User-Generated Content in New Product Development: A Data-Driven Approach to Consumer Insights

by

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Contenu généré par les utilisateurs dans le développement de nouveaux produits : une approche axée sur les données pour mieux comprendre les consommateurs

Mohamadreza AZAR NASRABADI

RESUME

Le contenu généré par les utilisateurs (CGU) offre des avantages majeurs pour le développement de nouveaux produits (DNP) en fournissant un flux continu et spontané de retours consommateurs en temps réel. Émergeant de manière organique sur les plateformes numériques, le CGU propose une source d'informations plus large et inclusive que les méthodes traditionnelles qui nécessitent une sollicitation active. En exploitant le CGU, les entreprises peuvent capturer efficacement des informations liées aux besoins et aux solutions, identifier des idées de produits innovantes, extraire des caractéristiques précieuses et mieux comprendre l'évolution des attentes des clients. Cette approche améliore l'efficacité de la conception produit, réduit les taux de rejet sur le marché et accélère le délai de mise sur le marché.

S'appuyant sur ces avantages, cette thèse étudie de manière approfondie le rôle du CGU dans le processus de DNP via une approche axée sur les données. La recherche poursuit trois objectifs principaux. Premièrement, une revue systématique de la littérature (RSL) synthétise les travaux existants sur le CGU dans le DNP, en identifiant les thèmes clés, les contextes et les méthodologies par des techniques multifacettes, mettant ainsi en lumière les lacunes et proposant des pistes futures. Deuxièmement, la thèse développe un cadre pour évaluer l'acceptation des consommateurs d'un nouveau produit à partir de l'analyse du CGU, en utilisant la modélisation thématique, l'analyse de sentiment et la modélisation statistique, illustré par une étude sur ChatGPT. Troisièmement, elle propose un cadre pour identifier les facteurs d'obsolescence produit et construire des indices d'obsolescence en séries temporelles (IO) à partir du CGU. Ce cadre s'appuie sur des modèles linguistiques de grande taille (LLM) tels que ChatGPT-4o, ainsi que sur la prise de décision multicritère et l'analyse de sentiment, afin d'apporter des insights sur la longévité des produits.

Globalement, cette thèse fait progresser la compréhension de l'exploitation systématique du CGU pour soutenir divers aspects du processus de DNP. En capturant des insights consommateurs en temps réel, le CGU facilite l'évaluation de l'acceptation du marché et la gestion du cycle de vie des produits. Les cadres proposés contribuent non seulement à la théorie à l'intersection du CGU et de la gestion de l'innovation, mais fournissent également des outils pratiques aux entreprises souhaitant améliorer l'efficacité, la réactivité et la durabilité de leurs efforts de développement produit.

Mots-clés: Contenu généré par les utilisateurs, Développement de nouveaux produits, Acceptation des consommateurs, Obsolescence produit, Avis consommateurs en ligne

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ABSTRACT

User-generated content (UGC) provides significant advantages for new product development (NPD) by providing a continuous, unsolicited stream of real-time consumer feedback. Emerging organically across digital platforms, UGC offers a broader and more inclusive pool of insights compared to traditional methods that require active solicitation. By mining UGC, firms can efficiently capture need- and solution-related insights, identify innovative product ideas, extract valuable features, and better understand evolving customer requirements. This approach enhances product design efficiency, reduces market rejection rates, and accelerate time-to-market.

Building on these advantages, this thesis comprehensively examines the role of UGC in NPD process through a data-driven approach. The research pursues three main objectives. First, a systematic literature review (SLR) synthesizes existing research on UGC in NPD, identifying key themes, contexts, and methodologies through multifaceted techniques. This review highlights research gaps and proposes future directions. Second, the thesis also develops a framework for assessing consumer acceptance of a new product by analyzing UGC, employing topic modeling, sentiment analysis, and statistical modeling, demonstrated through a study on ChatGPT. Third, it introduces a framework for identifying product obsolescence factors and constructing time-series obsolescence indexes (OI) using UGC. This framework leverages large language models (LLMs) such as ChatGPT-4o, along with multicriteria decision-making and sentiment analysis, to provide insights into product longevity.

Overall, this thesis advances the understanding of how UGC can be systematically leveraged to support diverse purposes within the NPD process. By capturing real-time consumer insights, UGC facilitates market acceptance evaluation, and product lifecycle management. The proposed frameworks not only make theoretical contributions to the intersection of UGC and innovation management but also deliver practical tools for firms seeking to enhance the efficiency, responsiveness, and sustainability of their product development efforts.

Keywords: User-generated content, New product development, Consumer acceptance, Product obsolescence, Online consumer review

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LIST OF ABREVIATIONS

ATT	Attitude
AHP	Analytic Hierarchy Process
AIDUA	AI device use acceptance
ANP	Analytic Network Process
AOI	Aggregated Obsolescence Index
AR	Augmented Reality
AV	Autonomous Vehicle
AVE	Average Variance Extracted
B2B	Business-to-Business
B2C	Business-to-Customer
BERT	Bidirectional Encore Representation
BI	Behavioral Intention
ChatGPT	Chat Generative Pre-trained transformer
CI	Consistency Index
COTS	Commercial-off-the-Shelf
CP	Customer Participation
CPSs	Cyber-Physical Systems
CR	Composite Reliability
CR	Consistency Ratio
DSR	Design Science Research
E-waste	Electronic Waste
EE	Effort Expectancy
EEE	Electrical and Electronic Equipment
FA	Factor Analysis
Freq-AHP	Frequency-Analytic hierarchy process

GPT	Generative Pre-trained transformer
HTMT	heterotrait-Monotrait
IoT	Internet of Things
KE	Kansei Engineering
LDA	Latent Dirichlet Allocation
LLMs	Large Language Models
MCDM	Multicriteria Decision-Making
Mt	Million Tone
NER	New Convolutional Net and Name Entity Recognition
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
NOI	Normalized Obsolescence Index
NPD	New Product Development
OEM	Original Equipment Manufacturer
OI	Obsolescence Index
OIC	Obsolescence Index Change
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PE	Performance Expectancy
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modeling
RI	Random Consistency Index
RoBERTa	Robustly Optimized Bidirectional Encoder Representations from Transformers Approach
SEM	Structural Equation Model
SLR	Systematic Literature Review
SVM	Support Vector Machine
SWOT	Strengths, Weaknesses, Opportunities, and Threats
TR	Trust
TAM	Technology Acceptance Model

TCM	T-theme, C-context, and M-methodology
TF-IDF	Term Frequency-Inverse Document Frequency
TOPSIS	Technique for order of preference by similarity to ideal solution
UTAUT	Unified Theory of Acceptance and Use of Technology
VADER	Valence-Aware Dictionary for Sentiment Reasoning
VCCs	Virtual Customer Communities
VIF	Variance Inflation Factor
VIKOR	VIšekriterijumsko Kompromisno rangiranje
VR	Virtual Reality
XGBoost	Extreme Gradient Boosting

LIST OF SYMBOLS

j	Obsolescence Factor.
μ_{jct}	Mean of the Normalized Sentiment Intensity of Reviews, Associated with Factor *j*, in Product Category *c*, During Period *t*.
A	Pairwise Comparison Matrix.
a_{ji}	Relative Importance of Factor a_j to Factor a_i.
c	Product Category.
C	Consistency Test.
c_{jct}	Consistency Vector Value for Factor j in Category *c* At Time *t*.
CV_{jct}	Consistency Value for Each Factor Within Each Product Category Over a Defined Period.
$\mathrm{E}\left[\mathrm{g}\left(x_{jct}\right)\right]$	The Sum of The Expected Values of The Emotional Impact of an Obsolescence Factor.
$\mathrm{E}\left[\mathrm{g}\left(x_{jctr}\right)\right]$	Expected Value of Normalized Sentiment Intensity.
f_i	Frequency of Obsolescence Factor a_i.
f_j	Frequency of Obsolescence Factor a_j.
$\mathrm{g}\left(x_{jctr}\right)$	Normalized Sentiment Intensity.
n_{jct}	Number of Reviews Mentioning Factor *j* in Category *c* in Period *t*.
$\mathrm{P}_{\mathrm{g}\,(x_{jctr})}$	Probability Distribution of Normalized Sentiment Intensity.
$\mathrm{P}_{\mathrm{norm}\,(x_{jctr})}$	Normalized Probability Distribution of Normalized Sentiment Intensity.

s_{jct}^2	Sample Variance of The Normalized Sentiment Intensity of Reviews, Associated With Factor *j*, in Product Category *c*, During Period *t*.
t	Period.
$t_I - t_i$	The Time Interval Between The Two Measurements of The NOI(jct) While I > i.
w_{ct}^T	Transposed Weight Vector of All Factors in Category *c* At Period *t*.
w_{jct}	Relative Importance of an Obsolescence Index Factor Within A Product Category Over a Defined Period.
x_{jctr}	Sentiment Intensity of A Single Review.
λ_{max}	Maximal Eigenvalue.

LIST OF VARIABLES

$NR_{(ct)}$	Number of Obsolescence-Related Reviews for Category *c* Across All Time Periods.
$NF_{(jct)}$	Number of Obsolescence Factor *j* Within Category *c* in period *t*.
$AOI_{(ct)}$	Aggregated Obsolescence Index of a Factor Within a Category Over Time.
$NOI_{(jct)}$	Normalized Time-Dependent Function of Obsolescence Index.
$OI_{(ct)}$	Sum of all Time-dependent Function of Obsolescence Index within Category *c* in Period *t*.
$OI_{(jct)}$	Time-dependent Function of Obsolescence Index.
$OIC_{(jct_{I-i})}$	Obsolescence Index Change of a Factor within a category.

INTRODUCTION

The success of new product development (NPD) is crucial for a firm's survival, especially in the highly competitive Industry 4.0 era, where companies must rapidly adapt to meet the demand for customized products (Belbaly et al., 2007; Buer et al., 2018; Ho-Dac, 2020; Kolberg et al., 2017). Effective NPD process enables manufacturing companies to adapt, thrive, and remain competitive in rapidly evolving business environments (M. Kang et al., 2021; F. Yang & Zhang, 2018).

Customer participation (CP) in NPD process enhances its effectiveness, leading to optimized outcomes by improving customer engagement in the process (Fang, 2008; Naeem & Di Maria, 2020a). CP has evolved to be integrated into all phases of NPD, positively influencing market performance, democratizing innovation, enhancing corporate creativity, and reducing uncertainty (Chang, 2019; Fuchs & Schreier, 2011; Morgan et al., 2018; Naeem & Di Maria, 2020a). Furthermore, CP in various NPD phases leverages their knowledge to enhance product outcomes, while their participation as information providers or co-developers accelerates development, reduces costs, and improves quality, ensuring long-term sustainability (Callahan & Lasry, 2004; Y. C. Chen et al., 2021; Cui & Wu, 2017; M. J. J. Lin et al., 2013). In the ideation stage, firms engage customers to gather insights and refining ideas; in the development stage, customers contribute technical knowledge and design input; and in the launch stage, they assist with prototype testing and market introduction (Chang & Taylor, 2016). So, engaging customers throughout NPD process has a positive impact on both financial and non-financial performance, strengthening firms' competitive advantage (Chang & Taylor, 2016). Building on this foundation, manufacturers have leveraged customer insights to generate new product, align offerings with market needs, and refine solutions to increase the likelihood of new product acceptance (Lamberti & Noci, 2009; Numprasertchai et al., 2014; Stock, 2014; Witell et al., 2014).

Concepts such as lead users, crowdsourcing, virtual customer communities, and user toolkits have emerged as approaches for involving customers in NPD within distributed innovation paradigm (Bogers & West, 2012; Ho-Dac, 2020; Naeem & Di Maria, 2020a).The lead user concept suggests that experienced users at the forefront of the market trends develop innovation solutions, which firms can leverage to enhance their NPD (Lilien et al., 2002; Moorman & Rust, 1999; von Hippel, 2005). Although there are many examples of lead user innovation in the literature (Franke et al., 2016; Lüthje, 2004; Urban & Von Hippel, 1988), decision-makers often underestimate its impact (Bradonjic et al., 2019), likely due to challenges in transferring these innovations to firms, leading to mixed results that limit their role in product development (Ho-Dac, 2020). These challenges may arise because firms want to maintain their traditional leadership in product development (Hoyer et al., 2010), or because user innovations are difficult and costly to transfer (Gambardella et al., 2017; von Hippel, 2005). In contrast, the open innovation literature examines how firms extend their boundaries to drive innovation (H. Chesbrough, 2006; H. Chesbrough et al., 2014) by incorporating external knowledge into product development (Dahlander & Gann, 2010; Enkel et al., 2009). Users serve as a key external source (F. Piller & Ihl, 2009), particularly through crowdsourcing (Djelassi & Decoopman, 2013), where firms collect input via online platforms (Palacios et al., 2016). While crowdsourcing has led to many successes (Piezunka & Dahlander, 2015; F. T. Piller, 2010), long-term studies highlight challenges in sustaining idea quality, as most contributions come from repeat participants who often submit similar ideas (Bayus, 2013). Compared to crowdsourcing, which focuses on soliciting a large pool of users, virtual customer communities (VCCs) emphasize engagement-driven participation, where users contribute primarily for the rewarding experience rather than direct benefits (Füller, 2006; Nambisan, 2002). Companies across industries use VCCs, such as Peugeot for early-stage design, Microsoft for product support, Ducati for design contributions, and Volvo for concept testing (Nambisan & Baron, 2007). However, challenges include motivating qualified users to participate and ensuring that virtual interaction remain engaging and contribute meaningfully to innovation (Y. Yang et al., 2019). In a distinct approach from the previously discussed concepts, user toolkits provide users with design freedom and prototyping capabilities through firm-provided tools, simplifying ideation and product creation through a trial-and-error process (Schäper et al., 2024; von Hippel, 2001). While user toolkits for innovation offer significant potential (Helminen & Ainoa, 2009), they face challenges, particularly in accessibility, as the most advanced toolkits are designed for expert users, whereas simpler versions tend to focus more on customization rather than true innovation (Goduscheit & Jørgensen, 2013).

Given the limitations of lead user, crowdsourcing, VCCs, and user toolkits concepts, this study utilizes a hybrid distributed innovation method. With the rise of social media, consumers increasingly share their product experiences, generating a vast repository of online user-generated content (UGC). This wealth of information has transformed social media into a valuable resource that significantly influences NPD, leading to meaningful improvement (Ho-Dac, 2020). Unlike lead user concept, which rely on engaging a select group of advanced users, UGC passively gathers insights from a broader and more representative consumer base, reducing the complexity of knowledge transfer while allowing firms to maintain full control over the development process (Nambisan, 2002). Crowdsourcing requires firms to actively solicit user input, but UGC provides an unsolicited and continuous flow of discussions, mitigating the challenges of sustaining long-term engagement and ensuring a steady stream of fresh insights (Ho-Dac, 2020). In addition, unlike VCCs, which struggle with maintaining user engagement and require continuous firm involvement to sustain participation, UGC emerges organically across digital platforms, eliminating the need for firms to actively encourage contributions (Mangold & Faulds, 2009). Additionally, extracting relevant insights from VCCs requires ongoing monitoring and investment, making the process resource intensive. User toolkits, on the other hand, face accessibility challenges, as advanced versions are designed primarily for expert users, while simpler toolkits focus more on customization than fostering true innovation. This structured approach limits broader user participation, making it difficult for firms to capture unfiltered and diverse consumer insights. UGC, in contrast, allows users of all backgrounds to share their experiences freely, offering firms a wide and more inclusive pool of product-related feedback (Y. Chen & Xie, 2008). Thus, online UGC can serves as a valuable resource in NPD process, offering distinct advantages such as real-time updates that enable companies to track consumer opinions and derive cost-effective insights for innovation (Timoshenko & Hauser, 2018).

