2
Applied Natural Sciences	Applied Sciences	1
Manufacturing Technology	CIRP Annals	1
Manufacturing Technology	CIRP Journal of Manufacturing Science and Technology	1
Industrial Engineering	Computers & Industrial Engineering	1
Data Science	Data Science and Management	1
Information Management	Electronic Commerce Research	1
Engineering Management	Engineering Management Journal	1
Information Management	Information Technology and Management	1
Information Management	Expert Systems with Applications	1
General Management, Ethics, Gender, and Social Responsibility	Global Journal of Flexible Systems Management	1
Product Design	International Journal of Mechanical Engineering and Technology	1
Information Management	Journal of Computing and Information Science in Engineering	1
Information Management	The Journal of Strategic Information Systems	1
Information Management	Journal of Intelligence Studies in Business	1
Marketing	Marketing Science	1
Marketing	Journal of Business & Industrial Marketing	1
Innovation	Technovation	1
Innovation	Research Policy	1
Operations & Technology Management	International Journal of Production Research	1

each article were generated (Clark et al., 2019; Jones et al., 2011; Liñán and Fayolle, 2015). Next, the articles were compared to one another and sorted iteratively to categorize them into their respective themes. These thematic names were then combined according to their similarities to create significant study themes, ultimately resulting in the formation of a taxonomic hierarchy (Clark et al., 2019; Jones et al., 2011; Liñán and Fayolle, 2015). Finally, the study themes were examined for any instances of duplication and amended as appropriate. In this study, themes embody the core goal that characterizes the content of each author's article (Ryan and Bernard, 2003). Therefore, the identified themes serve as the foundational ideas, arguments, and conceptual connections that underpin an article's research questions, constructs, and concepts (Thorpe et al., 2005). The entire content analysis procedure was carried out using a web-based version of the Atlas-ti software. The following

Table 3
Citation counts as on January 2023.

Authors	Title of article	Citation count	Journal
Qi, et al. (2016)	Mining customer requirements from online reviews: A product improvement perspective	197	Information and Management
Timoshenko, A.; Hauser, J.R.; 2019	Identifying customer needs from user-generated content	160	Marketing Science
Jeong, B. et al. (2019)	Social media mining for product planning: A product opportunity mining approach based on topic modeling and sentiment analysis	142	International Journal of Information Management
Dong, J.Q.; Wu, W.; (2015)	Business value of social media technologies: Evidence from online user innovation communities	136	Journal of Strategic Information Systems
Rathore, A.K. et al. (2016)	Social media content and product co-creation: an emerging paradigm	125	Journal of Enterprise Information Management
Jin, Jian et al. (2016)	Identifying comparative customer requirements from product online reviews for competitor analysis	116	Engineering Application of Artificial Intelligence
Muninger, M.-I. et al. (2019)	The value of social media for innovation: A capability perspective	116	Journal of Business Research
Yan, ZJ et al. (2015)	EXPRS: An extended pagerank method for product feature extraction from online consumer reviews	94	Information and Management
Xiao, SS et al. (2016)	Crowd intelligence: Analyzing online product reviews for preference measurement	89	Information and Management
Yang, Bai et al. (2019)	Exploiting user experience from online customer reviews for product design	86	International Journal of Information Management
Tuarob, S.; Tucker, C.S.; (2015)	Quantifying product favorability and extracting notable product features using large scale social media data	84	Journal of Computing and Information Science in Engineering
Zhou, F. et al. (2015)	Latent customer needs elicitation by use case analogical reasoning from sentiment analysis of online product reviews	83	Journal of Mechanical Design
Wang, W.M.et al. (2018)	Extracting and summarizing affective features and responses from online product descriptions and reviews: A Kansei text mining approach	81	Engineering Application of Artificial Intelligence
Wang, Wenxin et al. (2018)	Topic analysis of online reviews for two competitive products using latent Dirichlet allocation	74	Electronic Commerce Research and Applications
Ireland, Robert; Liu, Ang; (2018)	Application of data analytics for product design: Sentiment	66	CIRP Journal of Manufacturing Science and Technology

(continued on next page)

Table 3 (*continued*)

Authors	Title of article	Citation count	Journal
	analysis of online product reviews		
Kang, Yin; Zhou, Lina; (2017)	RubE: Rule-based methods for extracting product features from online consumer reviews	64	Information and Management
Chiu, Ming-Chuan; Lin, Kong-Zhao; (2018)	Utilizing text mining and Kansei Engineering to support data-driven design automation at conceptual design stage	55	Advanced Engineering Informatics
Zhang, H et al. (2018)	Product innovation based on online review data mining: a case study of Huawei phones	53	Electronic Commerce Research
Li, Yung-Ming et al. (2014)	Creating social intelligence for product portfolio design	50	Decision Support Systems
Liu, Yao et al. (2019)	Assessing product competitive advantages from the perspective of customers by mining user-generated content on social media	50	Decision Support Systems

four research themes were uncovered as a result of this process.

6.1.1. The impact of UGC on new product development and innovation process

The first theme comprehensively explores the impact of UGC on product development. It highlights how UGC streamlines the obtaining of customer insights efficiently and economically, fosters enhanced interaction and co-innovation with consumers, and exhaustively improves the product innovation process. To this end, Jiao et al. (2022) investigated UGC from a broad perspective, concluding that UGC markedly improves product design efficiency, underscoring its pivotal role in improving new product performance. In a more detailed manner, Rathor et al. (2016) advocated for an enhanced comprehension of customer dynamics through UGC, emphasizing both cost efficiency and timeliness. By viewing it through another prism, Vikram & Kumar

Table 4
Minimum 5 keyword occurrence.

keyword	No. of occurrences
product design	27
Data mining	22
Sentiment analysis	20
social networking (online)	16
Social media	15
Product development	13
Text mining	10
Online reviews	9
Online product reviews	9
Machine learning	8
opinion mining	8
Semantics	7
Online customer reviews	7
Customer requirements	7
New product development	6
User-generated content	6
Product attributes	5
Deep learning	5
Product improvement	5

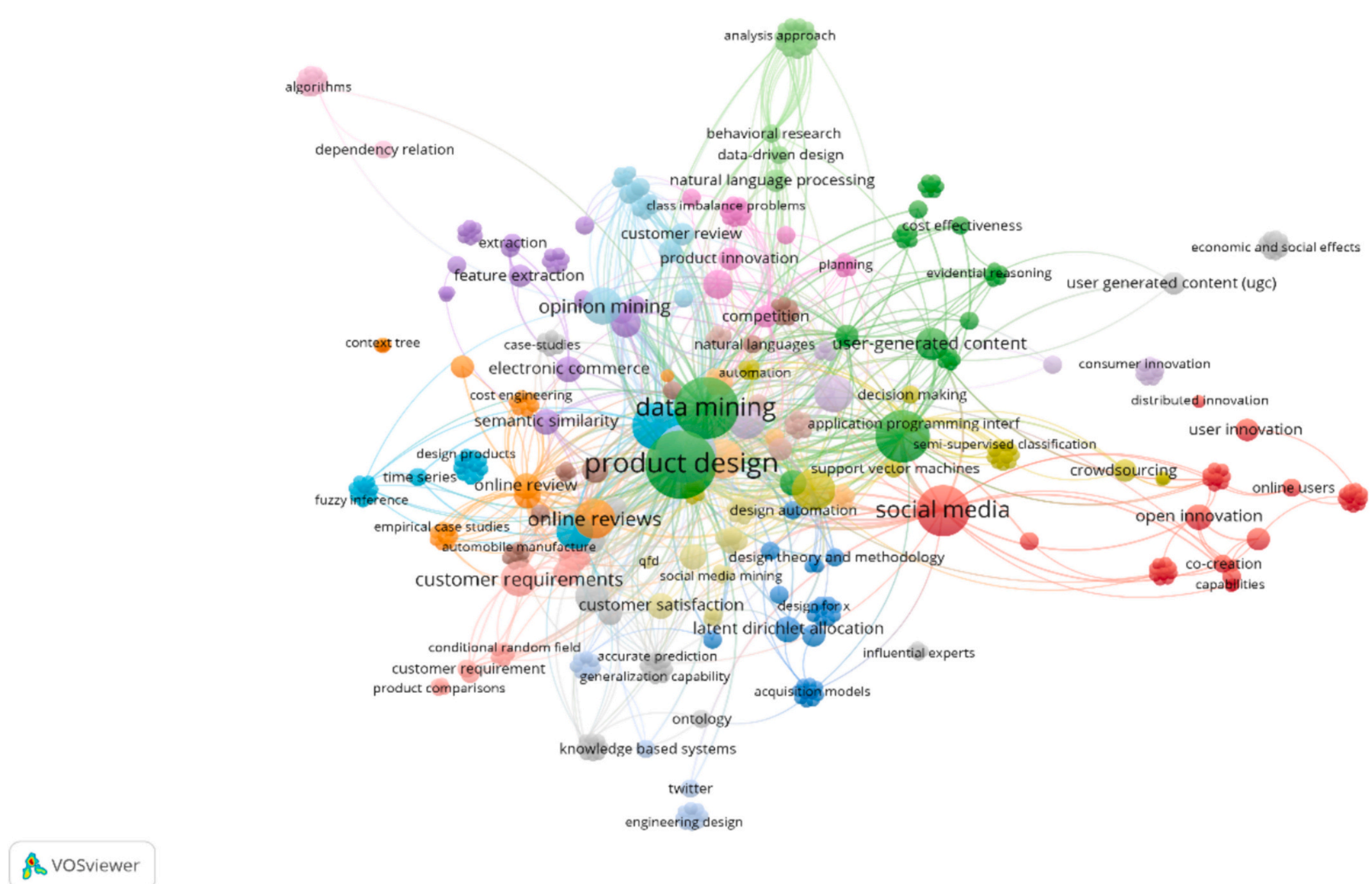

Fig. 3. Keyword co-occurrence networks of user-generated content in new product development.

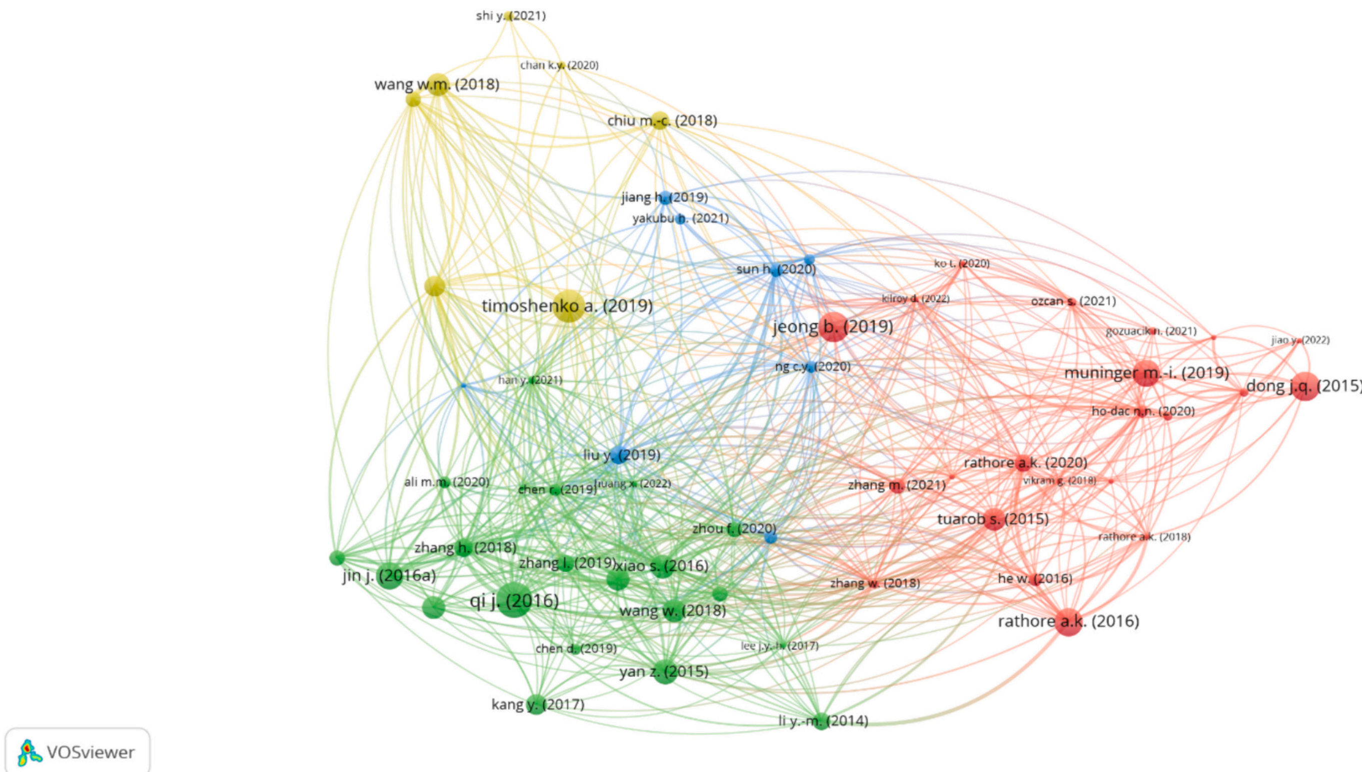

Fig. 4. Clusters combining topic-based with intersecting literature.

(2018) illustrated that analyzing UGC not only affirms the product's quality but also enhances the time-to-market, thereby efficiently addressing customer demands. Taking this analysis a step further than previous studies, He & Wang (2016) demonstrated that the benefits of analyzing UGC contribute to decreased market rejection rates and enhanced market acceptance.

Muninger et al. (2019) examined UGC's effects differently, illustrating how it fosters a co-creative environment throughout the product development process. This concept of co-creation diverges from former studies by highlighting the collaborative dynamics enabled by UGC, which enriches the discourse on its role in product innovation. In a more comprehensive analysis, Dong and Wu (2015) highlighted the importance of leveraging UGC in the ideation phase of product development, emphasizing its role in generating, transforming, and spreading innovative ideas that lead to the creation of new products. Ho-Dac (2020) emphasized UGC's crucial role in improving the ideation and completion stages of product development by facilitating selective information gathering, surpassing the lead user approach in efficiency and control. Furthermore, UGC guarantees a consistent supply of high-quality information, addressing the challenge of maintaining a continuous stream of superior ideas compared to traditional crowdsourcing methods. From a different vantage point, Zhang et al. (2018) explored how UGC—both positive and negative—can drive a firm's innovation investment, significantly enhancing performance. This perspective offers a nuanced understanding of UGC's role in shaping development strategies by acting as a catalyst for innovation.

Current studies have attempted to investigate various facets of UGC's impact on product development. However, due to their primary focus on tangible products, they have not provided a thorough understanding of how UGC affects a wide range of product types, particularly for companies that produce intangible products like digital services. Investigating UGC's function in these more intricate categories could enhance our understanding of its broader applicability and efficacy. Additionally, these studies only assess the impact of UGC volume on product development, overlooking the significance of UGC's diversity and quality.

6.1.2. *Mining UGC for identifying innovative product ideas*

Since the advent of social media, individuals have been empowered to exchange opinions and share ideas freely, thereby acting as both creators and disseminators of content. The concept of idea mining emerges as a pivotal method in this context, defined as the automated extraction of novel and innovative ideas from unstructured text through computational methods (Alksher et al., 2016). The principal aim of idea mining is to transform the extensive array of internet data into actionable innovation assets for enterprises. To this end, Lee et al. (2017) proposed a design science approach to scrutinize customer satisfaction levels regarding product characteristics that can be considered a source of ideas and knowledge for innovative product design. Satisfaction analysis cannot solely reveal hidden correlations and patterns between variables. Thus, Olmedilla et al. (2019) applied co-occurrence differential analysis to identify unique product attributes and discover distinct ideas. To achieve a more structured feedback analysis than Olmedilla et al. (2019), Lin et al. (2022) systematically categorized user suggestions into different groups, followed by theme analysis to understand the essence of each cluster. To uncover hidden thematic structures within text data without predefined categories, Jeong et al. (2019) integrated latent Dirichlet allocation (LDA) and sentiment analysis to identify product-related topics and assess their importance. They then calculated an opportunity score for each topic to identify product opportunities, guiding future enhancements based on topics with high potential.

Prior studies concentrated on identifying customer opinions and sentiments towards product characteristics to discover new ideas for improving the next version of products. In contrast, Zhang et al. (2021) introduced a deep learning approach to precisely identify innovative ideas at the sentence level in online product discussions. Adopting another perspective, Gozuacik et al. (2021) developed a multi-task neural network to identify the reasons behind innovation failures, promoting the analysis of past issues to encourage new ideas for product development.

None of the above-mentioned studies proposed an end-to-end framework that reveals clusters of ideas with a word network map in the field of sustainability. To end this, Ozcan et al. (2021) proposed a classification model to explore trends and retrieve ideas through tweets containing hashtags for ideas, sustainability, and new product development. This study demonstrates how mining social media for sustainability ideas can debunk the myth of low-quality data, providing actionable insights for product innovation. Contrary to prior research predominantly centered on user knowledge, Zeng et al. (2022) advanced the methodology by introducing a comprehensive product knowledge corpus compiled from various sources. They unveiled a framework that integrates LDA with an interactive knowledge map, underpinned by ontology and semantic similarity principles.