Problem Statement

The NPD process is vital for a firm's long-term growth and profitability (Sorescu et al., 2003; Wind & Mahajan, 1997). Companies need to prioritize enhancing NPD process, as conventional approaches often struggle to ensure product success in the market (Christensen, 2015; R. G. Cooper, 1990). A key strategy for improving NPD process is actively engaging customers in product development (Prahalad & Ramaswamy, 2004; von Hippel, 2005). Therefore, integrating customers into NPD process is crucial for business success, especially during socio-economic transformation (Prahalad & Ramaswamy, 2004; Vargo & Lusch, 2014a). Leveraging customer reviews can further support product innovation and diversification (Al-Zu'Bi & Tsinopoulos, 2012; Nishikawa et al., 2013). This collaborative effort is referred to as a co-creation program (Bartl et al., 2010). Co-creation is a strategic approach that directly involves customers in NPD process, fostering interactive, innovative, and social collaboration between customers and businesses (F. T. Piller, 2012; Prahalad & Ramaswamy, 2004). Through this strategy, customers contribute by generating ideas, refining concepts, customizing prototypes, and testing new products (Prahalad & Ramaswamy, 2004; Sawhney et al., 2005). Building on this foundation, advanced internet technology plays a crucial role in broadening the scope and effectiveness of co-creation (Nasrabadi et al., 2024). Digital platforms allow businesses to create interactive spaces for collaboration and content creation, significantly promoting the adoption of co-creation (Bartl et al., 2010). Simultaneously, a transformation in information and communication has occurred, shifting from traditional distribution channels to social media-based systems (Kietzmann et al., 2011). With the widespread use of social media, UGC has emerged as a major source of information, independently generated by digital platforms users, leading to expressive and communicative impacts (Santos, 2022a; Timoshenko & Hauser, 2018). Existing literature has thoroughly examined UGC through systematic reviews, focusing on its definitions and various forums (Naab & Sehl, 2017; (Naab & Sehl, 2017; Santos, 2022a), analytical techniques for UGC analysis (J. Lin et al., 2022; Manchanda, 2019), and its application across various research fields (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi & Karjaluoto, 2018). Despite these advances, a critical gap remains:

1. There is no comprehensive study that integrates key themes, contexts, and methodologies used to examine UGC's impact on NPD process, identifies gaps within these themes, and suggests future research directions to clarify UGC's role in NPD.

Following the initial gap analysis, the extant literature on the implication of UGC in NPD process has predominantly focused on four main themes: (1) the impact of UGC on NPD and innovation process; (2) mining UGC to identify innovative product ideas; (3) deriving product features from UGC; (4) analyzing UGC to understand customer requirements (Nasrabadi et al., 2024). Despite this comprehensive exploration, significant research gaps remain, warranting further investigation. Specifically, two critical research gaps have been identified:

2. Current research insufficiently explores the application of UGC in identifying and assessing risk factors in the NPD process. Traditional risk management methods often neglect unstructured qualitative data, limiting their capacity to anticipate significant market shifts (Groth & Muntermann, 2011); recent studies, however, demonstrate that incorporating textual data analysis can substantially enhance these approaches (Groth & Muntermann, 2011; Hsu et al., 2022). Therefore, employing UGC in NPD risk management – with specific focus on consumer acceptance – offers a transformative perspective that significantly enriches existing methodologies with qualitative insights.

3. Similarly, there is a notable research gap in leveraging UGC for product obsolescence risk management, an area crucial for enabling sustainable product design and fostering responsible development practices (Rivera & Lallmahomed, 2016; Sierra-Fontalvo et al., 2024). While previous studies have depended on time-consuming and costly methods (Timoshenko & Hauser, 2018) such as consumer interviews (İmir, 2010a; Oraee et al., 2024), expert interviews (Muñoz et al., 2015), and surveys (Magnier & Mugge, 2022; Pardo-Vicente et al., 2022) to identify product obsolescence factors, and have constructed obsolescence index based on product performance data and expert assessments (Salas Cordero et al., 2022; Z. Zhao et al., 2021), this research aligns with Industry 4.0 (Naeem & Di Maria, 2020a) aims to identify obsolescence factors through UGC analysis and introduce time-series UGC-based obsolescence indexes. This enables product designers to identify critical factors by analyzing real-time consumer opinions, prioritize improvements, and adapt strategies proactively,

advantages that traditional methods lack due to their limited scope and temporal rigidity (Bryman, 2016; Couper, 2000).

Research Objective

The primary goal of this research is to examine the role of UGC in NPD process by integrating key themes, context, and methodologies used to evaluate its contribution, while delineating future research avenues to further clarify its role. Accordingly, the first objective of this study is to:

- Employing a systematic literature review (SLR) incorporating multifaceted analytical approaches to ensure a comprehensive examination of existing research.

The objective has successfully achieved and is documented in a peer-reviewed article published in Technological Forecasting and Social Change (Nasrabadi, Mohamadreza Azar, Yvan Beauregard, and Amir Ekhlassi. "The implication of user-generated content in new product development process: A systematic literature review and future research agenda." *Technological Forecasting and Social Change* 206 (2024): 123551). The study marks the first SLR specifically focused on the influence of UGC in NPD process. It provides a valuable scholarly contribution by identifying four major thematic areas within the literature and , beyond mapping the current state of research, proposes innovative directions for future studies. These insights not only highlight existing gaps but also offer a structured agenda to guide interdisciplinary research efforts in this evolving field.

The secondary goal is to employ UGC in NPD risk management – with a specific focus on consumer acceptance. Thus, the second objective is to:

- Developing a framework for assessing consumer acceptance through UGC analysis, incorporating analytical techniques such as topic modeling, sentiment analysis, and statistical method.

This objective has been realized through a study that has been submitted to Technovation for peer review. The research offers a significant contribution to the field by introducing a novel framework that utilizes UGC to evaluate consumer acceptance of a new product. It advances beyond traditional survey-based approaches, often criticized for being time-consuming, costly, and prone to bias, by employing sentiment analysis and topic model techniques in conjunction with PLS-SEM to capture real-time consumer perceptions. The framework is validated through an empirical case study on ChatGPT, demonstrating its applicability to fast-evolving technologies. It allows for identification and quantification of latent risk-related factors and provides a scalable, domain-transferable methodology for assessing public engagement. In doing so, the study reconceptualizes consumer acceptance in the AI era, offering both theoretical innovation and practical tools that support dynamic, data-driven risk management in NPD.

The third goal is to leverage UGC in product obsolescence, recognizing that evaluating product obsolescence enables product designers to create more sustainable products that foster responsible development practices. Consequently, the third objective is to:

- Developing a framework for identifying product obsolescence factors and measuring time-series obsolescence indexes through UGC analysis, incorporating large language models (LLMs), multicriteria decision-making method, and sentiment analysis.

This objective has been addressed in a study currently under review at IEEE Transactions on Engineering Management. This study contributes to the engineering management literature by addressing a critical gap in understanding product obsolescence in consumer IoT products. It introduces an innovative framework that integrates online consumer reviews, pre-trained LLMs, Freq-AHP, and RoBERTa to identify and quantify product obsolescence factors over time. By developing four time-series obsolescence indexes based on consumer opinions, the study enables longitudinal tracking of product decline. Unlike traditional methods rely one performance metrics or expert judgment, this approach offers real-time, consumer-centric insight into obsolescence trends, uncovering both established and previously unrecognized factors. Practically, it equips manufacturers and product designers with a dynamic tool to inform decisions around product updates, support, and sustainability. Ultimately, the framework promotes longer product lifespans, reduced resource use, and enhanced consumer trust in the digital age.

The three goals form a cohesive research stream centered on the role of UGC in NPD. The first goal, a SLR, identifies key research gaps, specifically the underexplored areas of consumer acceptance and product obsolescence in the context of UGC. These gaps are directly addressed in the second and third goals. Second goal develops a framework to assess consumer acceptance of new products using UGC, while third goal builds a UGC-based framework for tracking product obsolescence over time. The second and third goals are closely related, as understanding the factors that drive acceptance (goal 2nd) and those that lead to eventual obsolescence (goal 3rd) provides a comprehensive view of product lifecycle. Insights from both studies can guide the design of products that are both initially well-accepted and more sustainable in the long term.

Thesis Structure

The thesis is structured into six chapters. Chapter 1 outlines the research methodology employed throughout the thesis and chapter 2 provides a comprehensive review of the relevant literature. They set the theoretical foundation for the study and describes the overall research design. Chapter 3 is presented in the form of a journal paper. It investigates the implication of UGC in NPD process through a SLR and proposes a future research agenda. The objective is to synthesize key themes, contextual factors, and the methodologies from existing studies, while highlighting areas for further exploration. Chapter 4, also structured as a journal paper, proposes framework for assessing consumer acceptance of a new product using UGC analysis. This study aims to leverage UGC as a data source to identify influential factors on consumer acceptance and quantify their statistical relationships. Moreover, chapter 5 is the third journal paper included in this thesis. It introduces UGC-based product obsolescence indexes, with a specific focus on consumer IoT devices. The chapter develops a novel approach to assess how UGC reflects product obsolescence over time. Chapter 6 is entitled discussion, and covers, among others, the topics of validation, generalization, limitations, and future research.

CHAPTER 1

RESEARCH METHODOLOGY

This part outlines the research methodology adopted in this thesis, which is composed of three interrelated articles. Each article addresses a distinct but complementary problem in the application of UGC in NPD. To integrate and align the three studies into a coherent research stream, the design science research (DSR) methodology (Dresch et al., 2015) is employed as a meta-methodological framework. This approach ensures the systematic development and evaluation of artifacts to solve relevant problems while generating perspective knowledge. The DSR methodology comprises five core phases: (1) awareness of the problem, (2) suggestion, (3) development, (4) evaluation, (5) conclusion. Each of these phases is describe below and contextualized within the scope of the thesis. Figure 1.1 visually map the DSR process across this thesis.

1.1 Awareness of the problem

This phase involves identifying, understanding, and justifying the research problems that the thesis aims to solve. The awareness was initiated through a comprehensive SLR, which to the best our knowledge represents the first structured SLR specifically focused on the application of UGC in NPD (Nasrabadi et al., 2024). This review was based on the framework proposed by (Tranfield et al., 2003). The SLR process included:

- Formulating precise research questions to explore the role of UGC in NPD as follows:
    1) What are the key themes, context, and methodologies utilized in studying UGC's implications for NPD process?
    2) What is the potential gap in each theme?
    3) What future research directions could further elucidate UGC's role in NPD process?
- Selecting comprehensive databases such as Scopus, Web of Science, and Science Direct (Caputo & Kargina, 2022a; Liñán & Fayolle, 2015a; Mongeon & Paul-Hus, 2016a; Zupic & Čater, 2015a) to ensure coverage of multidisciplinary insights.

- The research strategy incorporates Boolean operators ("AND" / "OR") to retrieve articles published between January 2012 and January 2023, using predefined keywords such as "user-generated content," "customer review," "consumer review," "user review," "product development," "new product development," and "product innovation."
- Applying inclusion/exclusion criteria: the selection criteria also include peer-reviewed journal articles written in English, while conference papers, book chapters, and articles outside the scope of UGC in NPD are excluded (Kushwaha et al., 2019; Schneider & Spieth, 2013; Shree et al., 2021). The dataset was further refined to focus on studies within Business, Management, Economics, and Engineering domains.
- Using Rayan QCRI software to manage screening and improve inter-rater reliability during abstract and title selection.
- Conducting full-text analysis of selected articles.

After conducting a full-text review of the articles to enable an in-depth analysis, a descriptive analysis is conducted to map the existing literature, including publications by year, country, research field, journal outlets (Tranfield et al., 2003), and citation analysis using Scopus (Del Vecchio et al., 2022; Kiduk & Meho, 2006; D. Zhao & Strotmann, 2007). Keyword co-occurrence analysis is also performed to visualize thematic relationships, employing network mapping techniques to identify research clusters and conceptual similarities among articles (Radhakrishnan et al., 2017; H. N. Su & Lee, 2010). Moreover, the bibliographic coupling approach, implemented through VOSviewer, enabled the identification of major research clusters by linking studies that share common references, thus providing insights into emerging scholarly debates and interdisciplinary collaborations (Kessler, 1963; Perianes-Rodriguez, Waltman, & Van Eck, 2016). To systematically categorize research themes, contexts, and methodologies, we employed T-theme, C-context, and M-methodology (TCM) framework, following prior studies (Mishra et al., 2021; Paul et al., 2017; Paul & Rosado-Serrano, 2019). Additionally, thematic clustering is conducted through content analysis using Atlas.ti, allowing for an in-depth examination of study objectives, research questions, methodologies, and theoretical perspectives. Articles are iteratively sorted into distinct thematic categories, forming a hierarchical taxonomy of research directions in UGC-driven NPD (Clark et al., 2019; M. V. Jones et al., 2011; Liñán & Fayolle, 2015b).

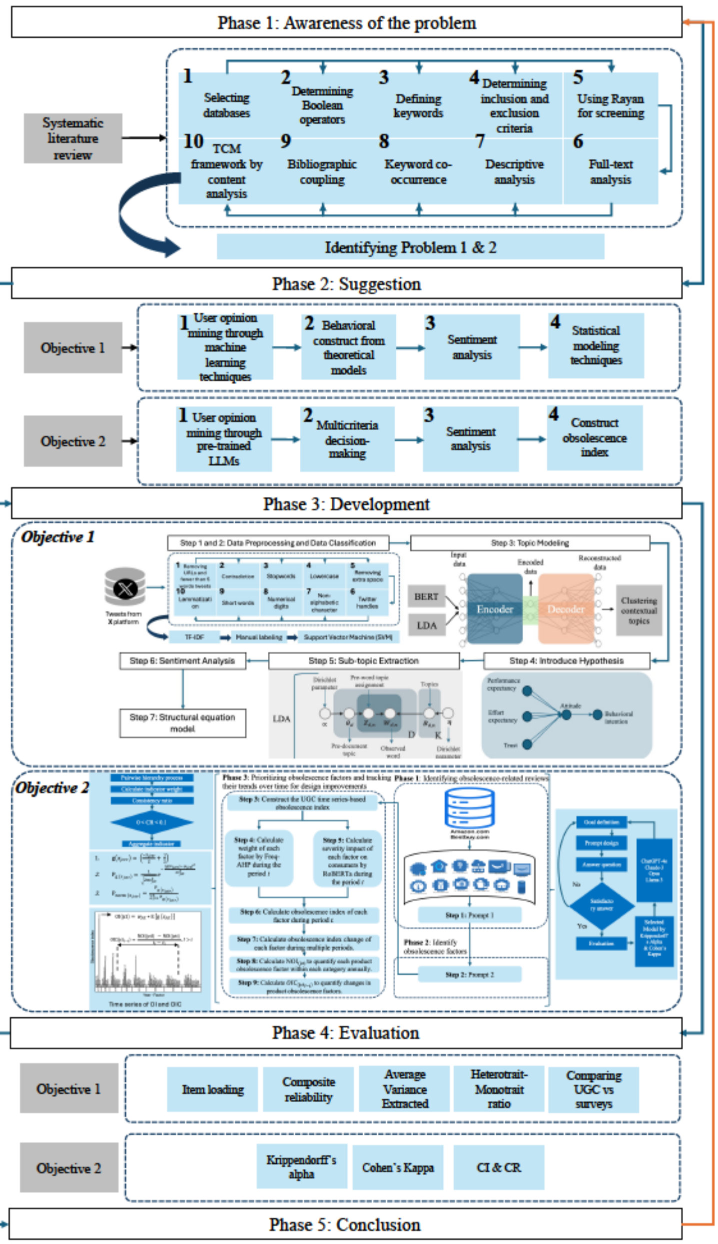

Figure 1.1 Design science research methodology of the thesis

This structured methodology ensures a comprehensive synthesis of existing literature, providing a robust foundation for identifying research gaps and shaping future investigations into the role of UGC in NPD (Ryan & Bernard, 2003; Thorpe et al., 2005).

The output of this phase, documented in chapter 3, identified two critical and underexplored areas:

1) The lack of framework that utilize UGC to assess consumer acceptance of new technologies or products in a scalable, real-world context.
2) The absence of analytical methods to assess product obsolescence over time based on online consumer-generated textual feedback.

These gaps directly motivated the formulation of objective 2 and 3 of the thesis.

1.2 Suggestion

In this phase, based on the problem awareness and existing knowledge, initial solutions or artifact designs were conceptualized. This required abductive reasoning to bridge the theoretical insights from the literature with practical frameworks that could be implemented using real-world data.

For objective 2, the suggested artifact was a multi-dimensional framework combining user opinion mining techniques, behavioral constructs from theoretical models, and statistical modeling technique. This artifact aimed to replace traditional survey-based methods with scalable analysis using UGC.

For objective 3, a novel hybrid framework was proposed to identify and quantify drivers of product obsolescence. The conceptual model integrated online consumer reviews, LLMs, Multicriteria decision-making (MCDM), and sentiment analysis.

1.3 Development

The third step of the method involves developing one of the artifacts proposed by the researcher in the previous step to address the problem. Once developed, these artifacts, if found suitable for solving the problem, are then evaluated in the fourth step.