All studies discussed in this theme have treated customer opinions and sentiments on product attributes or identifying creative concepts at the sentence level as a foundation for generating ideas. However, users also share narratives of how they utilized products in real-life situations, occasionally in manners unforeseen by the product designers. These anecdotal experiences can uncover novel contexts or uses for a product, indicating potential modifications or the development of entirely new product lines.

6.1.3. Deriving product features from UGC

Design researchers suggest utilizing web blogs and review sites to mine product feature information. However, these sources may encounter challenges related to timeliness, scope, bias, access, and diversity. Therefore, to address these challenges effectively, UGC can be considered as a valuable alternative, offering a vast resource of customer opinions on product features (Tuarob and Tucker, 2015). For this purpose, H. Zhang et al. (2018) utilized online review analysis for feature extraction and demonstrated a direct correlation between customer interest levels in different aspects of a product and feature development. In contrast to prior study, Li et al. (2014) utilized feature importance distribution and specification analyses across online reviews of lead users, going beyond merely measuring the satisfaction level of customers with a product feature. Previous research has been criticized for its reliance on a feature importance distribution approach that biases the outcomes and its restricted examination of customer feedback. To overcome these drawbacks, Tuarob and Tucker (2015) used sentiment analysis and natural language processing (NLP) to assess different customer groups' views on products. Their method distinguishes between strong and weak product features based on customer feedback, instead of feature importance distribution analysis.

Compared to earlier research, which overlooked analyzing phrase-level opinions and focused only on adjectives to measure customers' interest levels, Zhang et al. (2016) analyzed UGC across heterogeneous products within the same category, aiming to extract and relate product features and opinions using patterns formed from adjectives, adverbs, and verbs. From a different perspective, to prioritize product features for development, L. Zhang et al. (2019) used hierarchical clustering for semantic similarity to reduce redundancy, developed a preference model based on opinion sentiment, and introduced a redesigned index to prioritize features considering user preferences, engineering costs, lead time, and technical risk. In another approach to provide a more direct pathway from UGC to product development priorities, Asadabadi et al. (2022) integrated NLP, sentiment analysis, and quality function deployment (QFD) to increase efficacy through prioritized features.

To determine semantic patterns for a new product based on UGC compared to sentiment analysis approaches in the discussed research, Chiarello et al., (2020) used a novel lexicon, revealing that considering pros, cons, and product aspects in Twitter data filtering enhances precision and relevance. Earlier approaches typically categorized customer emotions into positive, negative, and neutral states to gauge satisfaction levels. In a novel approach, W. M. Wang et al. (2018) innovatively integrated Kansei engineering with text mining to extract product features and a wide range of consumer emotions from product descriptions and customer reviews, moving beyond simple sentiment analysis. Building upon their prior work, W. M. Wang et al. (2019) put forward a heuristic deep-learning strategy for the analysis of online reviews. This approach redefines Kansei engineering as a multi-class classification problem and merges rule-based extraction with deep learning to categorize seven pairs of affective attributes.

The aforementioned approaches have ignored implicit feature extraction in favor of focusing only on explicit features. In response to this challenge, Yan et al. (2015) combined a PageRank algorithm to exploit the relationship between product features and sentiment terms, augmented with the addition of relevant synonyms for feature expansion and the identification of implicit features. To further analyze UGC to predict product attribute significance, Yakubu and Kwong (2021) developed a system to evaluate product qualities from online reviews and Google Trends, assessing current and future feature importance using sentiment scores, frequency, and trend data. Previous studies have concentrated on experiential products, emphasizing the significant impact of subjective reviews on consumers' purchase behavior. In contrast, these studies overlooked search products, for which consumers prioritize the quality of information available on websites. To address this limitation, Huang et al. (2022) unveiled product feature extraction based on multi-feature fusion techniques to analyze search products via objective reviews.

To sum up, all studies within this theme have targeted product features that have attracted minimal customer interest. However, a more detailed examination can indicate that merely focusing on the aspects that receive the most negative feedback from customers is not always the most effective strategy for improving a product's position in the market. It can be more advantageous to conduct an in-depth analysis of which features, if improved, would significantly boost the product's attractiveness.

6.1.4. Analyzing UGC to understand customer requirements

Understanding customer needs is crucial for product development (Kano, 1984; Mikulić and Prebežac, 2011). Traditionally, this understanding has been gained through conventional methods that are time-consuming and costly. However, analyzing UGC emerges as an efficient and cost-effective approach to identifying customer needs and enhancing time-to-market and product relevance. To prove this claim, Jin et al. (2016) developed a kano model using UGC and product specifications to link satisfaction levels with product functionality, applying polynomial fitting and least squares. In contrast, instead of concentrating on connecting customer satisfaction levels with product functioning, Qi et al. (2016) used conjoint and sentiment analysis to weight product qualities, combining with the Kano method to quantitatively measure the relative importance of various product attributes. Unlike the previous study's data collection approach, Xiao et al. (2016) incorporated review data into the modified ordered choice model to measure preferences and the marginal effect-based kano model to categorize customer requirements. In a more comprehensive way than the preceding analyses, D. Chen et al. (2019) combined sentiment analysis, aggregating opinions into four distinct groups in 3-D space and employed anomaly and novelty detection to identify unusual opinions to improve clarity in customer needs identification. Lamrhari et al. (2019) pioneered combining LDA, fuzzy-kano model, and SWOT matrix into a decision support framework. Compared to the former analysis, LDA provided better performance and stability.

Instead of focusing solely on the content of opinions without regard to the surrounding context like former studies, R. Chen et al. (2019) emphasized the consideration of the context in which opinions are expressed by utilizing context-aware segmentation and opinion target extraction. To enable a deeper sense of language context understanding compared to R. Chen et al. (2019), Han and Moghaddam (2021a) introduced a domain-agnostic method using bidirectional encore representations (BERT), new convolutional net and named entity recognition (NER) to mine e-commerce reviews to identify consumer needs efficiently.

To incorporate the emotional needs of customers more effectively than in former studies, Chiu and Lin (2018) combined text mining and Kansei engineering (KE) to automate the identification of customer needs and emotions. While earlier studies primarily dealt with explicit sentiments, Ireland and Liu (2018) integrated NLP and machine learning to automate sentiment analysis on UGC, revealing implicit sentiments about product attributes to pinpoint customer needs. Recognizing that previous research did not fully capture the nuanced and often ambiguous nature of customer sentiment in UGC, Jiang et al. (2019) introduced a dynamic neural-fuzzy system, using evolving clustering and fuzzy scores for precise and adaptable outputs. More comprehensively than Jiang et al. (2019), Ng and Law (2020) combined sentiment analysis, fuzzy set theory, and evidential reasoning to effectively blend qualitative insights with quantitative precision to better understand customer needs. For a broader ecosystem-wide analysis of customer needs with greater automation and accuracy in sentiment detection, Feng Zhou et al. (2020) used LDA to identify needs and applied VADER for sentiment analysis across a product ecosystem. Whereas Feng Zhou used LDA, which relies on the subjective interpretation of topics and determining the optimal topic count, Ko et al. (2020) proposed a context tree approach that extracts contextual information from related keywords in a concept space.

Preceding analyses have not paid attention to the evolving nature of UGC from a lifecycle perspective. To fill this gap, X J. Choi et al. (2020) integrated sentiment analysis with aging theory-based algorithms to dynamically track and analyze consumer satisfaction and interests on social media. Beyond the scope of Choi's research with a more detailed approach, Ali et al. (2020) introduced an ontology-based reasoning system linking the middle-of-life and beginning-of-life phases for next-gen product design. Their approach features ontology development for product reviews to aid knowledge management and an NLP system to analyze customer reviews, extracting design-relevant information to populate the ontology.

Customer emotions and needs towards a product can change due to evolving preferences, trends, and technology, necessitating businesses to adapt and update their offering continuously. So, Sun et al. (2020) combined different text mining techniques to assess changes in attitudes towards product attributes over time, aiming to identify shifting customer needs. Beyond previous findings, Chan et al. (2020) predicted customer satisfaction from UGC by using opinion mining and sentiment ratings based on frequency and review rates to specify customer requirements. To analyze deeper than Chan et al. (2020), Kilroy et al. (2022) developed algorithms to generate a prioritized list of key phrases at defined periods, enabling the identification of terms from UGC that may predict future customer needs in product descriptions with as much lead time as possible. Existing methods overlooked the subtle, unobserved characteristics of consumers that can be inferred from their digital footprints and the sentiment expressed in their reviews. To solve this gap, J. Jeong (2021) integrated extreme gradient boosting (XGBoost) with deep learning to predict the sentiment of potential customers before they make a purchase, thereby identifying their needs more accurately.