1.3.1 Second objective: developing a framework for assessing consumer acceptance through UGC analysis

This study analyzes UGC on ChatGPT by collecting tweets form platform X (formerly Twitter) via Kaggle. The dataset was filtered to retain only English tweets, removing those with fewer than five words or containing URLs (Murshed et al., 2021a; Yoon-Eui Nahm, 2013). A manually labeled dataset of 10,000 tweets was used to train a support vector machine (SVM) classifier (Chiarello et al., 2020a; Lughbi et al., 2024), relevant tweets. To improve data quality, text preprocessing is performed, including noise reduction, contraction expansion, stopword removal, and lemmatization. Noise reduction involved removing special characters, excessive spaces, numerical digits, and Twitter handles to eliminate irrelevant content (Sarica & Luo, 2021; Srivastava et al., 2021). Contractions are expanded using a predefined dictionary to improve text uniformity (Jacquemin, 2001). Stopwords are removed using augmented natural language toolkit (NLTK) stopword list, and lemmatization converted words into their base forms to enhance consistency (Saranya & Usha, 2023; Srivastava et al., 2021). The dataset is then split into training, validation, and testing subsets, and Term Frequency-Inverse Document Frequency (TF-IDF) was applied for keyword extraction (Barkha, 2018; Gozuacik et al., 2021).

After preprocessing dataset, for topic modeling, LDA-BERT is chosen. After extracting main topics, to further refine topics, LDA was applied to identify sub-topics, measuring coherence scores (K) to structure and categorize them. After determining meaningful sub-topics, sentiment analysis is conducted on the most significant keywords per sub-topics using robustly optimized bidirectional encoder representations from transformers approach (RoBERTa) technique (Y. Liu, Ott, et al., 2019a). Then, to examine relationships among latent variables, partial least squares structural equation modeling (PLS-SEM) is chosen (Law & Fong, 2020; Ramli et al., 2019; Yong Ming et al., 2023a).

1.3.2 Third objective: developing a framework for identifying obsolescence factors and constructing time-series obsolescence indexes through UGC analysis

This study analyzes UGC on obsolescence of consumer IoT devices that are collected from Amazon.com and BestBuy.com. This study uses pre-trained LLMs instead of traditional text mining techniques. To do so, three LLMs – ChatGPT-4o, Llama 3, and Claude-3 Opus – are chosen to evaluate for their effectiveness in extracting obsolescence factors in consumer IoT devices. ChatGPT-4o is chosen for its adaptability and fine-tuning capabilities (X. Liu et al., 2023), while Llama 3 (Lu et al., 2024; Meta, 2024) and Claude-3 Opus (Anthropic, 2024) are included for comparison, with a temperature setting of 0.2 to ensure focused and deterministic outputs (Törnberg, 2023).

To ensure accurate identification of obsolescence factors, prompts were designed to guide the LLMs in classifying and analyzing consumer reviews. The first prompt filters relevant reviews by determining their connection to obsolescence, ensuring that only meaningful reviews are analyzed. Reviews are selected based on two criteria: (1) The review must explicitly indicate that the product has been removed from use by the consumer or disposed of; (2) The review should convey a definitive intention of discontinuing use or replacing the product with an alternative. These criteria ensure the study focuses on reviews that provide explicit reasons for obsolescence. The second prompt directs the model to extract obsolescence factors from the relevant reviews, providing insights into why products are considered obsolete based on consumer feedback. This process follows the GPEI framework (Velásquez-Henao et al., 2023), which involves defining a goal, designing the prompt, evaluating responses, and iterating to refine effectiveness.

After extracting obsolescence factors, the obsolescence index (OI) is introduced as a quantitative measure to assess the impact of these factors across different product categories. The $OI_{(jct)}$ function enables time-dependent monitoring of obsolescence trends by integrating two key components: (1) frequency-analytic hierarchy process (Freq-AHP), which assigns weights to obsolescence factors based on their frequency within each category over time, ensuring a data-driven and objective prioritization (Liang et al., 2021), and (2) sentiment intensity analysis using RoBERTa, which quantifies consumer dissatisfaction to account for the emotional impact of obsolescence issue. Since dissatisfaction can drive obsolescence even when a product remains functional (Hou et al., 2020; van den Berge et al., 2021), this approach ensures a comprehensive evaluation. To refine OI measurement, a probability distribution to weight sentiment intensity proportionally is incorporated, preventing anomalies from skewing results. Additionally, the aggregated obsolescence index ($AOI_{(ct)}$) is introduced to track overall obsolescence trends within a product category over time, normalizing variations in review volume to ensure consistency in longitudinal analysis. Finally, obsolescence index change ($OIC_{(\mathrm{jct}_{I-i})}$) measures how obsolescence factors evolve within each category, highlighting shifts in their influence over time. By incorporating these metrics, the study provides a structured and dynamic framework to identify, quantify, and track obsolescence factors, offering actionable insights for improving product longevity.

1.4 Evaluation

This phase assessed the effectiveness and quality of each developed artifact using rigorous empirical methods. For objective 2, to evaluate the proposed model, the PLS-SEM approach was employed using SmartPLS 4 (Version 4.1.0.1). The assessment involved both the measurement and structural models. To determine the statistical significance of path coefficients, a nonparametric bootstrapping procedure with 5000 resamples was applied, as recommended in the PLS-SEM literature. The measurement model was assessed through multiple reliability and validity indicators. Indicator reliability was evaluated by examining item loadings, with a minimum threshold of 0.708 considered acceptable. Internal consistency reliability was measured using Composite Reliability (CR), with values of 0.700 or higher indicating adequate consistency. Convergent validity was assessed using the Average Variance Extracted (AVE), which should meet or exceed the 0.500 threshold to confirm that a construct explains at least half of the variance of its indicators. Discriminant validity was examined through the Heterotrait-Monotrait ratio (HTMT), with values below 0.900 indicating that the constructs are sufficiently distinct from one another. These evaluation criteria collectively ensure that the model demonstrates sound psychometric properties and provides a reliable basis for hypothesis testing. In addition, to demonstrate the validity of our findings, we reference prior studies that used survey-based methods and reported results similar to those obtained in this study using UGC data. This alignment suggests that UGC can serve as reliable proxies for measuring consumer acceptance, consistent with traditional survey approaches.

For objective 3, to ensure the reliability of pre-trained LLM-generated outputs, this study applied a rigorous validation process involving human-coded data. Agreement metrics such as Krippendorff's alpha and Cohen's Kappa showed strong alignment between the model and human-coded results, indicating that the model reliably identifies obsolescence-related reviews in a manner consistent with expert judgment. Additionally, the Freq-AHP method was used to assign weights to the extracted obsolescence factors, with consistency indicators ($CI = 0$, $CR < 0.1$) confirming the reliability and internal consistency of the weighting process.

1.5 Conclusion

In the conclusion phase of the DSR methodology, the results of the study are critically evaluated to determine the effectiveness of the developed artifact. If the findings reveal that the initial understanding of the problem was incomplete or insufficient, the artifact may not fully address the intended issue. In such cases, the design cycle can be reinitiated, contributing to the refinement of theoretical understanding and guiding future iterations for more effective problem-solving (Dresch et al., 2015).

CHAPTER 2

LITERATURE REVIEW

2.1 Customer participation (CP) in new product development (NPD)

NPD has long been recognized as a pivotal driver of innovation and competitive advantage because it enables firms to strategically respond to evolving market demands (Berry et al., 2006; Dahan & Hauser, 2002; Griffin & Hauser, 1993; Mu et al., 2017). Traditionally, companies have been exclusively responsible for generating and selecting product concepts, adhering to a zero-empowerment strategy that places control firmly in the hands of the firm (Pitt et al., 2006). Although listening to the voice of the customer has been widely acknowledged as essential for successful NPD (Dahan & Hauser, 2002; Griffin & Hauser, 1993), power nonetheless remained centralized (Von Hippel, 1978). Over time, open-source software success stories (Von Hippel & Katz, 2002) have encouraged firms to empower customers, who were once passive but now actively engage in product development and often reward companies with increased loyalty (Sawhney et al., 2005; Sheth et al., 2000).

In tandem with these shifts, the literature on CP has introduced terms such as co-production, co-creation, and user innovation, all pointing to various ways customers can be involved in designing and producing products (H. W. Chesbrough, 2003; B. Dong & Sivakumar, 2017; Prahalad & Ramaswamy, 2004). By embracing open innovation, companies view customers as active collaborators whose insights enhance competitiveness (Foss et al., 2011), thus underscoring a paradigm in which customers play a central role in shaping firms' product offerings (Carbonell et al., 2009). CP is often defined as "the act of engaging customers in the design and production of products" (B. Dong, 2015) and is closely tied to both incremental and radical innovation (Berry et al., 2006; B. Dong & Sivakumar, 2017).

Companies often use customer inputs gathered via interviews and surveys for internal R&D (Cui & Wu, 2017), viewing this information to reduce uncertainty and improve product market-fit (Poetz & Schreier, 2012; Sawhney et al., 2005). Concurrently, the proliferation of digital technologies has transformed the way customers and firms interact, enabling new channels for collaboration (Bacile et al., 2014; Rossmann et al., 2016). Web 2.0 and industry 4.0 technologies have broadened opportunities for co-creation and customer-driven innovation (Cui & Wu, 2017; Vargo & Lusch, 2017). Customers can supply both needs-related knowledge about "what the problem is" and solution-related knowledge regarding "how to solve it" (Poetz & Schreier, 2012), while firms that integrate this input across multiple NPD stages – from ideation through launch – often observe improved innovation and profitability (Chang & Taylor, 2016; Fang, 2008; Gruner & Homburg, 2000). Considering these developments, multiple techniques have emerged to secure more direct customer involvement in NPD. One such method is the lead user approach, which focuses on individuals who face needs ahead of the general market, allowing companies to tap into future demand before it becomes mainstream (Lilien et al., 2002; Von Hippel, 1978). Another technique is crowdsourcing, whereby a firm solicits ideas from a large, diverse group of participants (Poetz & Schreier, 2012). Although the lead user method can yield highly novel insights, it requires identifying and engaging specialized users who possess advanced knowledge or experience. In contrast, crowdsourcing offers abundant input but demands careful management of idea quality, intellectual property, and participant motivation (Nambisan, 2002). More recently, UGC has gained prominence as a hybrid solution in which firms capture discussions and ideas from online communities such as social media without direct solicitation (Haavisto, 2014). Since UGC leverages naturally occurring conversations, it efficiently captures both needs- and solution-related insights from diverse contributors in a timely manner and at a relatively low cost (Timoshenko & Hauser, 2018), thereby helping firms address some of the challenges posed by traditional methods. However, while existing literature has thoroughly examined UGC through systematic reviews that explore its definitions and various forums (Naab & Sehl, 2017; Santos, 2022a), analytical methodologies for UGC analysis (J. Lin et al., 2022; Manchanda, 2019), and its application across various research fields (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi & Karjaluoto, 2018), the systematic examination of how UGC might specifically shape and benefit NPD process remains underexplored. Addressing this gap with a comprehensive SLR could clarify UGC's implications for NPD and offer insights that advance both theory and practice.

2.2 The role of user-generated content (UGC) in new product development (NPD)

UGC is information created by everyday individuals rather than paid professionals, typically shared on online platforms where ordinary users voluntarily contribute data (Daugherty et al., 2008; Krumm et al., 2008). It thrives on digital spaces such as social media, review websites, and online forums (Kietzmann et al., 2011; Santos, 2022a), reflecting a broader shift from traditional one-way information distribution to participatory social media systems in which individuals freely share their opinions and experiences (Bartl et al., 2010; Kietzmann et al., 2011). As a result, UGC differs considerably from conventional methods since it involves continuous and unsolicited data streams on a wide range of topics relevant to NPD (Ho-Dac, 2020; Nambisan, 2002).

UGC improves product design efficiency, underscoring its pivotal role in improving new product performance (Jiao et al., 2022). It deepens the understanding of customer dynamics, ensures cost efficiency, and accelerates time-to-market by validating product quality (Rathore et al., 2016; Vikram & Kumar, 2018). Moreover, leveraging UGC not only reduces market rejection rates and serves as a continuous asset for NPD by offering unsolicited customer insights while overcoming the limitations of lead user, crowdsourcing, VCCs, and user toolkits approaches with a steady flow of high-quality suggestions (Ho-Dac, 2020; Nambisan, 2002). Additionally, both positive and negative UGC drive innovation investment and significantly enhance performance, offering a nuanced view of UGC as a catalyst for shaping development strategies (W. Zhang et al., 2018).

Recent studies indicate that UGC is instrumental in NPD by serving three main functions: deriving product features, generating innovative ideas, and uncovering customer requirements (Nasrabadi et al., 2024). In terms of feature extraction, researchers have shown that UGC from online reviews and social media can be mined to reveal key product attributes (Tuarob & Tucker, 2015). In parallel, the concept of idea mining has emerged as a pivotal method for extracting innovative product ideas from UGC (Mostafa A. Alksher et al., 2016). In addition, to understand customer requirements, UGC has been incorporated into various analytical framework that offer a dynamic alternative to conventional, costly methods (Timoshenko & Hauser, 2018). Although UGC has been extensively used to extract product features, generate innovative ideas, and understand customer needs, its application for managing NPD risk and product obsolescence remains underexplored.

2.3 Potential application of user generated content (UGC) in underexplored areas

2.3.1 Consumer acceptance: theoretical foundations and potential role of user generated content (UGC)

An efficient NPD process is critical for business success in competitive market (R. G. Cooper, 1993; Ulrich & Eppinger, 2016). However, risks inherent to NPD arise from intense competition and rapid traditional advancements, affecting various stages of product development (Chin et al., 2009; Kayis et al., 2006). NPD risk includes technical, organizational, market, and financial uncertainties, potentially leading to product failure or underperformance (Keizer et al., 2003; Mu et al., 2009). Given the inherent characteristics of UGC, particularly its immediacy, real-time feedback, and direct consumer insights (Timoshenko & Hauser, 2018), this study specifically emphasizes market risk. Market risk encompasses uncertainties related to consumer acceptance, pricing dynamics, competitive pressures, and overall market conditions (Keizer et al., 2003; Mascitelli, 2007). Within market risk, consumer acceptance emerges as a pivotal dimension due to its direct impact on the adoption, diffusion, and eventual success of failure of new products (Barrios & Kenntoft, 2008; Griffin & Page, 1996; March-Chordà et al., 2002).

Researchers have predominantly employed structured, quantitative methodologies, frequently grounded in theoretical models like the technology acceptance model (TAM) (Davis, 1985), unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and their extensions (Talukder et al., 2020; Türker et al., 2022). Such studies typically utilize structured surveys analyzed through quantitative statistical methods, including structural equation model (SEM), factor analysis (FA), and partial least squares (PLS) (Liébana-Cabanillas et al., 2018a; Mehra et al., 2022; Talukder et al., 2020; Türker et al., 2022).

Although these methods provide statistically validated insights, they inherently depend on structured, predetermined questionnaire, which limit the exploration of nuanced, spontaneously expressed consumer opinions (Jing et al., 2023). In contrast, UGC offers real-time and naturally occurring feedback that reflects consumers' genuine experiences and perceptions regarding new products (Ding et al., 2021; Jefferson & McDonald, 2019; Jing et al., 2023).

In comparison to existing literature, which primarily measures statistical relationships among consumer acceptance factors through traditional survey-based methods, this study aims to adopt an innovative approach by integrating sentiment analysis of UGC with statistical methodologies. Sentiment analysis provides an understanding of emotional responses conceptualized as perceptual outcomes derived from product consumption experiences (Saha & Zhao, 2011). This method overcomes several limitations associated with conventional survey methods, such as time and cost inefficiencies, potential biases, and varying response rates (Bethlehem, 2010; Rice et al., 2017). Additionally, traditional survey instruments employing Likert scales generate ordinal data, constraining precise interpretation and limiting analytical rigor (Norman, 2010; Phillip A Bishop & Herron, 2015; Sullivan & Artino, 2013). So, by leveraging open-ended textual feedback, sentiment analysis offers deeper and richer insights than structured questionnaire, significantly expanding the scope and depth of consumer acceptance analysis (Rajput et al., 2016).

2.3.2 Product obsolescence: theoretical foundation and potential role of user-generated content (UGC)

IEC 62402:2019 defines obsolescence as the transition of a product from being available to unavailable by the original equipment manufacturer (OEM) according to its original specification. A product is considered obsolete when it is no longer produced with the components specified in its original design (Vasilev, 2024). In contrast, the AFNOR NF X60-012: 2006 standard defines "obsolete" as a product that is no longer used or outdated, without implying it is necessarily unavailable (Mellal, 2020). Obsolescence encompasses multiple dimensions, including technological, economic, functional, and aesthetic (Bilici & Özdemir, 2024; Hennies & Stamminger, 2016a; Tim Cooper, 2004). Recognizing these forms is vital for product design, as it encourages the development of durable, modular, and sustainable products, ultimately reducing environmental impacts and supporting sustainable consumption (Alzaydi, 2024; T. Cooper, 2010; Guillard et al., 2023; Proske & Jaeger-Erben, 2019a).

Existing research on obsolescence has explored diverse product contexts, such as non-smart residential electronics (Hennies & Stamminger, 2016a; Karagiannopoulos et al., 2024a; Tim Cooper, 2004), smartphones (Makov & Fitzpatrick, 2021; Proske & Jaeger-Erben, 2019a; Wieser & Tröger, 2018), and specialized sectors like aviation, aerospace, and military systems (Bowlds et al., 2018; Giovannoni & Boyles, 2016; Rajagopal et al., 2015; Rojo et al., 2009). In addition, different studies have proposed obsolescence index to measure and monitor product obsolescence; for example, Z. Zhao et al., (2021) developed an obsolescence index based on product performance metrics, while Salas Cordero et al. (2020) introduced an obsolescence critically index derived from expert assessments and system architecture models. However, these studies primarily employed traditional data collection methods, including consumer interviews (İmir, 2010; Oraee et al., 2024), expert interviews (Muñoz et al., 2015), and surveys (Magnier & Mugge, 2022; Pardo-Vicente et al., 2022). These traditional approaches are often time-consuming and costly (Timoshenko & Hauser, 2018) and suffer from limited scope and temporal rigidity, restricting their effectiveness in dynamically capturing evolving consumer perceptions and experiences (Bryman, 2016; Couper, 2000; Y. Zhang & Wildemuth, 2009). This study aims to bridge these research gaps by analyzing online consumer reviews to identify critical factors influencing obsolescence. Additionally, the study introduces an online consumer opinion-based, time-series obsolescence index (OI) and obsolescence index change (OIC). This framework enables dynamic tracking and real-time monitoring of obsolescence factors, empowering product designers to proactively identify critical issues, prioritize improvements, and effectively adapt their product strategies over time. Moreover, the literature on electrical and electronic equipment (EEE) product obsolescence has extensively explored various product categories. However, research into the obsolescence of consumer IoT devices remains underexplored, despite their increasing integration into everyday life (Poppe et al., 2021). Accordingly, this study seeks to implement the proposed framework in the context of consumer IoT devices.

CHAPTER 3

THE IMPLICATION OF USER-GENERATED CONTENT IN NEW PRODUCT DEVELOPMENT: 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. 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

Keywords: User-generated content, New product development, Product design, Product innovation, Systematic literature review, Social media

3.1 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 & Ramaswamy, 2004; Vargo & Lusch, 2014b). To foster innovation and enhance the diversity of products, some studies suggest that businesses should rely more on customer reviews (Al-Zu'Bi & 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 & 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 (F. T. Piller, 2012; Prahalad & 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 & 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, 2022b; Timoshenko & 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 request 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 review, focusing on its definitions, and various forms (Naab & Sehl, 2017; Santos, 2022a), techniques for its analysis (S. Li et al., 2022; Manchanda, 2019), and its utilization in other context of research (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi & 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 tole 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 words by: (1) Being the first systematic literature review study to explore the influence of UGC on NPD process. (2) Providing four major themes extracted form 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. Sections 2 describes the methodology and research design. Section 3 presents our findings using 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.

3.2 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 (Figure 3.1). 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 & Criado, 2020; Tranfield et al., 2003).

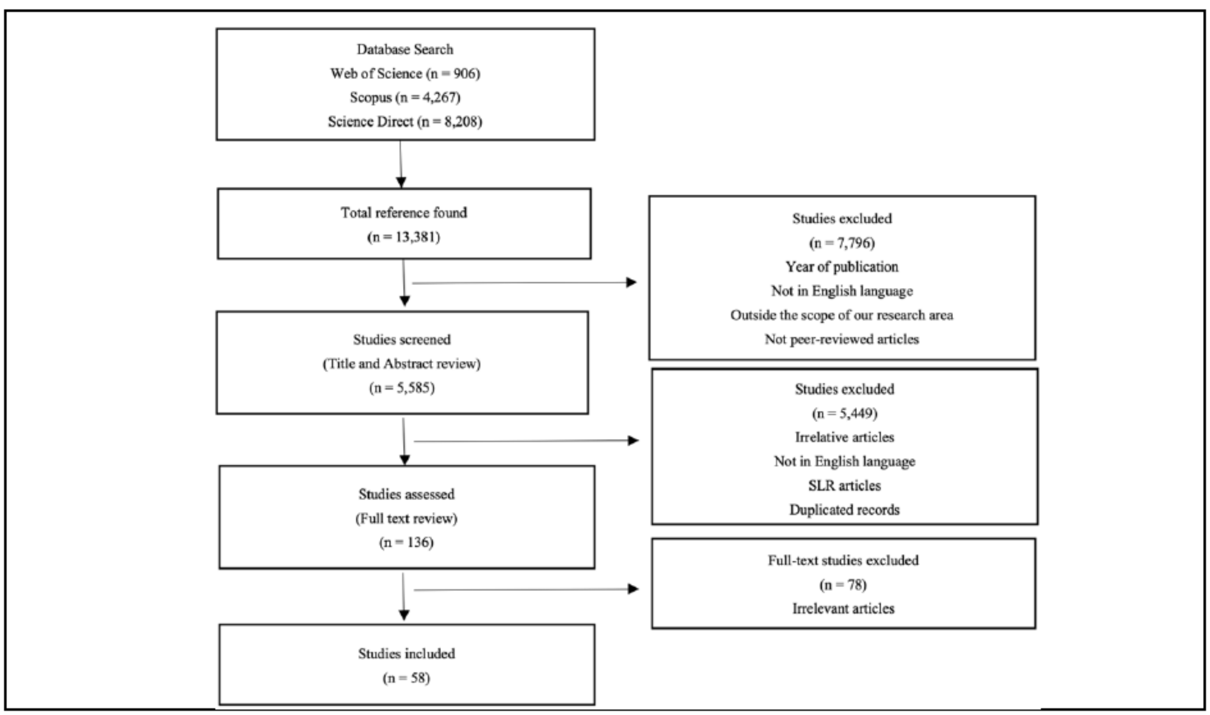

Figure 3.1 Search strategy

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 & Kargina, 2022b; Liñán & Fayolle, 2015b; Mongeon & Paul-Hus, 2016b; Zupic & Čater, 2015b).

3.2.1 Data extraction

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

3.2.2 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 search publications in English and excluding conference papers and proceedings, and book chapters (Kushwah et al., 2019; Schneider & Spieth, 2013a; 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 of scope of our research, were excluded. All excluded SLR or review articles focused on UGC's definitions and its various forms (Naab & Sehl, 2017; Santos, 2022a), techniques for its analysis (S. Li et al., 2022; Manchanda, 2019), and its utilization in other research contexts (Afrić Rakitovac et al., 2019; Gamble et al., 2016; Ukpabi & 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).

3.2.3 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 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 & Čater, 2015b). 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 detained consideration.

3.3 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.

3.3.1 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. Figure 3.2 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.

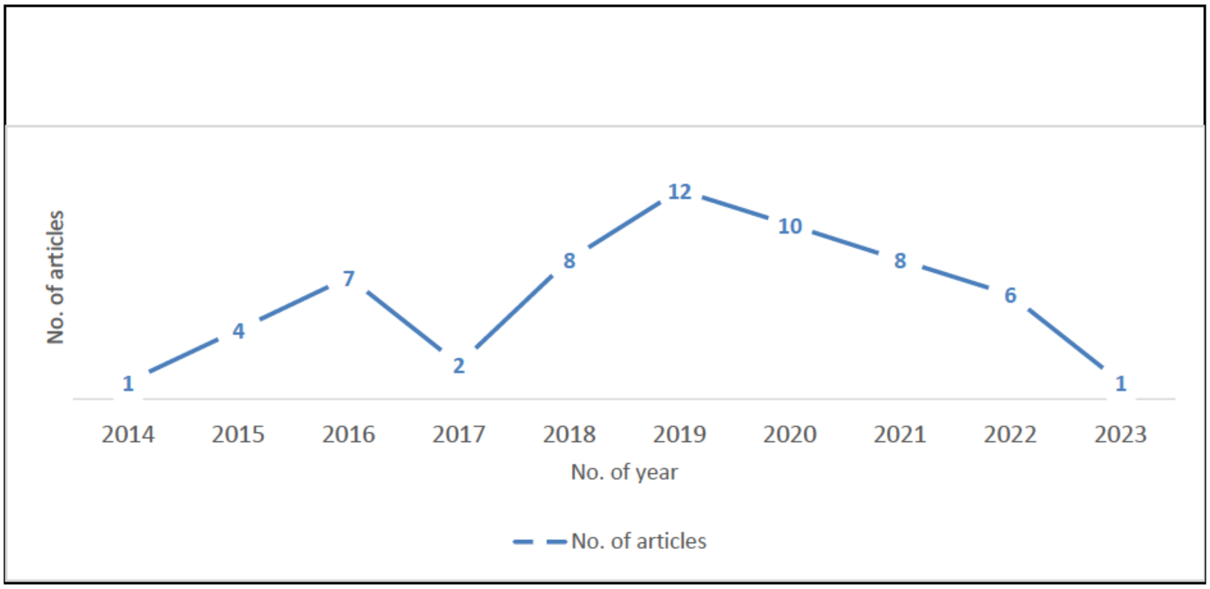

Figure 3.2 Number of articles per year

3.3.2 Publications by country

According to the number of papers and citations gathered from Scopus, Table 3.1 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.

Table 3.1 Countries by number of documents

Country	Documents	% Documents	Citation	% Citation
China	31	33.6 %	1599	37.8 %

Country	Documents	% Documents	Citation	% Citation
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 %
Netherland	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 %

3.3.3 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 profile 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 3.2.

Table 3.2 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

Research field	Journal	No. of articles
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

3.3.4 Citation analysis

Scopus was used to compile article citation data to evaluate the impact of previously published work (Del Vecchio et al., 2022; Kiduk & Meho, 2006; D. Zhao & Strotmann, 2007). In Table 3.3, 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 form 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.

Table 3.3 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

Authors	Title of article	Citation count	Journal
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 analysis of online product reviews	66	CIRP Journal of Manufacturing Science and Technology
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

3.4 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 display and comprehension of the keywords architecture of a specific scientific topic (H. N. Su & 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 (H. N. Su & Lee, 2010). The frequency of certain keywords in 58 different articles is shown in Figure 3.3. Authors, editors, and publishers use keywords to report on the most relevant themes discussed in the articles. A minimum of 5 keywords occurrences is shown in Table 3.4.

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; H. N. Su & 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 (Karl T. Ulrich, 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 result 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.

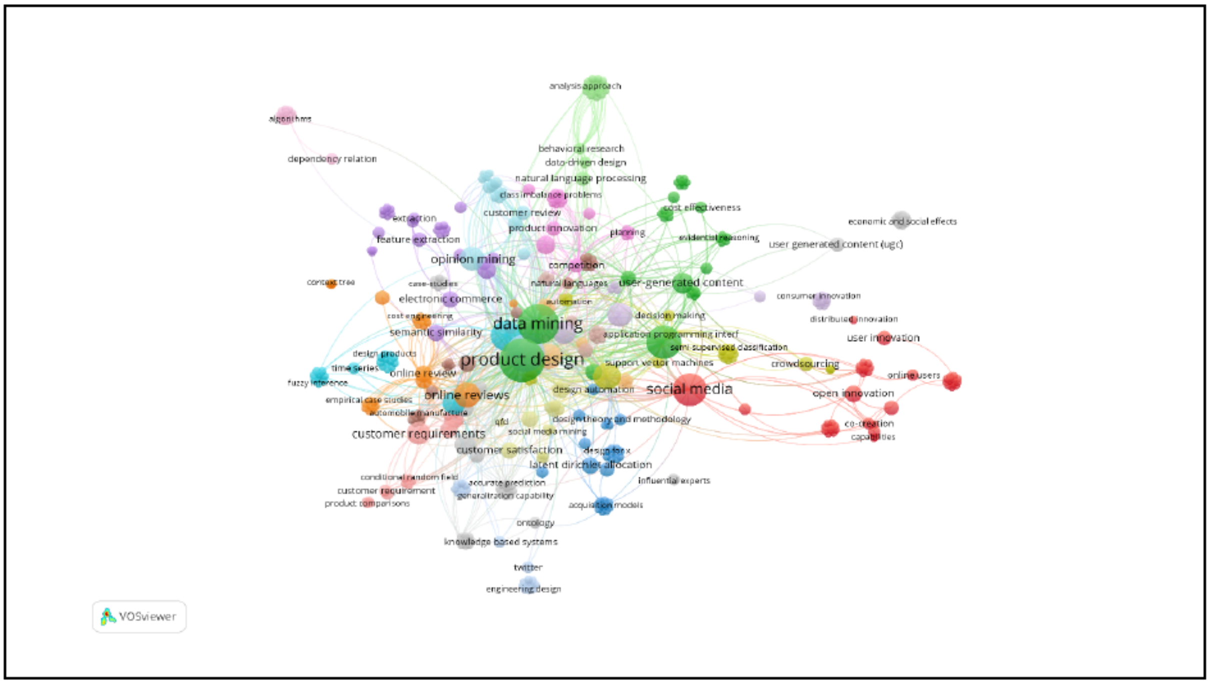

Figure 3.3 Keyword co-occurrence networks of user-generated content in new product development

Table 3.4 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

keyword	No. of occurrences
Deep learning	5
Product improvement	5

3.5 Bibliographic coupling

Articles citing the same references are linked because the sources they reference help clarify the issue (Kessler, 1963; Perianes-Rodriguez, Waltman, & van Eck, 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 & 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 I, Figure 3.4). The VOSviewer software, developed by van Eck and Waltman (2010), is used to build bibliometric maps, and has been frequently used in the literature (F. A. F. Ferreira, 2018; J. J. M. Ferreira et al., 2016; Merigó et al., 2015). VOSviewer software is preferable to multidimensional scaling for the construction of bibliometric maps (van Eck & Waltman, 2010; Van Eck & Waltman, 2014).

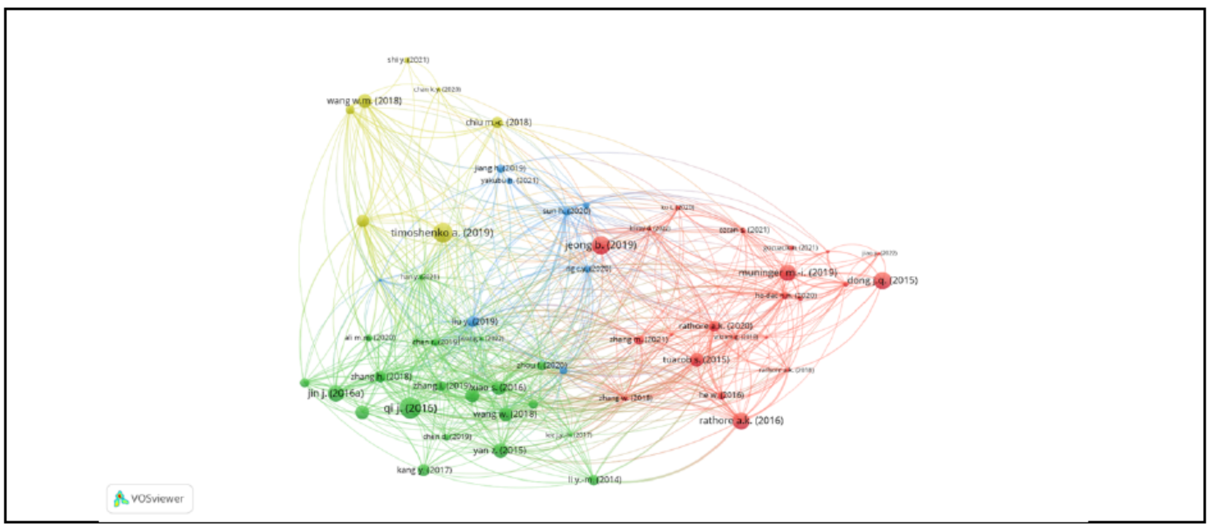

Figure 3.4 Clusters combining topic-based with intersecting literature

3.6 Key findings: themes, contexts, and methodology 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 & 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 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 filed (Billore & Anisimova, 2021; Paul et al., 2021). The findings of this study have been organized into specific sub-sections based on this framework.

3.6.1 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 each article were generated (Clark et al., 2019; M. V. Jones et al., 2011; Liñán & Fayolle, 2015b).

Next, the articles were compared to one another and sorted iteratively to categorize them into their similarities to create significant study themes, ultimately resulting in the formation of a taxonomic hierarchy (Clark et al., 2019; M. V. Jones et al., 2011; Liñán & Fayolle, 2015b). 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 & 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 four research themes were uncovered as a result of this process.

3.6.1.1 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, Rathore 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 and Kumar (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 enables by UGC, which enriches the discourse on its role in product innovation. In a more comprehensive analysis, Dong & 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, W. 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.

3.6.1.2 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 (Mostafa A. 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, M. Zhang et al. (2021) introduced a deep learning approach to precisely identify innovative ideas at the sentence level in online produce 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 this end, 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 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.