All the above-mentioned studies relied on direct analysis of explicit sentiments or attributes, potentially overlooking the latent aspects of customer preferences. To delve deeper into the underlying dimensions of UGC and introduce a significant evolution in the approach to identifying customer needs, Zhou et al. (2015) innovatively proposed a dual-layered sentiment analysis approach to deduce latent customer needs by juxtaposing product attributes with user preferences across diverse scenarios. This method marks a departure from traditional analysis by offering a nuanced understanding of customer preferences. Contrastingly, Timoshenko and Hauser (2018) employed NLP with a focus on discerning product attributes that fulfill customer needsby examining the benefits sought by consumers. This approach shifts the analytical lens towards the utility and satisfaction derived from products. In a further departure, Yang et al. (2019) crafted a complex computational model aimed at constructing knowledge bases from user reviews, encapsulating the user experience. Lastly, von Hippel and Kaulartz (2021) diverged from conventional direct needs assessment and prototype solution extraction methods by introducing an NLP-based framework. This framework synthesized semantic space analysis with network analysis, adeptly identifying need-solution pairs within web content, thus paving the way for early innovation.

Contrary to the above approaches that have concentrated exclusively on the introspective examination of their products, competitive analysis facilitates the identification of market discrepancies and consumer predilections, thereby unveiling unmet needs. To this end, Jin et al. (2016) applied part-of-speech technique for comparative analysis of similar products to enhance design insights. In a more comprehensive way than Jin et al. (2016), Wang et al. (2018b) used LDA to provide a deeper understanding of distinctive subjects, as well as the competitive advantages and shortcomings of a product and its rivals. Advancing even further, Liu et al. (2019) introduced a domain-specific sentiment analysis approach. This method goes beyond the general themes revealed by LDA in the prior approach, providing a detailed categorization of sentiments to pinpoint unmet needs through thorough competitive analysis.

Although the mentioned studies have utilized diverse techniques to identify customer needs, an innovative method that goes beyond the simple emotion analysis of particular product characteristics can be adopted. To identify latent needs —subtle, frequently unspoken desires that customers might not blatantly realize or fully comprehend themselves — this new approach would delve deeper into the tasks customers hope to perform with the product. The core goal of this approach is to reveal hidden ambitions, which offer invaluable information for product innovation.

6.2. *Context*

6.2.1. *Industry*

The studies conducted covered a broad spectrum of industries. Some research focused on a particular industry to gather pertinent data, while others collected data from diverse industries to achieve their research objectives. Fig. 5 provides an industry-wise analysis, showcasing the allocation of research efforts by displaying the number of studies conducted for each respective industry. Fourteen research studies involving UGC in NPD process were primarily conducted in the mobile industry (e.g., Jeong et al., 2019; Tuarob and Tucker, 2015; Yan et al., 2015; Asadabadi et al., 2022). Twelve studies related to electronic devices like iPad, thermostat, hair dryer, speaker, and etc. (e.g., Jiao et al., 2022; Zhang et al., 2021; Yan et al., 2015; Kilroy et al., 2022; Zhou et al., 2020). Nine studies focused on manufacturing industry products like laptop, compressor, packaging (e.g., Vikram & Kumar, 2018; Dong & Wu 2015; Ozcan et al., 2021; Wang et al., 2018a). Six studies focused on automobile industry and three related to education industry like e-learning platform (e.g., Zeng et al., 2022, Lee et al., 2017, He & Wang, 2016). Three studies about food & beverage industry (e.g., Muninger et al., 2019; Dong & Wu 2015; Rathore and Ilavarasan, 2020). Three studies related to health products like personal care products (e.g., Timoshenko and Hauser, 2018; Shi & Peng, 2021). Three studies focused on home appliances like coffee machines (e.g., Zhang et al., 2021; Ko et al., 2020; Chen et al., 2019a). Two studies are related to energy industry and two studies focused on video equipment industry like digital camera (e.g., Yan et al., 2015; Ali et al., 2020; Muninger et al., 2019; Ozcan et al., 2021). Two studies about mobile apps industry (e.g., Olmedilla et al., 2019; Chen et al., 2019a). One study is about logistics, telecommunication, advisory, transportation, pharmaceutical, communication agency, news group, and retail like sneakers (e.g., Muninger et al., 2019; Han & Moghaddam, 2021). In the figure, it is observed that three studies did not specify the type of product from which they obtained their information. These studies are categorized as “no specific” in terms of the products used. Despite this lack of specificity, these studies still contribute to the overall analysis and findings, albeit without a distinct product focus (e.g., Rathor et al., 2016; Zhang et al.,

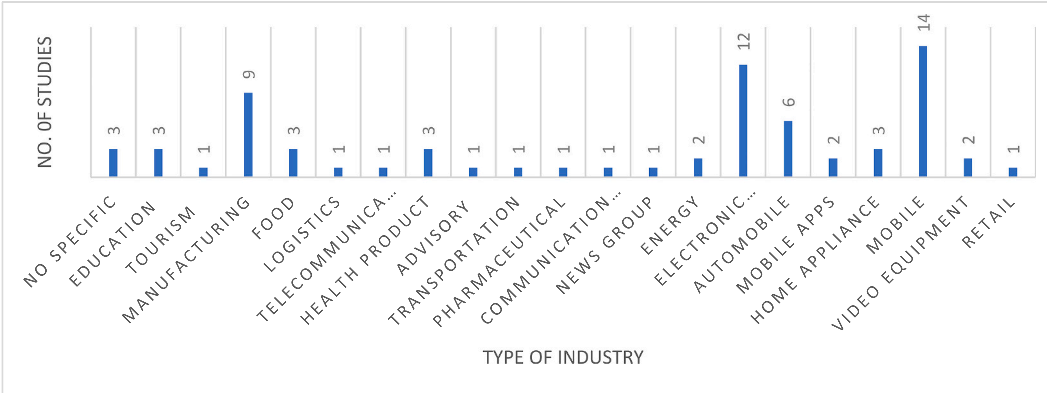

Fig. 5. Number of studies across different industries.

2018; Lin et al., 2022).

6.2.2. *Online platforms*

The studies employed a variety of online platforms to gather the necessary information for their research. Fig. 6 presents an analysis of the platforms used, illustrating the number of distinct platforms utilized for data collection purposes. This analysis provides insights into the diversity and scope of online platforms leveraged by the studies to access and collect relevant data.

6.3. *Methodology*

The methodologies employed to collect and analyze data in the research studies that centered on UGC within the context of NPD are synthesized and presented in Table 5. For a more extensive exploration of these methodologies, including valuable insights into the specific approaches employed, readers are encouraged to refer to Appendix B. This appendix offers a comprehensive breakdown of the various methodologies utilized by researchers, alongside key findings from each study.

Table 5
Methodologies/tools and analytical methods used to collect and analyze data.

Research methods/tools – analytical methods	No. of studies
Machine learning	45
Kano model	6
Fuzzy set theory	6
Deep learning	4
Statistical analysis	4
Kansei engineering	3
Ontology engineering	2
Content analysis	2
Interview	1
Survey	1
Quality function deployment	1

7. Future research avenues

SLR is a proficient approach for arranging research articles in a comprehensive, structured, and analytical manner, enabling the identification of gaps in the literature (Klassen et al., 1998; Paul and Criado, 2020) and emphasizing understudied areas that require further attention (Snyder, 2019). This SLR identified four themes: (1) the impact of UGC on new product development and innovation Process, (2) Mining UGC for identifying innovative product ideas, (3) deriving product features from UGC, and (4) analyzing UGC to understand customer requirements. The current systematic literature review offers valuable insights into the role of UGC in NPD process. Despite identifying a gap for each theme and acknowledging these at the conclusion of each theme, our analysis highlights several critical themes that remain under-researched and deserve more scholarly focus. In the following section, we propose future research directions to fill these gaps and enrich the body of existing literature.

Proposition 7.1. Exploring the potential biases of using UGC in new product development.