3.6.1.3 Deriving product features from UGC

Desing researchers suggest utilizing web blogs and review sites to mine produce 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 & 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, Y. M. 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 & Tucker, 2015) used sentiment analysis and 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, H. 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 adjective, 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 level. In a novel approach, W. 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 word, 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 feature attribute significance, Yakubu & 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 such as iPad, 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.

3.6.1.4 Analyzing UGC to understand customer requirements

Understanding customer needs is crucial for product development (Kano, 1984; Mikulić & Prebežac, 2011). Traditionally, this understanding has been gained through conventional methods such as interview, focus group, and survey 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 preference and the marginal effect-based kano model to categorize customer requirements. In a more comprehensive way than the preceding analyses, 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 strengths, weaknesses, opportunities, and threats (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 (2021) introduced a domain-agnostic method using bidirectional encoder representations from transformers (BERT), new convolutional net and named entity recognition (NER) to mine e-commerce reviews to identify customer 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 precious 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, Zhou et al. (2020) used LDA to identify needs and applied valence-aware dictionary for sentiment reasoning (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 extract 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, Choi et al. (2020) integrated sentiment analysis with aging theory-based algorithm 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 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 form UGC 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 customers 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 needs by 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), W. Wang et al. (2018) 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.

3.6.2 Context

3.6.2.1 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. Figure 3.5 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 & 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., ikram & Kumar, 2018; Dong & Wu 2015; Ozcan et al., 2021; Wang et al., 2018). 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 et al., 2020). Three studies related to health products like personal care products (e.g., Timoshenko et al., 2019; 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., 2019). 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., 2019). 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., 2018; Lin et al., 2022).

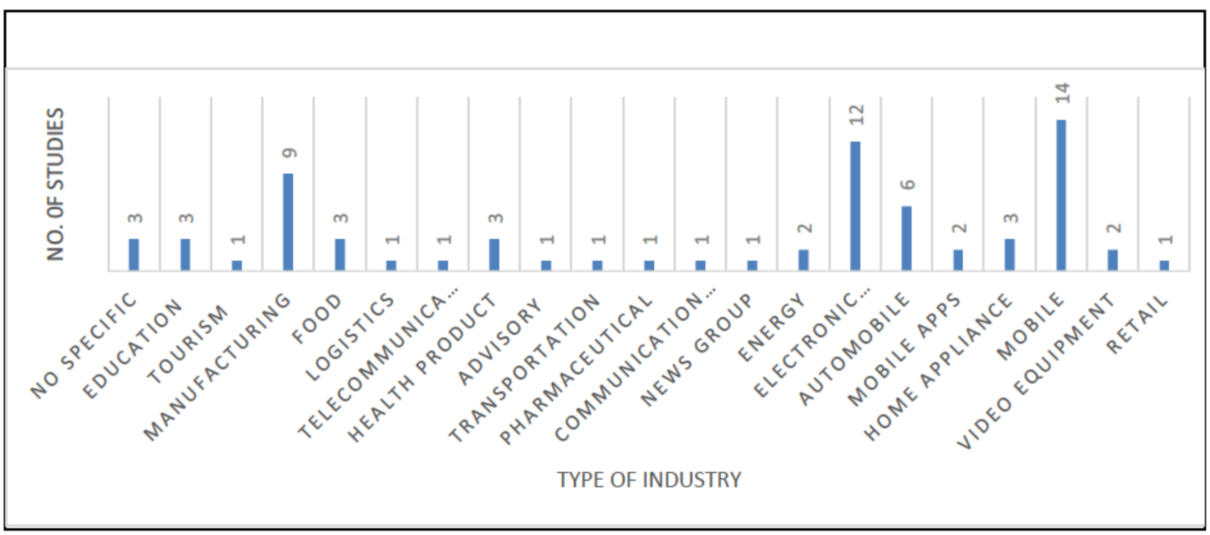

Figure 3.5 Number of studies across different industries

3.6.2.2 Online platforms

The studies employed a variety of online platforms to gather the necessary information for their research. Figure 3.6 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.

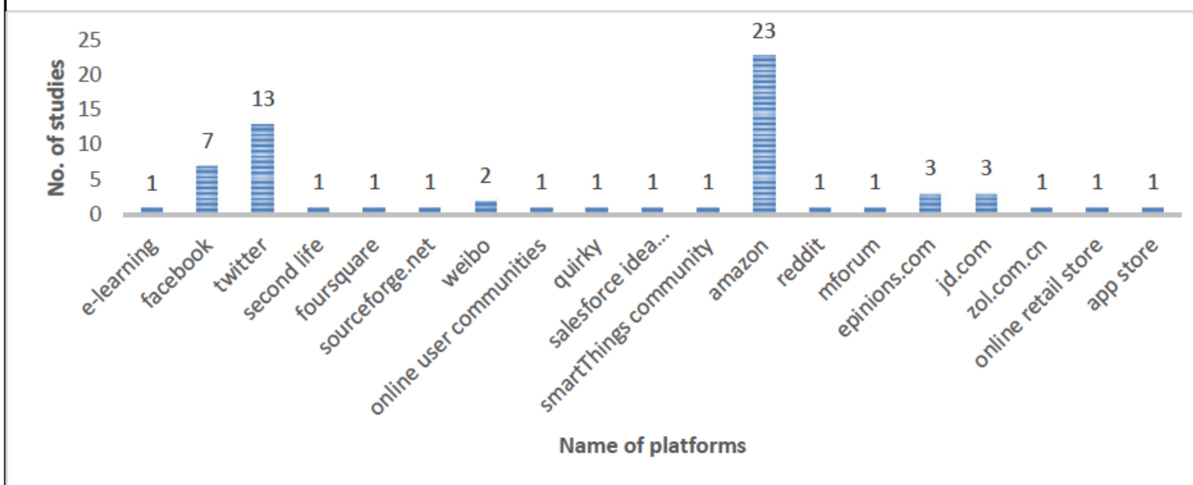

Figure 3.6 Number of platforms across different studies

3.6.3 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 3.5. for a more extensive exploration of these methodologies, including valuable insights into the specific approaches employed, readers are encouraged to refer to Appendix II. This appendix offers a comprehensive breakdown of the various methodologies utilized by researchers, alongside key findings each study.

Table 3.5. 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

3.7 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 & 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.

3.7.1 Exploring the potential biases of using UGC in new product development

Studies conducted by Cui & Wu (2017); Naeem & Di Maria (2020); and L. 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 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.

3.7.2 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 (R. G. Cooper & Kleinschmidt, 2007; H. Ernst, 2002; Lam & Chin, 2005). The use of customer feedback can greatly impact the success of new products (R. G. Cooper, 2019; R. G. Cooper & Kleinschmidt, 2007; H. 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.

3.7.3 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 (H. G. Choi & 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 & 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.

3.7.4 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, Kshetri, et al., 2023). Moreover, ChatGPT can assist in developing software components, writing code, automating simple tasks, and managing errors during the development and post-deployment phases (Dwivedi, Kshetri, et al., 2023), 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 & Tselikas, 2023; T. 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, Hughes, et al., 2023). 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, Hughes, et al., 2023). 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 837x 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.

3.7.5 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., 2020), and B2B buyers are less hedonistic and emotionally driven (Dibb & 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., 2020). This has led researchers to investigate the potential benefits of UGC in the B2B context. For example, X. Liu (2020) 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.

3.8 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.

3.8.1 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.

3.8.2 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.

CHAPTER 4

DEVELOPING A FRAMEWORK FOR ASSESSING CONSUMER ACCEPTANCE OF A NEW PRODUCT THROUGH USER-GENERATED CONTENT: INTEGRATING TOPIC MODELING WITH SENTIMENT ANALYSIS

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Abstract

Consumer acceptance is a critical factor in new product development (NPD) process, influencing the success of emerging products or technologies. This study uses ChatGPT as a case to explore innovative ways to measure consumer acceptance beyond traditional methods. Conventional approaches rely on surveys to gather consumer perceptions and employ statistical methodologies to evaluate acceptance. However, surveys are often criticized for being time-consuming, costly, and prone to biases, with response variability limiting their reliability, and their reliance on predetermined questions may further overlook unexpected factors influencing consumer acceptance. To address these issues, this study proposes a novel framework that leverages user-generated content (UGC) to assess consumer acceptance by integrating sentiment analysis with statistical modeling. BERT, LDA, and clustering techniques have been applied for topic modeling, while RoBERTa measured sentiment intensity from 21,988 tweets containing the hashtag #ChatGPT. These sentiment scores are then analyzed using PLS-SEM to examine relationships among key variables. The results indicate that performance expectancy and trust positively influence attitudes, whereas effort expectancy does not have a significant impact. Furthermore, positive attitudes enhance behavioral intentions. These findings underscore the value of sentiment analysis using UGC

as a dynamic and real-time source of customer insights to traditional survey-based methods. Unlike structured surveys, which are static, time-bound, and potentially biased by self-reporting, UGC offers more organic insights into consumer sentiment by analyzing naturally occurring language. It efficiently processes vast datasets from social media, enabling the tracking of real-time sentiment shifts and providing a deeper understanding of evolving factors influencing consumer acceptance.

Keywords: User-generated content, New product development, Consumer acceptance, Market risk, Sentiment analysis, Topic modeling, ChatGPT

4.1 Introduction

An efficient and agile NPD process is essential for businesses to succeed in a competitive marketplace (R. G. Cooper, 1993; Ulrich & Eppinger, 2016). Risks is present at every stage of NPD process due to intense competition and rapid technological advancement (Chin et al., 2009; Kayis et al., 2006). NPD decisions are characterized by significant uncertainty, complicating the achievement of desired performance outcomes for decision-makers (Kahraman et al., 2007; Ozer, 2005). Effective risk management is essential for assessing the viability of a new product project, as it increases the chances of project success (L. P. Cooper, 2003; Kayis et al., 2007; Oehmen et al., 2014).

Risk within NPD process is categorized into several types. Sicotte and Bourgault (2008) identified four main types of risk: technical and project uncertainty, market uncertainty, fuzziness, and complexity. O’Connor and Rice (2013) highlighted four key areas of uncertainty: technical, market, organizational, and resource uncertainties. Moreover, Park (2010) categorized 24 risk factors into five groups: market, technological, organizational, operational, and supplier risks. However, Keizer et al. (2003) and Mansor et al. (2016) highlighted the main risk categories of NPD including market, organizational, technical, and financial aspects. Keizer et al. (2003) provided a comprehensive definition of each category: technical risk includes design, manufacturing, and intellectual property aspects, while market risk involves consumer acceptance, public acceptance, and competition factors; financial risk concerns the project’s feasibility, and organizational factors involve internal communications and collaborations.

Among these categories, consumer acceptance is defined as a pivotal subset of market risk (Keizer et al., 2003; Mansor et al., 2016). It refers to the positive reception of a product or technology by potential users, serving as a crucial determinant of its successful market introduction and widespread diffusion (Herbig & Day, 1992). It captures the extent to which consumers are inclined to embrace and integrate a new product, service, or idea into their lives (Ahn et al., 2016; N. Wang et al., 2018). Consumer acceptance is primarily assessed using quantitative methods, focusing on surveys (Ahn et al., 2016; Manis & Choi, 2019; Ponzoa et al., 2021; Türker et al., 2022) to understand user perceptions based on psychological models like technology acceptance model (TAM) (Davis, 1985), the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003), and combination or extensions thereof (Cheng et al., 2006; Talukder et al., 2020; Türker et al., 2022). Moreover, statistical methodologies such as structural equation modeling (SEM), factor analysis (FA), and partial least squares (PLS) (Ahn et al., 2016; McKenna et al., 2013; Mehra et al., 2022) are frequently employed to elucidate the relationships among factors affecting consumer acceptance. However, Jing et al. (2023) stated quantitative methods using theoretical models may overlook significant factors in public concerns about consumer acceptance of a product, while novel approaches such as online UGC analysis can reveal these issues by bypassing the limitation of predetermined questionnaire. UGC represents a valuable and real-time source of feedback, offering companies an invaluable window into their target audience’s perceptions and interactions with a product (Timoshenko & Hauser, 2018; Ho-Dac, 2020), thereby enabling a more dynamic evaluation of consumer acceptance that goes beyond the traditional survey-based method (Ding et al., 2021; Jing et al., 2023; Jefferson & McDonald, 2019; Penmetsa et al., 2021). Thus, Jing et al. (2023) bridged the qualitative–quantitative divide in exploring public perceptions of autonomous vehicles (AV) by integrating qualitative insights with quantitative statistical analysis to identify the key factors influencing consumer acceptance of AV vehicles.

In contrast to Jing et al. (2023), this study adopts an innovative framework by shifting away from traditional survey-based and statistical methodologies. Instead, this study uses sentiment analysis of UGC, coupled with PLS-SEM as a statistical method. Emotional analysis is conceptualized as a spectrum of perceptual outcomes from product consumption experiences

(Saha & Zhao, 2011). This approach is preferred over conventional survey methods, often criticized for their time and cost inefficiency, potential biases, and varying response rates (Bethlehem, 2010; Rice et al., 2017; Timoshenko & Hauser, 2018). Additionally, academic studies have illuminated the characteristics of Likert scales as producers of ordinal data, which restricts the interpretation of responses as representing equal intervals or precise units. Acknowledging and accounting for these limitations is indispensable for conducting rigorous and reliable empirical analysis (Norman, 2010; Phillip A Bishop & Herron, 2015; Sullivan & Artino, 2013). Research by Rajput et al. (2016) highlights that sentiment scores provide additional insights compared to Likert scales, due to open-ended nature of textual feedback, as opposed to predetermined questionnaires that limit the scope of responses. Moreover, the combination of sentiment analysis of UGC with statistical methods enables product managers to identify and measure critical factors over time and across a broader scope, unlike traditional methods, which are constrained by limited scope and temporal rigidity (Bryman, 2016; Couper, 2000; Y. Zhang & Wildemuth, 2009). This longitudinal capability provides a dynamic view of user perceptions, allowing changes to be tracked over time and enabling more accurate forecasting and prediction of future trends .Thus, this study highlights the potential of UGC for assessing market risks associated with consumer acceptance of ChatGPT. It argues that UGC, applied in the category of market risk, can provide valuable insights into consumer acceptance. To rigorously analyze UGC's efficacy in this realm, the study employs an array of analytical techniques. Performing topic modeling and sentiment analysis using advanced natural language processing tool and RoBERTa (a robustly optimized BERT pretraining approach). Additionally, the research utilizes PLS-SEM to thoroughly examine the relationships among identified risk factors, enhancing the robustness of its findings (Jing et al., 2023). This research offers multifaceted contributions that advance the extant scholarly discourse on consumer acceptance: (1) it introduces a framework to evaluate consumer acceptance of a new product by analyzing UGC; (2) it presents a novel approach by using sentiment intensity in PLS-SEM to measure the interrelationships among risk factors, moving away from traditional survey-based method to capture consumers' perceptions; (3) the study also goes beyond theoretical applications by implementing its methodologies to assess the consumer acceptance of ChatGPT as a new product. The remaining of the paper is organized as follows: in the next section, the literature review is explained. Section 3 describes the methodology. Results are presented in section four. In section five, discussion, future research, and limitations are included. Section six discusses implications, and the conclusion is presented in section seven.

4.2 Literature

4.2.1 Risk in NPD process

Risk in NPD is a multifaceted concept defined as "a function of the amounts at stake and uncertainties in the venture" (R. G. Cooper & More, 1979). It involves outcome uncertainty, level of control, perceived impact on NPD performance (Keizer et al., 2005, 2009), potential failure due to technological, organizational, and market uncertainties (Mu et al., 2009). Risk appears at any stage of NPD process (Y. H. Park, 2010), and is classified into various categories. R. G. Cooper (1981) identified risk dimensions such as technical complexity, newness to the firm, marketing and managerial synergy, product determinateness, product customness, technical, production synergy and proficiency. Kuczmarski and Middlebrooks (1993) proposed strategic, market and internal risks. In addition, Unger & Eppinger (2011; 2009) expanded the risk framework by introducing schedule and financial risks, while Hall et al. (2016) further broadened it to encompass external, enterprise, management, and operational risks. Drawing from a comprehensive perspective, Park (2010) classifies risk into two categories – internal and external – wherein internal risk comprises operational, technological, and organizational factors, and external risk primarily revolves around market-related and supplier-related elements (Akpolat & Pitinanondha, 2009; Frame, 2003; Nellore & Balachandra, 2001; Y. H. Park, 2008; Raz & Hillson, 2005). Table 4.1 summarizes the diverse types of risk in NPD as identified by extant literature.