Studies conducted by (Cui and Wu, 2017; Naeem and Di Maria, 2020; Wang et al., 2020) explored the contingent negative effects of customer participation on NPD process. Despite the potential benefits of incorporating UGC into NPD process, there is a lack of research exploring its

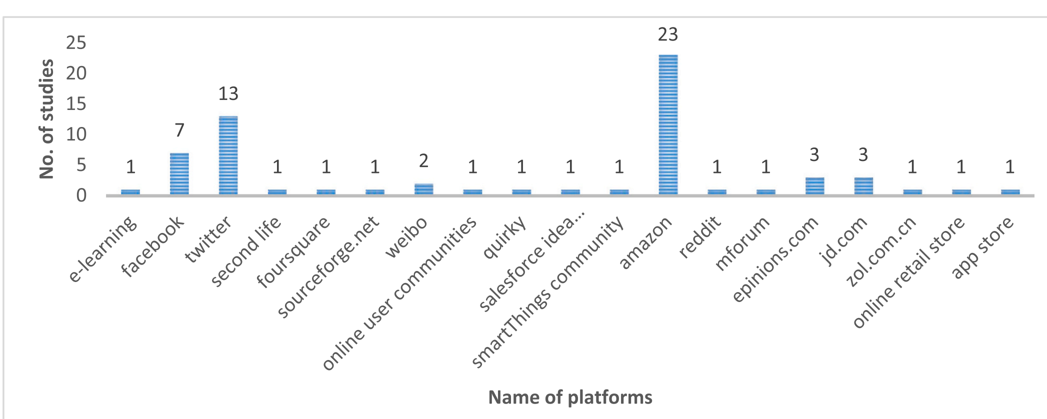

Fig. 6. Number of platforms across different studies.

possible negative effects. Therefore, it is crucial to investigate whether replacing conventional market research methods with UGC to gather consumer insight can potentially mislead the product team in NPD process.

Proposition 7.2. Exploring failure/success rate of new products developed based on ideas extracted from UGC.

A significant variable in determining the long-term performance of an organization might be the ongoing creation and launch of novel products. Years of conceptual and empirical study have been devoted to figuring out what makes a new product successful, such as new product strategy, resource availability, NPD process and communication (Cooper and Kleinschmidt, 2007; Ernst, 2002; Lam and Chin, 2005). The use of customer feedback can greatly impact the success of new products (Cooper, 2019; Cooper and Kleinschmidt, 2007; Ernst, 2002), as it allows companies to align their products with customer needs and preferences. Thus, incorporating UGC into product development can be seen as a key factor in achieving success. However, the success of UGC-based products may also depend on other factors beyond customer feedback. Further research could investigate the overall success rate of UGC-based products in the market.

Proposition 7.3. Deploying UGC for risk analysis: a potential approach to predict new product failure.

Several key factors contribute to the challenges of the product development process, including unforeseen risks and their consequences, coupled with the firm's ineffectiveness and inefficiency in mitigating these risks (Choi and Ahn, 2010). Conventional risk management tools do not consider unstructured qualitative data, making it difficult to predict significant market movements caused by new information (Groth and Muntermann, 2011). However, recent studies have shown that analyzing textual data can be a valuable addition to risk management approaches. For instance, Groth and Muntermann (2011) utilized text analysis to identify corporate disclosures from unstructured textual data, and (Hsu et al., 2022) employed an automated text-mining process to extract operational risks from accounting narratives.

Considering the expanding corpus of literature on the utilization of textual data for risk mitigation, it is prudent to examine UGC as a means of assessing market risk. By analyzing UGC, risk managers can gain valuable insights into customer sentiment, opinions, and feedback regarding their products or services. Moreover, they possess the ability to recognize potential emergent hazards and forecast market patterns. Furthermore, the utilization of UGC can serve as an additional source of information to complement conventional risk management mechanisms that predominantly depend on organized quantitative data. Analyzing UGC can reveal risks that traditional risk management methods might overlook, highlighting its potential to identify unforeseen threats.

Proposition 7.4. Exploring consumer insights via UGC analysis on AI-driven platforms.

As AI technology advances, new platforms have emerged, offering users the opportunity to share information on a wide range of topics. One of these innovative platforms is ChatGPT. Generative pre-trained transformer (GPT)-based tools like ChatGPT can play as an innovator in NPD process (Bouschery et al., 2023). Moreover, ChatGPT's ability to generate creative concepts is remarkable, often seems human-like in its execution (Stevenson et al., 2022). This has led researchers to investigate the potential benefits of generative AI like ChatGPT in the development process. ChatGPT can be used as a tool for brainstorming and ideation in the product development process, by exploring a larger problem and solution space, and generating creative and innovative ideas (Dwivedi et al., 2023b). Moreover, ChatGPT can assist in developing software components, writing code, automating simple tasks, and managing errors during the development and post-deployment phases (Dwivedi et al., 2023b), which are integral to the functioning of physical products. In contrast, UGC is not typically used in product development in the same way that ChatGPT can be. Further research is necessary to explore the comparative impact of generative AI in the product development process and determine if generative AI can substitute UGC in NPD process to identify customers' needs or preferences. This inquiry is particularly pertinent given that ChatGPT's training incorporates human feedback (Roumeliotis and Tselikas, 2023; Wu et al., 2023), potentially providing access to a vast array of user opinions and insights.

Another innovative platform is the Metaverse. Damar (2022) defined the Metaverse as a “3D virtual world where all activities can be carried out with the help of augmented and virtual reality services”. The Metaverse's immersive nature, facilitated by augmented reality (AR) and virtual reality (VR), offers unprecedented tracking and monitoring opportunities, providing firms with dense streams of customer data and new metrics on object and user interactions (Dwivedi et al., 2023a). The Metaverse can expand experimentation, leading to “mega data” and fast-tracking of concept testing, prototyping, product design, and A/B testing at low cost. It offers ample opportunities for data accumulation and understanding of consumer responses, making it a crucial tool for NPD process (Dwivedi et al., 2022). A metaverse environment enables firms to deploy multiple competing designs for faster and more accurate product development and quickly detect changes in customer preferences. This facilitates a quantum leap in concept development and product evolution through more realistic product representations and their use (Dwivedi et al., 2023a). Notably, the Metaverse allows businesses to create virtual places where consumers can communicate with one another and interact with the products offered by businesses. For instance, several businesses have held events and introduced new showrooms, such as Nikeland by Nike, and Samsung 837× by Samsung, on Roblox, which is a gaming platform and a part of the Metaverse (Mileva, 2022). Customers can have a more immersive experience with the products, allowing for more informed purchasing decisions. This feature holds enormous promise for businesses that sell physical products since it enables customers to gain that experience. In addition, the Metaverse allows companies to use UGC regarding their virtual products to guide the creation of physical versions before they are released to the public. Because of Metaverse's capabilities in VR and AR, this input can provide significant insights into user preferences, concerns, and pain points that are more closely linked with reality. By utilizing the virtual environment provided by the Metaverse, companies can collect UGC, participate in co-creation, and gain a more in-depth insight into user behavior. Armed with this information, businesses can better adjust their products and services to suit the ever-changing requirements and expectations of their customers. It is reasonable to predict that UGC in Metaverse will play an increasingly significant role in developing new products as the popularity of this platform continues to rise.

Proposition 7.5. Exploring the potential impact of UGC on product development process of business-to-business firms.

In the context of business-to-business (B2B), businesses seek a variety of online external resources to gather different points of view, identify previously unconsidered aspects, and make better decisions (Steward et al., 2018). B2B Innovative companies engage customers in their development process through methods like open innovation, lead-user method, and distributed innovation, particularly in the early stages, to incorporate their ideas (Suominen et al., 2015).

Marketplaces are transforming due to the impact of the Internet and social media networks on business practices. B2B customers can generate UGC via platforms like LinkedIn, Epinions, and Alibaba, sharing endorsements, needs-based tagging, and hashtags. Similarly, suppliers share reviews on Twitter to advise those in similar positions (Marder et al., 2022). B2B UGC is defined as “statements made about products or services offered by a firm, or about the firm itself, which are made available by and to relevant external stakeholders” (Marder et al., 2022). The difference between customers in B2B and business-to-customer (B2C) is that industrial purchasers are often more knowledgeable and competent than consumers (Herhausen et al., 2020a, 2020b), and B2B buyers are less hedonistic and emotionally driven (Dibb and Simkin, 1993). Consequently, UGC in the B2B context significantly differs from that in B2C environments (Marder et al., 2022), reflecting the unique characteristics and motivations of each group. As a result, gaps in knowledge and practice regarding the generation and utilization of UGC in B2B commerce are becoming more pronounced (Herhausen et al., 2020a, 2020b). This has led researchers to investigate the potential benefits of UGC in the B2B context. For example, X. Liu (2022) focused on the impact of UGC on B2B firms' stock performance, and Hewett et al., (2016) analyzed Twitter data to examine the feedback loops that exist between firms' messages, news media, and UGC.

However, the potential of integrating B2B UGC as a supplementary information source during NPD process has been underexplored. Recognizing the value of B2B UGC could offer businesses a more comprehensive perspective and additional benefits, particularly because it is a cost-effective and swift method to enhance product development strategies.

8. Conclusion

This study represents the first systematic literature review (SLR) to explore the role of UGC within NPD process. By analyzing research articles published between 2012 and 2023, we offer a comprehensive assessment of how UGC impacts NPD. Employing a systematic review methodology, we searched globally recognized electronic databases using specific search keywords and the TCM framework to identify key themes, contexts, and methodologies pertinent to leveraging UGC in NPD. We delineated four main themes: the implication of UGC on NPD and innovation process, mining UGC for identifying innovative product ideas, deriving product features from UGC, and analyzing UGC to understand customer requirements. The study highlights the mobile industry and Amazon platform as predominant areas of research in this domain. Our findings present a nuanced overview of methodologies used in existing research, guiding academics and practitioners alike in refining their research approaches or adopting new methodologies for future studies. We underscore potential research gaps at the end of each theme, offering a roadmap for future research. This research serves as a valuable resource for businesses seeking to understand UGC's role in NPD, enabling them to harness customer insights for cost-effective and timely product development in a competitive global market. Additionally, businesses striving to align their products with customer needs may find strategic insights to innovate their NPD processes. This study is crucial for businesses and academics aiming to broaden their understanding of UGC's implications on NPD, thereby enriching the knowledge base for stakeholders. Identified future research avenues promise to expand the understanding of scholars, researchers, and academics, furthering the investigation of UGC's impact on NPD. In addition, this study emphasizes the potential of UGC to replace traditional methods of capturing customer insights. It highlights the necessity for researchers to explore new methods and AI platforms for a more accurate analysis of UGC. By addressing the knowledge gap on UGC's effectiveness in NPD, this research sets the stage for future thematic investigations, enriching the academic discourse on the real implications of UGC in NPD processes.

8.1. Theoretical and managerial implications

This research provides essential insights for academic and industrial stakeholders regarding the use of UGC in NPD process. It explores the vital roles and possible uses of UGC in NPD, highlighting the principal obstacles and important areas of knowledge. Our analysis has revealed four main issues that now drive the conversation about UGC's incorporation into NPD, each with a corresponding research gap. Additionally, the study offers a thorough analysis of the approaches used in previous research, providing guidance to academics and professionals on how to improve or develop their research methods for future investigations. While the results offer an initial understanding of the complex and diverse opportunities that UGC presents for NPD, the identified gaps in each theme and neglected thematic areas for future research underscore the need for further investigations.

The study advocates for incorporating UGC in product development, highlighting its benefits in speeding up development and enhancing competitiveness by tailoring products more closely to user needs. It suggests forming or improving social media profiles on different platforms, where user discussions can directly inform product improvements. UGC is an invaluable asset in NPD process, yet its full potential can only be harnessed when organizations pinpoint the digital spaces where relevant conversations occur. By establishing or enhancing their online communities, companies can facilitate product-centric discussions and collect valuable feedback directly from users. To achieve a comprehensive understanding, it is essential to recognize the stakeholders who can derive significant benefits from UGC analysis:

- Product designers and developers: By integrating UGC into the design and development stages, they obtain critical insights into consumer opinions on product features. This enables a deep understanding of their products' strengths and weaknesses, guiding strategic development planning.
- Innovation managers: UGC empowers innovation managers to discover and assess groundbreaking ideas within the innovation cycle. This intelligence can steer organizations towards introducing novel products or refining existing offerings to better meet consumer desires.
- Marketers: Offering a cost-effective substitute for traditional market research methods such as surveys and interviews, UGC provides rich insights into consumer behavior and preferences. Moreover, it equips marketing teams with the data needed to fine-tune their strategies, enhancing customer engagement and interaction.

This strategic approach to leveraging UGC not only facilitates direct consumer input into NPD process but also aligns product development with genuine user needs and preferences, fostering innovation and market relevance.

8.2. Limitations

Although this study provides valuable insights into the use of UGC in NPD process, it is important to acknowledge some limitations.

Keywords search: The evaluation was confined to articles obtained through selected keywords used in the search process, potentially excluding relevant articles that employed different or unrelated keywords. To mitigate this limitation, the search strings can be crafted with a mix of broader keywords for the concepts of “user-generated content” and “new product development,” and distinct research fields were included.

Scope: The study's scope was limited to subject areas such as "business management and accounting," "business economics," and "engineering" to control search results related to engineering and marketing. Notably studies from the field of hospitality and tourism were excluded as it is not related to the context of this research despite the extensive literature available in this area about UGC.

- Time frame: The studies analyzed in this research span from 2012 to 2023. Investigating different periods could provide further insights into the evolving role of UGC in NPD process.
- Type of journals and language: This study is confined to articles published in peer-reviewed journals in the English language. Broadening the research to include studies from books and non-peer-reviewed journals in languages other than English could enrich the existing body of knowledge.

- Database: This study sourced articles from three databases: Web of Science, Scopus, and Science Direct. Expanding the search to additional databases such as Google Scholar, IEEE Xplore, and EBSCO could facilitate the discovery of a broader range of related articles.

Despite these limitations, this study provides valuable insights into the use of UGC in NPD process and lays a foundation for future research in this field. Researchers should consider these limitations when interpreting the results and designing future studies to further investigate the role of UGC in NPD process.

CRediT authorship contribution statement

Mohamadreza Azar Nasrabadi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Yvan Beauregard:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Amir Ekhlassi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

None.

Data availability

No data was used for the research described in the article.

Appendix A. Bibliographic coupling clusters

Cluster	Author (Year)	Title of the article
Cluster 1 (22 items) - Red	Dong j.q.; Wu w. (2015)	Business value of social media technologies: evidence from online user innovation communities
	Gozuacik n. et al. (2021)	Social media-based opinion retrieval for product analysis using multi-task deep neural networks
	He W et al. (2016)	A process-based framework of using social media to support innovation process
	Ho -doc n.n. (2020)	The value of online user-generated content in product development
	Jeong et al. (2021)	Identifying consumer preference from user-generated content on amazon.com by leveraging machine learning
	Jeong et al. (2019)	Social media mining for product planning: a product opportunity mining approach based on topic modeling and sentiment analysis
	Jiao et al. (2022)	Does crowdsourcing lead to better product design; the moderation of network connectivity
	Kilroy et al. (2022)	Using machine learning to improve lead times in the identification of emerging customer needs
	Ko et al. (2020)	A novel framework for identifying customers' unmet needs on online social media using context tree
	Lin et al. (2022)	Converting consumer-generated content into an innovation resource: a user idea processing framework in online user innovation communities
	Muninger et al. (2019)	The value of social media for innovation: a capability perspective
	Olmedilla (2019)	Identification of the unique attributes and topics within smart things open innovation communities
	Rathore et al. (2016)	Social media content and product co-creation: an emerging paradigm
	Rathore et al. (2018)	Social media data inputs in product design: case of a smartphone
	Rathore et al. (2020)	Pre and post launch emotions in new product development: insights from Twitter analytics of three products
	Ozcan et al. (2021)	Social media mining for ideation: identification of sustainable solutions and opinions
	Tuarob et al. (2015)	Quantifying product favorability and extracting notable product features using large scale social media data
	Vikram et al. (2018)	Implementation strategy of social helpful reviews for product quality improvements – a special reference to engineering products
	Von Hippel and Kaulartz (2021)	Next-generation consumer innovation search: identifying early-stage need-solution pairs on the web
	Zeng et al. (2022)	User-interactive innovation knowledge acquisition model based on social media
	Zhang et al. (2018)	From buzz to bucks: the impact of social media opinions on the locus of innovation
	Zhang et al. (2021)	Mining product innovation ideas from online reviews
Cluster 2 (21 items) - Green	Chen et al. (2019)	Intelligent Kano classification of product features based on customer reviews
	Ali et al. (2020)	Ontology-based approach to extract product's design features from online customers' reviews
	Chen et al. (2019)	Mining user requirements to facilitate mobile app quality upgrades with big data
	Han et al. (2021)	Eliciting attribute-level user needs from online reviews with deep learning models and information extraction
	Huang et al. (2022)	Feature extraction of search product based on multi-feature fusion-oriented to Chinese online reviews
	Jin et al. (2016)	Identifying comparative customer requirements from product online reviews for competitor analysis
	Jin et al. (2016)	What makes consumers unsatisfied with your products: review analysis at a fine-grained level
	Kang et al. (2017)	RUBE: rule-based methods for extracting product features from online consumer reviews
	Lamrhari et al. (2019)	Business intelligence using fuzzy-kano model
	Lee et al. (2017)	Understanding customer opinions from online discussion forums: a design science framework
	Li et al. (2014)	Creating social intelligence for product portfolio design
	Qi et al. (2016)	Mining customer requirements from online reviews: a product improvement perspective
	Wang et al. (2018)	Topic analysis of online reviews for two competitive products using latent Dirichlet allocation
	Xiao et al. (2016)	Crowd intelligence: analyzing online product reviews for preference measurement
	Yan et al. (2015)	EXPRS: an extended PageRank method for product feature extraction from online consumer reviews
	Yang et al. (2019)	Exploiting user experience from online customer reviews for product design
	Zhang et al. (2016)	Jointly identifying opinion mining elements and fuzzy measurement of opinion intensity to analyze product features
	Zhang et al. (2018)	Product innovation based on online review data mining: a case study of Huawei phones
	Zhang et al. (2019)	Identification of the to-be-improved product features based on online reviews for product redesign
	Zhou et al. (2015)	Latent customer needs elicitation by use case analogical reasoning from sentiment analysis of online product reviews
	Zhou f et al. (2020)	A machine learning approach to customer needs analysis for product ecosystems
Cluster 3 (8 items) - Blue	Asadabadi et al. (2023)	Enhancing the analysis of online product reviews to support product improvement: integrating text mining with quality function deployment
	Chiarello et al. (2020)	Technical sentiment analysis, measuring advantages and drawbacks of new products using social media
	Choi et al. (2020)	Identification of time-evolving product opportunities via social media mining
	Jiang et al. (2019)	Dynamic modeling of customer preferences for product design using defis and opinion mining
	Liu et al. (2019)	Assessing product competitive advantages from the perspective of customers by mining user-generated content on social media