Upon examining risk categorization in NPD process, it becomes evident that the main risk categories encompass market, technical, organizational, and financial aspects (Keizer et al., 2003; Mansor et al., 2016). Following broad product launch messages via various social media channels, potential users have a unique chance to share their views on social media, creating UGC. This, UGC is essential for businesses to understand market-related risks, distinguishing it from other types of risks in NPD process. Consequently, the focus of this study is primarily on the domain of market risk, highlighting the unique value that UGC offers in this context. Market risk refers to uncertainties in the success of a NPD, including consumer acceptance, pricing, and competition (Keizer et al., 2003; Mascitelli, 2007). The primary risk involves the possibility of encountering low acceptance or outright rejection of a new product withing the market (L. P. Cooper, 2003). So, consumer acceptance is a pivotal subset under the umbrella of market risk (Cheng et al., 2006; Keizer et al., 2003; Liébana-Cabanillas et al., 2018a; Mansor et al., 2016; Valor et al., 2022; N. Wang et al., 2018).

Table 4.1 Risk categories in NPD process

Risk types	**Reference**
Technical – Market - Internal	Klink et al. (2002)
Technical – Market – Organizational - Financial	Keizer et al. (2003); Mansor et al. (2016)
Operational – Technological – Organizational – Market – Supply chain	Akpolat and Pitinanondha (2009); Frame (2003); Nellore and Balachandra (2001); Park (2008); Raz and Hillson (2005)
Commercial viability – Consumer acceptance – Manufacturing technology – Organization and project management – Product family and brand positioning – Screening and appraisal – Public acceptance – Competitor – Trade customer – Product technology – Intellectual property – Supply chain and sourcing	Keizer et al. (2005); Keizer and Halman (2007)
Changing project requirements – Changing market or customer needs – Lost or changing team members – Changing organizational priorities – Conflict – Changing management commitment – Environment quality problem – Technical difficulties – Technology changes – New regulatory requirements – Intellectual property disputes	Thamhain and Skelton (2007)

4.2.2 Consumer acceptance

Consumer acceptance refers to the willingness and intention of consumers to adopt a new product (Liébana-Cabanillas et al., 2018; Valor et al., 2022; N. Wang et al., 2018). The level of consumer acceptance of a new product is a significant risk factor (Barrios & Kenntoft, 2008;

March-Chordà et al., 2002), and an important success factor (Griffin & Page, 1996; Hultink & Robben, 1995). Recent research in consumer acceptance have illustrated a diverse application of extended theoretical framework and innovative methodologies across technological domains. Talukder et al. (2020) examined the acceptance and usage of wearable healthcare technology among the elderly in China by extending the UTAUT, employing a two-stage approach that first applied SEM to identify key factors and then used a neural network model to validate the findings on cross-sectional survey data via a five-point Likert scale. Liébana-Cabanillas et al. (2018) analyzed QR code mobile payment systems through an expanded TAM, likely utilizing SEM to test casual relationships and benchmarking their results against TAM, UTAUT, and diffusion of innovation frameworks. Similarly, Ponzoa et al. (2021) explored the perception, acceptance, and economic valuation of disruptive technologies such as augmented reality glasses and 3D printers among generation Y and Z by applying a modified TAM through self-reported surveys with a seven-point Likert scale and factor reduction analysis to isolate determinants of purchase intention. Ahn et al. (2016) extended UTAUT to assess the adoption of sustainable household technology in residential settings, incorporating sustainable consumption-specific attitudes and behavioral tendencies measured with adapted scales on a five-point Likert survey and analyzed through measurement model testing and SEM. In comparison with previous studies, (Jefferson & McDonald, 2019) analyzed tweets using frequency, forwarding frequency, and sentiment analysis to gauge consumer acceptance of AV vehicles. Similarly, Penmetsa et al. (2021) performed sentiment analysis by analyzing tweets, and Ding et al. (2021) used Latent Dirichlet Allocation (LDA) alongside sentiment analysis on tweets, finding that sentiment and acceptance of AV are closely associated with reactions to significant event. Despite their valuable insights, these studies lacked the statistical interdependencies among the factors that shape public acceptance of AV. Thus, to bridge this gap, Jing et al. (2023) proposed a novel hybrid approach that integrates qualitative exploratory analysis with quantitative techniques, thereby enabling a comprehensive understanding of the interplay between public perceptions and the key determinants of AV acceptance. While the study's integration of social media analysis with quantitative analysis offers valuable insights, its reliance on conventional survey methods is fraught with weaknesses. Traditional surveys are often criticized for inefficiencies, biases, and inconsistent response rates, which can delay insights and reduce reliability (Bethlehem, 2010; Rice et al., 2017; Timoshenko & Hauser, 2018). Fixed questions and response biases, such as socially desirable answers, may overlook subtle or emerging consumer opinions. Moreover, the common use of Likert scales produces ordinal data, limiting the accuracy of interpreting responses as equal intervals or precise units (Norman, 2010; Phillip A Bishop & Herron, 2015; Sullivan & Artino, 2013). These limitations present a critical gap in capturing timely, nuanced, and scalable insights into consumer acceptance, especially in the context of fast-evolving technologies like generative AI, where public perceptions can shift rapidly. To address this gap, this study proposes a comprehensive framework that leverages sentiment analysis of UGC alongside a robust statistical method to quantitatively evaluate consumer acceptance of ChatGPT.

4.2.2.1 Consumer acceptance of ChatGPT

OpenAI's Chat Generative Pre-Trained Transformer (ChatGPT) is designed to generate human-like text based on the inputs it receives, facilitating interactions with humans (Hosseini et al., 2023; OpenAI, 2022). ChatGPT is engineered to engage with a wide range of topics, positioning it as a potentially invaluable tool (Gilson et al., 2023). Consequently, there is increasing debate about the acceptance of ChatGPT among various scholarly groups. These discussions highlight the distinct attitudes of different users towards adopting this AI technology in diverse fields such as education, public, healthcare, finance, and co-working spaces. The details of the research studies are detailed in Table 4.2.

Table 4.2 Literature on consumer acceptance of ChatGPT

Context	Theoretical model	Analysis methodology	Data source	Author
Education	TAM	EFA	Survey	(Sallam et al., 2023a)
Health Care	UTAUT	PLS-SEM	Survey	(Shahsavar & Choudhury, 2023)
Public	A self-proposed model	PLS-SEM	Survey	(Choudhury & Shamszare, 2023)
Education	Extended UTAUT	PLS-SEM	Survey	(Foroughi et al., 2023)

Context	Theoretical model	Analysis methodology	Data source	Author
Finance	Extended TAM	PLS-SEM	Questionnaire	(Yong Ming et al., 2023b)
Education	TAM	SEM	Survey	(Zou & Huang, 2023)
Education	Extended TAM	SEM	Questionnaire	(Lai et al., 2023)
Education	TAM	SEM	Questionnaire	(Saif et al., 2023)
Public	AIDUA	SEM	Questionnaire	(X. Ma & Huo, 2023)
Education	TAM/UTAUT	PLS-SEM	Survey	(Faruk et al., 2023)
Education	TAM	SEM	Survey	(Albayati, 2024)
Coworking space	UTAUT	PLS-SEM	Survey	(Kopplin, 2022)
Education	Extended UTAUT	SEM	Survey	(Goyal et al., 2023)
Education	TAM	SEM	Survey	(Kingsley Ofosu-Ampong, 2023)
Education	Extended UTAUT	PLS-SEM	Survey	(Strzelecki, 2023)
Education	UTAUT/ Extended UTAUT	PLS-SEM	Survey	(Habibi et al., 2023)
Education	A self-proposed model	PLS	Survey	(Camilleri, 2024)
Public	TAM	SEM	Survey	(J. Ma et al., 2024)
Note: The acronyms referenced in Table 4.2 are clarified as follows: “TAM”: technology acceptance model – “SEM”: structural equation modeling – “PLS”: partial least square – “EFA”: Exploratory factor analysis –”UTAUT”: Unified theory of acceptance and use of technology – “AIDUA”: AI device use acceptance.				

Table 4.2 demonstrates that all included studies have applied quantitative methodologies, complemented by established theoretical models. Despite the robustness of the above approach, this study employs UGC posted with the hashtag #ChatGPT on platform X (formerly Twitter), as a novel means of extracting latent factors and capturing public perception. This method represents a departure from traditional questionnaire-based inquiries, offering a more open and less biased avenue for expressing opinions, as illustrated by Raats et al. (2020). It exemplifies the evolving landscape of research methodologies, leveraging the vast, dynamic

repository of social media data to gain deeper insights into consumer attitudes and behaviors (Ding et al., 2021; Jefferson & McDonald, 2019; Jing et al., 2023; Penmetsa et al., 2021).

4.3 Methodology

4.3.1 Data gathering and preprocessing

The methodology (Figure 4.1) of this study begins with data collection from social media concerning ChatGPT, using UGC's marked with the hashtag #ChatGPT on X, provided by Kaggle. The dataset includes 478,347 tweets form November 30, 2022 – to April 8, 2023. To ensure data quality, we filtered the dataset to include only English tweets, removing those with fewer than five words and containing URLs (Murshed et al., 2021b; Yoon et al., 2013), resulting in 151,232 tweets. From these, 10,000 tweets were manually labeled by researchers as relevant or irrelevant according to predefined criteria (Chiarello et al., 2020b; Lughbi et al., 2024). A tweet was considered relevant if it was authored by users and contained words, opinions, or discussions directly referring to the product of interest. Conversely, a tweet was labeled irrelevant if it contained advertising content, spam, or references to other products or unrelated subjects. These labeled tweets formed the training set for the support vector machine (SVM) classifier (Airlangga, 2024; Chiarello et al., 2020b). To improve data quality, text preprocessing has been performed by expanding contractions, eliminating stopwords, purifying the text through lowercasing and removal of extraneous characters, and applying lemmatization to standardize word forms (Chiarello et al., 2020b; Jacquemin, 2001; Murshed et al., 2021b; Saranya & Usha, 2023; Sarica & Luo, 2021; Srivastava et al., 2021). Then, the dataset has been split into training, validation, and testing subsets, and term frequency-inverse document frequency (TF-IDF) is applied for keyword extraction (Barkha, 2018; Gozuacik et al., 2021; Popoola et al., 2024).

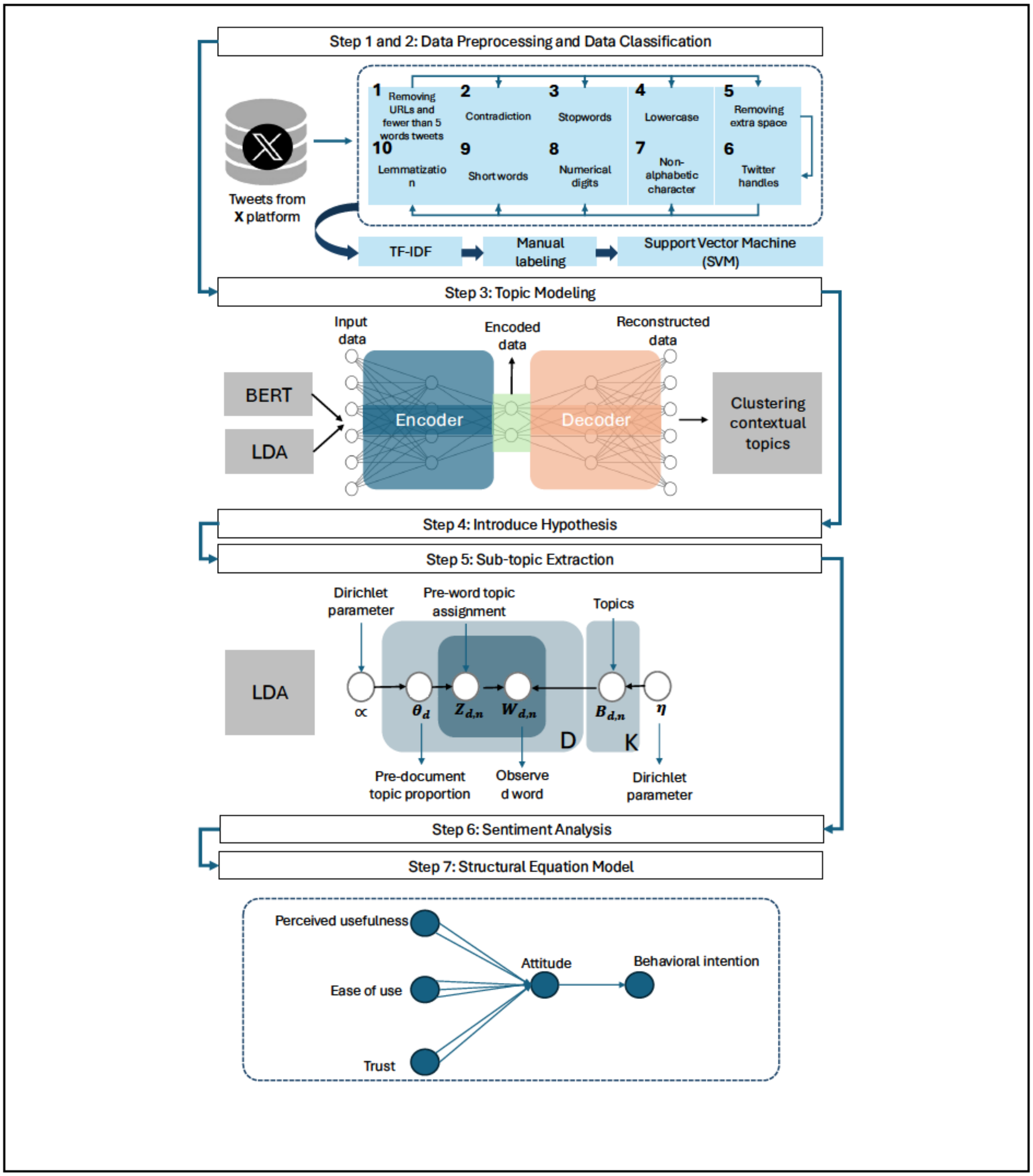

Figure 4.1 The proposed framework to assess consumer acceptance through UGC

4.3.2 Topic modeling

Topic modeling in textual analysis primarily employs two approaches: clustering based on vector space similarity via LDA and embedding entire text content into a vector space like BERT (bidirectional encoder representations from transformation). LDA identifies topics by detecting frequently occurring, coherent words within texts (W. M. Wang et al., 2018; Zeng et al., 2022b; F. Zhou et al., 2020) but faces challenges with short texts and context-dependent reviews due to its reliance on word co-occurrence (Campbell et al., 2014; Mahadevan & Arock, 2020). In contrast, BERT embeds text into a vector space while considering contextual relationships bidirectionally, enabling a deeper understanding of word association (George & Sumathy, 2023; Gozuacik et al., 2021). Given LDA's limitations, BERT provides a more comprehensive text representation and facilitates more effective topic clustering (Atagün et al., 2021; Palani et al., 2021).

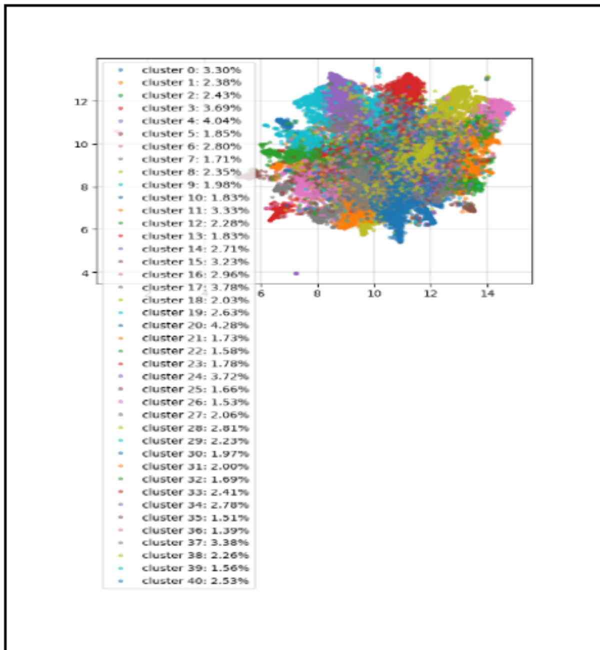

Figure 4.2 LDA-BERT topic modeling

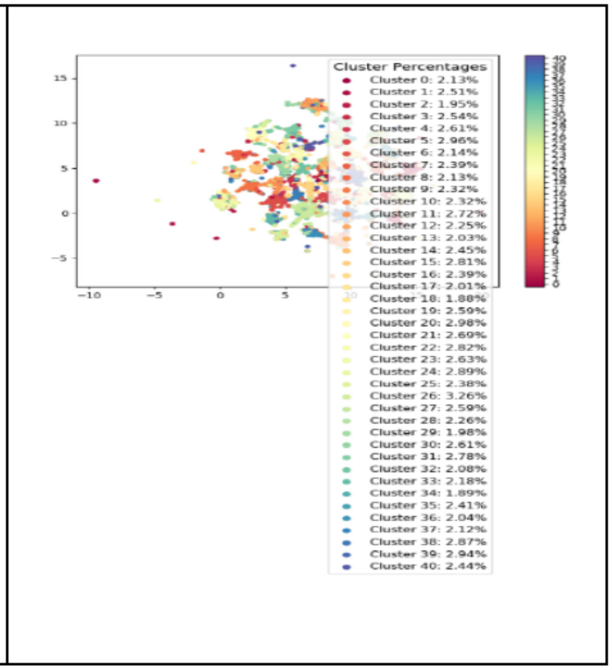

Figure 4.3 LDA topic modeling

So, this study integrates LDA, BERT, and clustering techniques to provide a powerful approach to topic identification by combining statistical word patterns with deep semantic understanding (George & Sumathy, 2023; Gozuacik et al., 2021; Zeng et al., 2022b; F. Zhou et al., 2020). To balance information from both sources, their vector representations are merged with a weighting parameter, and an autoencoder reduces dimensionality by capturing essential features while eliminating redundancy (Palani et al., 2021). This refined representation is then clustered, effectively blending LDA's topic patterns with BERT's contextual depth, resulting in clearer and more accurate topic separation, as demonstrated in Figures 4.2 and 4.3. To determine the autoencoder configuration, UMAP is applied to evaluate each setting and identify the more efficient one.