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Cluster	Author (Year)	Title of the article
	Ng et al. (2020)	Investigating consumer preference on product designs by analyzing opinions from social networks using evidential reasoning
	Sun et al. (2020)	Dynamical mining of ever-changing user requirements: a product design and improvement perspective
	Yakubu et al. (2021)	Forecasting the importance of product attributes using online customer reviews and google trends
Cluster 4 (7 items) - Yellow	Chiu et al. (2018)	Utilizing text mining and Kansei engineering to support data-driven design automation at conceptual design stage
	Chan et al. (2020)	Predicting customer satisfaction based on online reviews and hybrid ensemble genetic programming algorithm
	Ireland et al. (2018)	Application of data analytics for product design: sentiment analysis of online product reviews
	Shi et al. (2021)	Enhanced customer requirement classification for product design using big data and improved kano model
	Timoshenko and Hauser (2019)	Identifying customer needs from user-generated content
	Wang et al. (2018)	Extracting and summarizing affective features and responses from online product descriptions and reviews: a Kansei text mining approach
	Wang et al. (2019)	Multiple affective attribute classification of online customer reviews: a heuristic deep learning method for supporting Kansei engineering

Appendix B. Methodologies/tools and analytical methods used by each study with main findings

Author	Title	Research methods/tools – analytical methods	Main findings
Rathor et al. (2016)	Social media content and product co-creation: an emerging paradigm	Methodological review	Social media is a valuable informational source to extract customers' insight.
He & Wang (2016)	A process-based framework of using social media to support innovation process	Case study research method & interview	Social media enables users to evaluate ideas or prototypes using virtual objects.
Vikram & Kumar (2018)	Implementation strategy of social helpful reviews for product quality improvements – special reference to engineering products	Interview	Product quality can be improved by utilization of customer reviews form social networking platforms.
Muninger et al. (2019)	The value social media for innovation: a capability perspective	Interview	Social media facilitates co-creation of products throughout the entire development process.
Ho-Dac (2020)	The value of online user generated content in product development	Empirical study	UGC has positive impact on both the ideation and completion stages of product development.
Zhang et al. (2018)	From buzz to bucks: the impact of social media opinions on the locus of innovation	Sentiment analysis	Social media perceptions impact commercial organizations' innovation investment strategies.
Dong & Wu (2015)	Business value of social media technologies: evidence from online user innovation communities	Event study methodology	The utilization of user innovation communities found online enables the invention, transformation, and dissemination of ideas, which can result in the creation of new products, services, and process.
Jiao et al. (2022)	Does crowdsourcing lead to better product design: the moderation of network connectivity	Fuzzy-set qualitative comparative analysis & two-stage least square	Product design may also benefit from crowdsourcing since it increases the efficiency with which new products perform.
Zeng et al. (2022)	User-interactive innovation knowledge acquisition model based on social media	Latent Dirichlet Allocation model & User demand ontology & semantic similarity matching	User-interactive innovation knowledge acquisition model could assist enterprises by providing ideas for follow-up innovation and product development.
Lin et al. (2022)	Converting consumer-generated content into an innovation resource: a user ideas processing framework in online user innovation communities	User idea cluster algorithm & logistic regression model	In comparison with “3C” methods, their suggested novel idea vectorization approach converts the idea semantic included in UGC more accurately into numerical vectors.
Olmedilla et al. (2019)	Identification of the unique attributes and topics within smart things open innovation communities	Text mining and TF-IDF	They found that unique attributes are more prevalent among words with higher TF-IDF, and the frequency of unique attributes increases with the number of attributes.
Zhang et al. (2021)	Mining product innovation ideas from online reviews	Recurrent neural network-based ensemble embedding technique & long short-term memory (LSTM) model	Adopting the focal loss function in REE-LSTM model yielded the greatest performance.
Gozuacik et al. (2021)	Social media-based opinion retrieval for product analysis using multi-task deep neural networks	Machine learning & natural language processing techniques	This study shows that sentiment analysis and NLP methods are useful for product or technology reviews and community opinions.
Jeong et al. (2019)	Social media mining for product planning: a product opportunity mining approach based on topic modeling and sentiment analysis	Topic modeling & sentiment analysis & opportunity algorithm	Social media helps planners during the design phase by identifying untapped opportunities for new or enhanced products.
Lee et al. (2017)	Understanding customer opinions from online discussion forums: A design science framework	Design science approach: text analysis & text network analysis	Unique web expression is an important element that should be interpreted, and it can help designers during the design process.
Ozcan et al. (2021)	Social media mining for ideation: identification of sustainable solutions and opinions	Conventional text representation approach & TF-IDF & BERT & SMOTE	Social media mining can provide valuable sustainability ideas, debunking misconceptions about data quality and explore product innovations and community sustainability.
Yakubu & Kwong (2021)	Forecasting the importance of product attributes using online customer reviews and Google Trends	Rough set method in fuzzy time series	Suggested fuzzy rough set time series approach had a superior performance in terms of predicting that the fuzzy time series method, fuzzy K medoid clustering time series method, and ANFIS method.
Kang & Zhou (2017)	RubE: rule-based methods for extracting product features from online consumer reviews	Rule-based extraction methods	Utilizing the recommended techniques for feature extraction helps enhance recall and improve the precision of feature extraction.

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Author	Title	Research methods/tools – analytical methods	Main findings
Wang et al. (2018)	Extracting and summarizing affective features and responses from online product descriptions and reviews: a kansei text mining approach	Text mining & kansei engineering	The study shows successful information extraction with high recall and precision, emphasizing the importance of product descriptions and the challenge of analyzing critical reviews accurately.
Wang et al. (2019)	Multiple affective attribute classification of online customer product reviews: a heuristic deep learning method for supporting kansei engineering	Heuristic deep learning & text mining	Combining rule-based extraction with machine learning models outperformed both approaches alone.
Li et al. (2014)	Creating social intelligence for product portfolio design	Text mining	The proposed system filters data, improves quality, and reduces costs for enterprises. It predicts market trends and customer acceptance, generating feature specifications based on social media opinions for products with clear features and shorter life cycles.
Zhang et al. (2016)	Jointly identifying opinion elements and fuzzy measurement of opinion intensity to analyze product features	Fuzzy logic & opinion mining extraction algorithm	Advantages of the approach: opinion extraction using phrase-level patterns, feature relations based on semantic meaning, and fuzzy logic for sentiment evaluation.
Huang et al. (2022)	Feature extraction of search product based on multi-feature fusion-oriented to Chinese online reviews	Text mining: Product feature extraction based on multi-feature fusion model (PFEMF)	PFEMF outperforms traditional algorithms such as TF-IDF, word span, and semantic similarity in product feature extraction.
Zhang et al. (2019)	Identification of the to-be-improved product features based on online reviews for product redesign	Opinion mining	This approach is an efficient tool for determining which aspects of the product require further development.
Tuarob and Tucker (2015)	Quantifying product favorability and extracting notable product features using large scale social media data	Text mining	Incorporating suggested features extracted from UGC into next-generation products can result in favorable sentiment from social media users.
Yan et al. (2015)	EXPRS: an extended pagerank method for product feature extraction from online consumer reviews	Text mining: Extended pagerank algorithm enhance by s synonym lexicon	The suggested technique outperformed baseline methods in precision, recall, and F-measure, indicating improved extraction performance through synonym expansion and implicit feature inference.
Asadabadi et al. (2022)	Enhancing the analysis of online product reviews to support product improvement: integrating text mining with quality function deployment	NLP sentiment mining & quality function deployment (QFD)	The proposed method improves the reliability of QFD by generating prioritized lists of product features and calculating engineering requirements weightings for different products.
Zhang et al. (2018)	Product innovation based on online review data mining: a case study of Huawei phones	Text mining & empirical study	There is a significant correlation between the degree to which customers are satisfied with the product and its ongoing feature development.
Timoshenko et al. (2019)	Identifying customer needs from user-generated content	Convolutional neural networks & dense word & sentence embeddings	UGC is a valuable and efficient source of customer needs, aided by machine learning, reducing research time and expediting time-to market.
Kilroy et al. (2022)	Using machine learning to improve lead times in the identification of emerging customer needs	Machine learning	Social media trends are connected to forthcoming products, while there may be additional latent casual linkage such as various types of exploratory product development leading to new products.
Sun et al. (2020)	Dynamical mining of ever-changing user requirements: a product design and improvement perspective	Text mining & natural language processing (NLP)	The proposed method clearly illustrates the changing behavior of each product attribute over time.
Chiu & Lin (2018)	Utilizing text mining and kansei engineering to support data-driven design automation at conceptual design stage	Text mining: energy material signal (EMS) model & Kansei engineering	The proposed strategy can speed up the process of recognizing customer needs and aid in the development of products that meet those needs.
Han & Moghaddam (2021)	Eliciting attribute-level user needs from online reviews with deep language models and information extraction	deep language representation model bidirectional encoder representations from transformers (BERT) and named entity recognition (NER)	Pretrained language models like BERT decrease reliance on labeled datasets, improving efficiency and scalability in need finding. BERT-NER enables automated, large-scale need identification from user reviews.
Zhou et al. (2020)	A machine learning approach to customer needs analysis for product ecosystems	LDA & rule-based sentiment analysis called Valence Aware Dictionary & sentiment reasoner (VADER) & kano model	The identification of customer needs may be used to determine where there are gaps in the product ecosystem that can be filled by new products.
Ko et al. (2020)	A novel framework for identifying customers' unmet needs on online social media using context tree	Context tree using hierarchical search concept space (HSCS) algorithm & natural language processing	Extracting users' context with related keywords enables professional interpretation and quantitative evaluation for unfulfilled customer requirements in NPD.
Zhou et al. (2015)	Latent customer needs elicitation by use case analogical reasoning from sentiment analysis of online product reviews	Sentiment analysis & analogical reasoning	The latent customer needs elicited by the proposed method will delight the customers if they are met or disgust them if they are not.
Yang et al. (2019)	Exploiting user experience from online customer reviews for product design	Text mining & machine learning	The proposed approach shows promising results in UX data extraction, leveraging mutual information, with potential for further enhancement using advanced techniques. It suggests including nouns and adverbs for sentiment extraction.
Chen et al. (2019)	Mining user requirements to facilitate mobile app quality upgrades with big data	Context-aware segmentation method & a domain-dependent filtering approach	The result results proved that the suggestions based on our ranking method have a higher probability of improving the upgrade quality.
Ali et al. (2020)	Ontology-based approach to extract product's design features from online customers' reviews	Natural language processing (NLP) & ontology approach	The research findings indicate that the implementation of natural language processing techniques based on ontology can be advantageous in facilitating the identification and extraction of crucial product design attributes.

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Author	Title	Research methods/tools – analytical methods	Main findings
von Hippel & Kaulartz, (2021)	Next-generation consumer innovation search: identifying early-stage need-solution pairs on the web	Natural language processing (NLP) based semantic word space models with semantic network analytic methods	Unlike traditional practices where producers identify needs and develop solutions or lead user studies where producers identify needs and seek prototype solutions from lead users, the proposed method outsources both need formulation and solution development.
Ng & Law (2020)	Investigating consumer preferences on product designs by analyzing opinions from social networks using evidential reasoning	Sentiment analysis & fuzzy set & evidential reasoning	The proposed technique improves sentiment interpretation, accelerates qualitative social media review, and incorporates weighted customer preference. Fuzzy set theory and the ER algorithm address opinion uncertainty using SentiWords.
Jiang et al. (2019)	Dynamic modeling of customer preferences for product design using DENFIS and opinion mining	Neural-fuzzy inference system (DENFIS)	The study's findings indicate that the suggested DENFIS technique can provide both crisp and fuzzy outputs, as opposed to the current DENFIS approach for modeling, which can generate only crisp outputs.
Jeong (2021)	Identifying consumer preferences from user-generated content on Amazon.com by leveraging machine learning	Machine learning	Incorporating DFs and sentiment variables in HETOP models improves model fit and prediction accuracy compared to basic models, highlighting the significance of DF mining and sentiment analysis for prediction and estimation.
Xiao et al. (2016)	Crowd intelligence: analyzing online product reviews for preference measurement	Modified ordered choice model & kano model	The proposed MOCM model outperforms existing models and the MEKM model provides a viable method for further categorizing and prioritizing customer requirements.
Chen et al. (2019)	Intelligent kano classification of product features based on customer reviews	Sentiment analysis & kano model	The findings point to the fact that the expansion of the categorization from two dimensions to three dimensions makes it easier to sort product features that are close to the boundaries and to compare product features that fall into the same category.
Shi & Peng (2021)	Enhanced customer requirements classification for product design using big data and improved kano model	Customer requirements Classification method by Kano model & importance-performance analysis (IPA) model	In terms of defining the product's function implementations, the proposed customer requirements classification method outperforms the existing methods.
Qi et al. (2016)	Mining customer requirements from online reviews: a product improvement perspective	Sentiment analysis & conjoint analysis & kano model	Big data and classical management models can double results with half the work. This suggests that combining these two methods can yield more accurate and efficient big data insights.
Lamrhari et al. (2019)	Business intelligence using the fuzzy-kano model	Text mining: LDA & fuzzy-kano model	LDA approach has correctly extracted aspects with 97.4 % accuracy and 92.4 % precision.
Chan et al. (2020)	Predicting customer satisfaction based on online reviews and hybrid ensemble genetic programming algorithms	Machine learning	The CSPF can more accurately forecast CS dimensions by considering the historical time series of CS dimensions.
Choi et al. (2020)	Identification of time-evolving product opportunities via social media mining	Aging theory-based event detection & tracking (EDT) algorithm &opportunity algorithm & sentiment analysis	This methodology can also help businesses dynamically track customer product satisfaction and dissatisfaction over the course of the customer's lifecycle.
Jin et al. (2016);	What makes consumers unsatisfied with your products: review analysis at a fine-grained level	Sentiment classification techniques	The results clearly indicate that the proposed CRFs approach outperformed the HMM-based approach.
Liu et al. (2019)	Assessing product competitive advantages from the perspective of customers by mining user-generated content on social media	Supervised learning & Sentiment analysis	The suggested method is a beneficial supplement to the more conventional approaches to analyze product performance, and better reflects the perspective of customers.
Jin et al. (2016)	Identifying comparative customer requirements from product online reviews for competitor analysis	Sentiment analysis	The research demonstrated the utility of clustering opinionated statements, analyzing customer requirements, and assessing product attributes to aid product designers in understanding customer preferences and improving product development.
Wang et al. (2018)	Topic analysis of online reviews for two competitive products using latent dirichlet allocation	Text mining	Contradictory reviews shared topics, revealing complementarity between positive and negative product features.
Rathore et al. (2020)	Pre and post launch emotions in new product development: insights from twitter analytics of three products	Machine learning-based sentiment classifier	This study highlights the influence of emotions on product intentions and user behavior, emphasizing the value of semantic information in understanding overall sentiment and user preferences.
Ireland & Liu (2018)	Application of data analytics for product design: sentiment analysis of online product reviews	Natural language processing (NLP) & machine learning	The findings of this study demonstrate the noteworthy accomplishments of the framework, including the resemblance between Machine and Human Models, the model's accuracy, and its suitability for design decision-making.
Rathore et al. (2018)	Social media data inputs in product design: case of smartphone	Content analysis & network analysis	The study highlights the significance of analyzing user-generated content (UGC) in identifying shared interests and facilitating a unified understanding of emotional expectations for product qualities.
Chiarello et al. (2020)	Technical sentiment analysis: measuring advantages and drawbacks of new products using social media	Supervised machine learning	Utilizing a novel lexicon that considers the pros and cons of products, along with their functional and physical aspects, when filtering Twitter data, provides more precise and pertinent information compared to conventional sentiment analysis methods.

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