After the LDA-BERT revealed 41 topics, the following steps were implemented for labeling: First, researchers independently summarized each topic by examining tweets to understand the central themes. Second, the researchers gathered latent variables and their definitions from seminal literature on established behavioral theoretical frameworks like TAM (Davis, 1985), UTAUT (Venkatesh et al., 2003), their extensions (Venkatesh et al., 2012), and AI device use acceptance (AIDUA) (Gursoy et al., 2019). Third, each topic was assigned a label corresponding to a latent variable from these behavioral theories. This process involved all three researchers working independently to match topics with appropriate latent variables, followed by a collaborative discussion to confirm the consistency and accuracy of these matches. The result of labeling each topic became the basis for hypothesis development, focusing on performance expectancy, effort expectancy, trust, attitude, and behavioral intention. The final topic labels are presented in Table 4.3.

Table 4.3 Results of labels of each topic

Latent Variable	**Topic Number**	**Definition of Variable**
Performance expectancy	1 – 3 – 4 – 6 – 7 – 10 – 12 – 13 – 15 – 16 – 18 – 20 – 23 – 24 – 25 – 27 – 31 – 34 – 35 – 39 – 40	It refers to an individual's belief in the potential of a system to enhance their work (Venkatesh et al., 2003).
Effort expectancy	21 – 36	Effort expectancy is defined as the perceived ease of use by consumers when interacting with technology (Viswanath Venkatesh et al., 2012).
Trust	2 – 5 – 19 – 32 – 38 – 41	The trust construct refers to an individual's belief in the reliability and integrity of technology, ensuring that its performance meets expectations

		and protects their interests (Gursoy et al., 2019; Lazarus, 1991).
Latent Variable	**Topic Number**	**Definition of Variable**
Attitude	8 – 14 – 17 – 22 – 26 – 28 – 29 – 30 – 33 – 37	The strong influence of emotion on readiness to use technology shows that users' acceptance of AI devices is mainly driven by their emotional reactions to these devices (Castelfranchi & Falcone, 2001; Christine et al., 2001).
Behavioral intention	9 – 11	Behavioral intention simply means planning to perform a specific behavior (Davis, 1985; Icek Ajzen, 1985).

Figure 4.4 Word clouds related to each latent variable

Furthermore, the WordCloud methodology is employed to visualize all associated identified topics to each latent variable (Figure 4.4). This tool highlights word prominence based on frequency or significance, effectively accentuating key data points. Its applicability is notably prevalent in the examination of data derived from social media platforms (Atagün et al., 2021; Chaturvedi et al., 2018).

4.3.3 Hypothesis development

4.3.3.1 Performance expectancy

Performance expectancy in ChatGPT refers to users' expectations of its potential to boost efficiency and productivity across a range of tasks (X. Ma & Huo, 2023). A study conducted by (Venkatesh et al., 2012) disclosed that the utilitarian features enhancing user productivity serve as crucial motivators for adoption. This implies that the likelihood of users embracing ChatGPT increases if they regard it as a beneficial instrument capable of augmenting their efficiency and productivity (X. Ma & Huo, 2023). Consequently, users' expectations are shaped by their anticipation of the service's reliability and consistency (Gursoy et al., 2019; Lv et al., 2022). As a result, the following hypothesis is proposed:

H_1**.** performance expectancy positively influences users' attitudes.

4.3.3.2 Effort expectancy

In the context of ChatGPT, users' perceptions of effort expectancy and the quality of interaction play a significant role in their willingness to adopt this technology for various tasks (X. Ma & Huo, 2023). If users perceive that utilizing AI tools demands excessive effort, it will lead to the generation of negative emotions (Gursoy et al., 2019; Lazarus, 1991). Previous research has shown that effort anticipation positively influences users' views on the use of AI for services (Chi et al., 2022). A study conducted by Moriuchi (2021) demonstrates that ease of interaction with ChatGPT greatly enhances users' AI experiences, making positive outcomes more likely. Therefore, we postulate as follows:

H_2. effort expectancy positively influences users' attitudes.

4.3.3.3 Trust

The trust construct pertains to an individual's conviction in the dependability and integrity of technology, ensuring its performance aligns with expectations and secures their interests (Castelfranchi & Falcone, 2001; Christine et al., 2001). Trust plays a pivotal role in shaping individuals' behavior toward the adoption of technology (Kesharwani & Bisht, 2012). Users' trust in a system's accuracy and helpfulness fosters positive attitudes, leading to higher usage and future intentions to use it (Albayati, 2024). A study conducted by I. L. Wu & Chen (2005) demonstrates that if an individual lacks trust in a technology, they might perceive technology as less useful, despite its apparent advantages. Therefore, it is hypothesized that:

H_3. Trust positively impacts users' attitudes.

4.3.3.4 Attitude

The significant impact of emotion on the readiness to adopt AI tools underscores that user acceptance is primarily influenced by their emotional assessment of these tools (S. V. Jin & Youn, 2022; H. Lin et al., 2020). Moreover, emotional reactions not only positively affect consumer behavioral intentions, but evidence also suggests that affective evaluation, covering passionate and hedonic dimensions of social learning, is vital in explaining users' views and attitudes towards the source (Le et al., 2020). Additionally, initial evaluations of AI in corporate settings indicate that the user's reaction to the technology is closely linked with emotional attitudes (Y. Te Chiu et al., 2021). Thus, the following hypothesis is proposed:

H_4. Attitudes positively affect users' behavioral intention.

4.3.4 LDA and sentiment analysis using VADER and RoBERTa models

To better understand and identify the key tweets within each latent variable topic, we applied LDA techniques, measuring coherence score (K) to determine the number of sub-topics. Each sub-topic is seen as a collection of words that share a common theme. Following earlier research (Guan et al., 2022), we eliminated some repetitive topics and organized the tweets across all latent variable topics into 11 specific sub-topics. In LDA model, every topic is shown as a mix of keywords, each with a probability distribution. To achieve our objectives, we performed sentiment analysis on the 15 most significant keywords within each sub-topic. Sentiment values were assigned on a scale from -1 (negative) to 1 (positive) to represent documents (Penmetsa et al., 2021) and then normalized to a range of 0 (negative) to 5 (positive) for consistency in interpretation. To evaluate the accuracy of different sentiment analysis techniques, we first manually labeled 1,000 tweets as negative, neutral, or positive. The initial approach utilized the valence-aware dictionary for sentiment reasoning (VADER) package (Hutto & Gilbert, 2014), which closely matched human accuracy (88.8% vs. 88.1%) and outperformed humans in recall and precision (Bonta et al., 2019). Additionally, we implemented a more advanced adaptation of the BERT model (Devlin et al., 2019), specifically RoBERTa, which is fine-tuned to address BERT's training complexity and optimize hyperparameters that were previously missing (Y. Liu, Ott, et al., 2019a). Both the polarity and sentiment intensity of the input text were evaluated using VADER and RoBERTa techniques. RoBERTa was selected for its superior performance, achieving an F1 classification accuracy of 0.78. As shown in Figure 4.5, RoBERTa provides deeper insights into sentiment, whereas VADER struggles to differentiate between negative and neutral tweets. Following the evaluation of sentiment intensity for these keywords, the results of the sentiment analysis were fed into PLS-SEM to assess the statistical relationships between the factors.

4.3.5 PLS-SEM

After performing sentiment analysis, we employed PLS-SEM to examine the causal relationships among latent variables. As a subset of SEM, PLS-SEM integrates Ordinary Least Squares (OLS) regression and Principal Component Analysis (PCA) to estimate partial regression relationships, prioritizing the maximization of explained variance while minimizing error terms (Hair et al., 2011; Mateos-Aparicio, 2011). Unlike traditional covariance-based SEM, PLS-SEM excels in handling complex models with both reflective and formative constructs, making it particularly suitable for exploratory research and predictive analysis (Law & Fong, 2020). Additionally, its ability to accommodate small sample sizes, non-normal data, and moderator variables strengthens its applicability in behavioral research (Ramli et al., 2019). Given these advantages, PLS-SEM is optimal choice for our study, allowing for a more comprehensive analysis of structural relationships and enhancing the robustness of our findings (Yong Ming et al., 2023b).

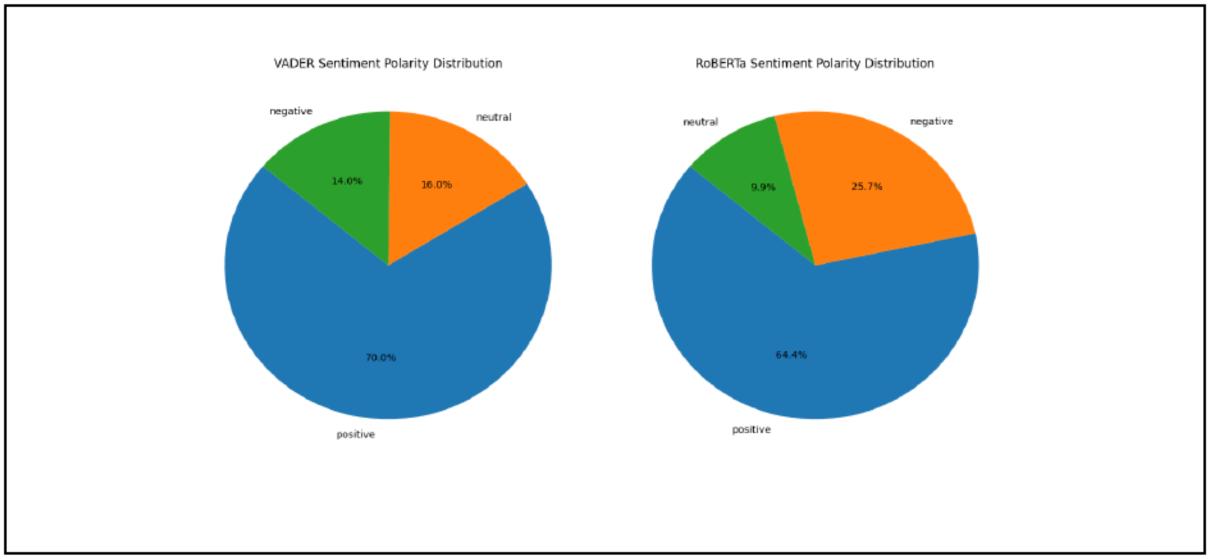

Figure 4.5 Analysis of VADER and RoBERTa sentiment

4.4 Result

4.4.1 Measurement model evaluation

The model was estimated using PLS-SEM with the SmartPLS 4 software package (Version 4.1.0.1). To evaluate the statistical significance of the PLS-SEM findings, a nonparametric method known as bootstrapping was implemented, which processed 5000 samples. (Ringle et al., 2015). To assess the reliability and validity of the suggested model for all variables, the measurement model was used. The threshold for loadings was established at a minimum of 0.708, as referenced by Manley et al., (2021) and Sarstedt et al., (2022). Computed values of this study fell within the range of 0.720 to 0.962. Composite reliability (CR) serves as a measure of data reliability within PLS-SEM procedures. All values must meet or exceed a threshold of 0.700. Table 4.4 shows CR scores are higher than 0.700 (Manley et al., 2021; Sarstedt et al., 2022). The CR's scores range from 0.766 (Behavioral Intention), and 0.898 (effort expectancy). The Average Variance Extracted (AVE) is used to assess convergent validity, which indicates the extent to which a variable can capture the variance of the item it is intended to measure. The AVE value must be 0.500 or greater, indicating that it accounts for 50% or more of the variance (Becker et al., 2023; Russo & Stol, 2021). The computational outcomes for AVE indicate that all variables exhibit satisfactory values. The minimum AVE value for behavioral intention is 0.622, explaining 62% of the variance, while the highest for performance expectancy is 0.787, accounting for 79% of the variance.

Table 4.4 Load, CR, AVE

Variable	**Item**	**Load**	**CR**	**AVE**
Attitude	ATT1	0.864	0.874	0.776
	ATT2	0.897		
Behavioral Intention	BI1	0.720	0.766	0.622
	BI2	0.852		
Effort expectancy	EE1	0.836	0.898	0.746
	EE2	0.851		
	EE3	0.902		
Performance expectancy	PE1	0.962	0.880	0.787
	PE2	0.805		
Trust	TR1	0.831	0.824	0.700
	TR2	0.842		

Discriminant validity assesses the distinctiveness of one variable from others. For evaluating discriminant validity, we utilized heterotrait-monotrait (HTMT) ratios (Ab Hamid et al., 2017; Habibi et al., 2020). When the HTMT value exceeds 0.900, discriminant validity is compromised as it implies that the constructs may share similar theoretical concepts. HTMT values above 0.900 serve as evidence of issues with discriminant validity, indicating that the constructs might not be sufficiently differentiated (Ab Hamid et al., 2017; Henseler et al., 2015). The HTMT values for this study are proper, no value exceed 0.900, as presented in Table 4.5.

Table 4.5 HTMT

	ATT	**BI**	**EE**	**PE**	**TR**
ATT					
BI	0.897				
EE	0.508	0.359			
PE	0.588	0.523	0.257		
TR	0.590	0.497	0.309	0.429	

Note: The acronyms referenced in Table 4.5 are clarified as follows: ATT: Attitude; BI: Behavioral Intention; EE: Effort expectancy; PE: Performance expectancy; TR: Trust.

4.4.2 Structural model

Before evaluating the structural model, a collinearity assessment was conducted to verify the integrity of the regression results. It is indicated by variance inflation factor (VIF) values, which should not surpass 3.3 (Foroughi et al., 2023; Lai et al., 2023). If they do, it suggests a likelihood of collinearity among predictors. For accurate regression analysis, optimal VIF readings should be 3.3 or below. As shown in Table 4.6, all VIF values fall within acceptable limits, indicating that collinearity is not a concern in the current scenario. The structural relationships among the model's constructs are tested using SmartPLS (PLS-SEM) and bootstrapping procedure (5000 re-samples procedure). The results of hypothesis testing are presented in Table 4.6. Three hypotheses were supported, while one was not. The effect of performance expectancy on attitude is found to be significant ($\beta = 0.597$, $p = 0.004$), thereby supporting hypothesis H_1. However, effort expectancy has no effect on attitude ($\beta = 0.300$, $p = 0.273$), hence the hypothesis H_2 is not supported. Trust significantly affects attitude ($\beta = 0.486$, $p = 0.048$*)*, providing evidence to accept hypothesis H_3. Likewise, hypothesis H_4 is also supported, indicating the significant effect of attitude on behavioral intention ($\beta = 0.479$, $p = 0.021$).

Table 4.6 Summary of hypothesis testing (structural model)

Hypothesis	Path	VIF Value	Std. β	T Statistic	P Value	Status
H_1	PE→ ATT	1.102	0.597	2.892	0.004	Supported
H_2	EE→ ATT	1.044	0.300	1.096	0.273	Not supported
H_3	TR→ ATT	1.115	0.486	1.978	0.048	Supported
H_4	ATT→ BI	1.000	0.479	2.306	0.021	Supported
Note: The acronyms referenced in Table 4.6 are clarified as follows: ATT: Attitude; BI: Behavioral Intention; EE: Effort expectancy; PE: Performance expectancy; TR: Trust.						

4.5 Discussion

4.5.1 Main outcomes

The results from our study confirm the significant effect of performance expectancy on the attitude toward ChatGPT usage among X (formerly Twitter) users, consistent with prior TAM research (Davis, 1989). When users perceive ChatGPT as useful, their attitude toward adoption improves, aligning with studies on AI tools in educational and organizational contexts (Sallam et al., 2023b; Songkram et al., 2023). This supports the broader argument that goal-oriented utility drives positive attitudes, as technologies that efficiently fulfill user needs are more likely to be adopted (AlHogail, 2018; Venkatesh et al., 2003). Contrary to expectations, our findings revealed no significant relationship between effort expectancy and attitude, corroborating recent work by X. Ma and Huo (2023). This challenges the assumptions from earlier frameworks like UTAUT, which posited effort expectancy as critical (Venkatesh et al., 2003). Our results suggest that for generative AI tools like ChatGPT, effort expectancy may be secondary to functional value, possibly due to their conversational interface reducing perceived complexity (Dwivedi, Kshetri, et al., 2023). As users become more familiar with these tools, their focus appears to shift from effort expectancy to the perceived benefits and capabilities, such as enhanced productivity, creativity, and problem-solving support (Dwivedi, Kshetri, et al., 2023). This evolving user behavior highlights the need to reconsider traditional technology adoption models when evaluating the impact and acceptance of advanced AI tools.

Notably, trust emerged as a strong predictor of attitude, mirroring findings in AI adoption literature. Users with higher trust in ChatGPT's reliability and ethical design exhibited more favorable attitudes, a pattern observed in studies on AI-driven healthcare and financial systems (Albayati, 2024; Mcknight et al., 2011). Trust-building mechanisms, such as transparency in AI outputs, may thus be critical for sustained adoption (Gefen et al., 2003). Finally, attitudes significantly predicted behavioral intentions, reinforcing the theory of planned behavior (TPB) (Icek Ajzen, 1985). This aligns with recent ChatGPT-specific studies (Saif et al., 2023; Zou & Huang, 2023) and the expectancy-value model, which posits that attitudes reflect users' evaluations of outcomes (Ajzen & Fishbein, 2008). When users hold favorable views of

ChatGPT's capabilities, they are more likely to integrate it into daily tasks, underscoring attitude's role as a behavioral antecedent (Viswanath Venkatesh et al., 2012).

4.5.2 The proposed framework to evaluate consumer acceptance

This study introduces an innovative framework that reconceptualizes consumer acceptance within the context of NPD in AI era. Moving beyond traditional survey-based approaches, often criticized for being time-consuming, cost-intensive, and subject to biases, this framework leverages UGC and advanced natural language processing techniques to continuously monitor consumer acceptance through real-time UGC. This is particularly relevant for rapidly evolving technologies like generative AI, where public opinion shifts quickly in response to technological advancements, policy changes, or emerging use cases. By integrating sentiment analysis of UGC with PLS-SEM, the framework allows for the identification and quantification of latent factors influencing consumer acceptance. This approach not only addresses the methodological limitations of fixed-question surveys but also enables a dynamic and scalable analysis of consumer perceptions. The empirical application of this framework validates that information collected by sentiment analysis is instrumental in analyzing consumer acceptance. Moreover, the framework is scalable and transferable across domains, providing researchers and practitioners with a robust toolset for assessing public engagement with emerging technologies. In doing so, the study contributes to a paradigm shift in how consumer acceptance is conceptualized, measured, and applied, moving beyond the limitations of traditional methods toward a more dynamic, real-world understanding of user attitudes.

To substantiate the proposed model, its reliability and validity were assessed using CR and AVE, both of which surpassed acceptable thresholds. Discriminant validity was verified through the HTMT, affirming the model's robustness. Additionally, the hypotheses are supported by prior studies, indicating that the statistical results derived from sentiment analysis of UGC are consistent with those obtained through conventional survey-based methods.

4.5.3 Limitations and future research directions

This study highlights the importance of sentiment analysis in understanding consumer acceptance, yet certain limitations must be considered. First, data from platform like X may introduce demographic bias by overrepresenting tech-savvy users (Gensler et al., 2013; Kozinets, 2010). Future research should incorporate data from other sources, such as YouTube, Reddit, and non-English social media, to enhance representativeness. Expanding analysis to multilingual UGC could also reveal cultural differences in technology adoption, particularly in AI trust thresholds across different regions (Conneau et al., 2020). Additionally, our approach to topic modeling using LDA-BERT did not account for sentence length, which can obscure sentiment accuracy in longer sentences. A more refined text analysis method that recognizes conjunctions and complex sentence structures could improve the precision of topic-specific sentiment extraction. Another limitation is the challenge of interpreting linguistic nuances like sarcasm, irony, and contextual ambiguity, which traditional sentiment analysis tools often misinterpret (Pang & Lee, 2008). Future research could mitigate this issue by leveraging large language models (LLMs) fine-tuned on conversational datasets to better detect these complexities (Kocoń et al., 2023). Additionally, fine-tuning LLMs on domain-specific UGC could further improve sentiment classification, enabling more accurate assessments of consumer attitudes toward emerging technologies. While this study used UGC to identify risk factors affecting consumer acceptance, its potential for predicting product obsolescence remains underexplored. Future research could analyze longitudinal sentiment trends to detect early signs of obsolescence, such as declining satisfaction or increasing complaints about outdated features. These advancements would provide a more comprehensive understanding of consumer behavior and obsolescence risks in evolving technological landscapes.

4.6 Managerial and theoretical implications

Traditional survey-based methods, while widely used, suffer from inherent limitations such as response bias, recall errors, and the inability to capture real-time consumer sentiment. Our research challenges this conventional approach by demonstrating the superiority of UGC as a data source for assessing risks associated with new products, particularly in consumer acceptance and market risk analysis. Unlike surveys, which rely on structured questions and predefined response categories, UGC enables the extraction of organic, unsolicited consumer opinions, providing a richer and more authentic reflection of market dynamics. By leveraging sentiment analysis from X users' tweets and integrating it with statistical modeling, our framework offers a novel paradigm that directly quantifies the factors influencing technology adoption. This real-time assessment not only circumvents the delays and biases associated with surveys but also enhances predictive accuracy by capturing spontaneous consumer reactions. The ability to analyze large-scale UGC data ensures a more comprehensive understanding of evolving consumer preferences, making it a superior alternative for identifying adoption barriers and market risks. Furthermore, our framework advances the methodological rigor of technology adoption studies by statistically validating key relationships derived from real-world discourse rather than self-reported data. This positions UGC as a more reliable and real-time approach, enabling researchers and practitioners to develop data-driven, context-aware strategies for new product launches. By demonstrating the efficacy of sentiment analysis in consumer perception evaluation, our study not only extends existing literature but also underscores the critical need to move beyond outdated survey-based techniques in favor of more dynamic and representative analytical frameworks.

Moreover, this study reveals that performance expectations and trust greatly influence users' attitudes toward ChatGPT, which in turn affects their willingness to adopt. Highlighting the utility of ChatGPT can enhance its adoption rates, but it's vital to address the risks associated with it, such as the potential spread of misinformation due to biases in the data that ChatGPT learns from. To combat these issues, a proactive strategy is needed to refine ChatGPT's training models by filtering out biased or incorrect information, ensuring accuracy and reliability. Enhancing performance expectancy and trust can cultivate a more positive attitude toward generative AI tools, ultimately driving greater adoption and encouraging responsible use. This targeted approach highlights the critical role of building user trust and optimizing technological performance in fostering acceptance and supporting the ethical advancement of AI.

4.7 Conclusion

This study analyzed 478,347 tweets with the hashtag #ChatGPT, collected from Kaggle. Advanced analytical techniques, including BERT, LDA, and clustering, were deployed to sift through the tweet data, pinpointing key factors such as performance expectancy, effort expectancy, trust, attitude, and behavioral intention. This approach bypassed traditional surveys, utilizing LDA to extract sub-topics of each latent variable and RoBERTa to measure sentiment intensity within these themes. The sentiment data were then processed using PLS-SEM to understand the interrelationships among the identified factors. The findings validate UGC as a reliable source for measuring consumer acceptance. Notably, performance expectancy and trust are shown to positively influence user attitude toward ChatGPT, underscoring the importance of perceived effectiveness and reliability in fostering user acceptance. Interestingly, effort expectancy does not significantly influence attitude, indicating that X users may prioritize other factors over effort expectancy in their evaluation of ChatGPT. Additionally, a favorable attitude is strongly linked to increased behavioral intentions, suggesting that positive perceptions significantly boost usage. The research contributes profoundly to the field by offering a real-time and cost-effective framework for using UGC to evaluate consumer acceptance, moving beyond traditional surveys to a dynamic analysis of consumer sentiments on social media. This approach not only enriches our understanding of consumer behavior but also provides strategic insights that can guide the development of ChatGPT. This study highlights the efficacy of UGC as an innovative tool for new product risk assessment and promises to reshape how companies gauge consumer acceptance and manage market risks in launching new products.

CHAPTER 5

DEVELOPING A USER-GENERATED CONTENT–BASED PRODUCT OBSOLESCENCE INDEX: A STUDY ON CONSUMER IOT DEVICES

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Abstract

Identifying product obsolescence factors is essential for guiding sustainable design and extending product longevity. Unlike prior studies, this research leverages online consumer reviews to explore product obsolescence factors. ChatGPT-4o, an advanced pre-trained large language model (LLM) that outperformed Claude-3 opus and Llama 3 in this study, is utilized to identify these factors. User-generated content (UGC) time series-based product obsolescence indexes are then defined to quantify each factor's impact, offering a UGC-based complement to earlier methods that depended on expert judgment, supplier input, or survey data. By leveraging real-time customer insights, this approach aligns with Industry 4.0 principles, offering a UGC-based method that can support product design to proactively address product obsolescence. It integrates factors' relative importance, determined through frequency-analytic hierarchy process (Freq-AHP), with their severity impact on consumers, assessed using robustly optimized bidirectional encoder representations from transformers approach (RoBERTa). This study focuses on consumer IoT devices, an area underexplored in existing literature, analyzing 47,695 online consumer reviews across nine product categories, selecting 4,771 online obsolescence-related reviews for detailed analysis. Findings highlight nineteen key factors associated with obsolescence in consumer IoT devices and demonstrate

their shifting influence over time, underscoring this method's potential to inform product obsolescence mitigation strategies.

Keywords: Product obsolescence, User-generated content, online consumer review, Large language models, Internet-of-Things (IoT)

Managerial relevance statement

This study introduces a practical, data-driven framework to address product obsolescence in consumer IoT devices by leveraging UGC and analyzing it with LLMs. This method offers a fast, scalable, and cost-effective alternative to traditional surveys or expert opinion-driven approaches. A major contribution is the creation of dynamic product obsolescence indexes that help product managers continuously monitor product obsolescence factors based on real consumer experiences. The study highlights that while some drivers are consistent across all product categories, others are unique to specific types of products. This distinction enables more precise and context-aware strategies for managing product obsolescence. It also reveals a rising trend in product obsolescence across most consumer IoT product categories, with indirect software-driven factors often having a stronger long-term impact than direct ones. Additionally, it uncovers previously overlooked signs of product obsolescence related to user experience and business models, shifting the focus beyond technical specifications. This broader understanding enables more adaptive and forward-looking policy responses. For engineering managers, the study offers actionable insights to support early intervention and strategic planning, prioritizing high-impact or emerging factors identified through user feedback. Ultimately, the approach supports data-informed design improvements and fosters the development of more resilient, user-centered products.

5.1 Introduction

Product obsolescence poses environmental and social challenges by depleting non-renewable resources and increasing waste from production and disposal (Proske, 2022; Sierra-Fontalvo et al., 2023). While manufacturers once prioritized high-quality, durable products (Y. Su & Hwang, 2020), technological advancements now drive them to introduce feature-enhanced models to boost sales and meet consumer requirements (Munten et al., 2021; Tim Cooper, 2004). This shift has shortened product lifespans, rendering products obsolete through mass production, even when they remain functional (Rivera & Lallmahomed, 2016).

The fast-growing electrical and electronic equipment (EEE) sector exemplifies this issue, as electronic gadgets, though essential in daily life, have unsustainable production, use, and disposal that harm the environment (Habib et al., 2022; Mathiyazhagan et al., 2022). Rapid technological advancements (Singh et al., 2019), a competitive market (M. Chen et al., 2016), and evolving consumer preferences drive frequent replacement of EEE devices with newer models (Lyu et al., 2023; Sierra-Fontalvo et al., 2023). Over the past two decades, the rapid growth of the EEE sector has accelerated product obsolescence, significantly increasing electronic waste (E-waste) in developed countries (Nguyen et al., 2019). In 2019, E-waste totaled 53.6 million tones (Mt), a 21% rise over five years, and is projected to reach 74.7 Mt by 2030 (Adrian et al., 2020). With E-waste growing at over 4% annually and global EEE consumption increasing by 2.5 Mt per year, the rising prevalence of EEE products has led to extensive research on obsolescence to address the escalating E-waste challenge (Sharma et al., 2024). For example, residential EEE products, such as washing machines, televisions, dishwashers, and laptops have widely been studied (Hennies & Stamminger, 2016b; Karagiannopoulos et al., 2024b; Tim Cooper, 2004). Smartphones have also been a key focus, with various factors identified as contributing to consumer discontinuation (Makov & Fitzpatrick, 2021; Proske & Jaeger-Erben, 2019b; Wieser & Tröger, 2016). Additionally, the aviation, aerospace, and military sectors have been explored (Bowlds et al., 2018; Giovannoni & Boyles, 2016; Rajagopal et al., 2015) where software plays a critical role in influencing product lifespan and functionality (Poppe et al., 2021). Although software does not degrade and is replicable, it can still drive obsolescence when it becomes unsupported or incompatible with newer system (Rojo et al., 2009; Shuai et al., 2018).

Existing research on EEE product obsolescence has mainly focused on specific contexts, such as smartphones, laptops, non-smart home appliances, and applications in aviation, aerospace, and military sectors. However, these studies often lack broader applicability due to their industry-specific scope. With the increasing integration of consumer IoT devices in daily life, understanding their obsolescence factors, an area previously overlooked in literature has become essential. This study aims to identify the key factors influencing consumer IoT device obsolescence using a novel approach. Instead of relying on time-consuming and costly methods (Timoshenko & Hauser, 2018) such as consumer interviews (İmir, 2010a; Oraee et al., 2024), expert interviews (Muñoz et al., 2015), and surveys (Magnier & Mugge, 2022; Pardo-Vicente et al., 2022), this study analyzes 47,695 online reviews of consumer IoT devices collected from Amazon.com and BestBuy.com, categorizing them into smart speaker and display, smart lighting, smart thermostats, smart security systems, smart kitchen appliances, smart climate control, smart entertainment systems, smart blinds, and smart health devices. To identify product obsolescence factors, the advanced pre-trained large language model (LLM) ChatGT-4o, which outperformed Claude-3 Opus and Llama 3 in detecting product obsolescence-related reviews, is employed to analyze 4,771 online reviews. The study then defines UGC time-series-based product obsolescence indexes to quantify the impact and shifts of each factor across product categories. Unlike previous studies, where (Z. Zhao et al., 2021) constructed obsolescence index (OI) based on product performance data, and (Salas Cordero et al., 2022) used expert assessments and system architecture models for the obsolescence critically index, this research aligns with Industry 4.0 by leveraging real-time UGC data to develop time-series-based product obsolescence indexes (Naeem & Di Maria, 2020b). Enabled by industry 4.0 digital platforms, this approach enhances customer participation and enables continuous tracking of product obsolescence factors, offering a dynamic, UGC-based alternative to static methods like interviews or surveys. By integrating the relative importance of each factor, determined through the Freq-AHP, with their severity impacts on consumers, assessed using RoBERTa model, this approach offers a comprehensive and time-sensitive analysis. This enables product designers to identify critical factors, prioritize improvements, and adapt strategies proactively, advantages that traditional methods lack due to their limited scope and temporal rigidity (Bryman, 2016; Couper, 2000; Y. Zhang & Wildemuth, 2009).

This study makes significant contributions to the engineering management literature by addressing a critical gap in understanding product obsolescence in consumer IoT products, an area previously overlooked. It introduces an innovative research framework that integrates online consumer reviews, pre-trained LLMs, Freq-AHP, and RoBERTa, providing a broader and more insightful approach to identify and quantify product obsolescence factors over time compared to traditional methods. The development of four online consumer opinion-based time-series product obsolescence indexes enables longitudinal tracking of product obsolescence trends, offering a new methodological tool for research on product lifecycle and obsolescence management. Unlike prior studies that rely on product performance data and expert evaluations, this approach leverages real consumer opinions, offering actionable insights for product design improvements. Moreover, identifying previously unrecognized obsolescence factors beyond well-established ones like malfunction, durability, design flaws, battery drain, performance deterioration, working costs, and storage limitation, enhances the understanding of product obsolescence across various smart product categories, providing a foundation for future research. From a practical perspective, this study offers manufacturers, product designers, and engineering managers a consumer-centric approach to monitor product decline in real time, using actual user feedback instead of performance metrics or expert judgements. This real-world insight enables more responsive and informed decision-making regarding software support, hardware upgrades, and customer experience strategies. Ultimately, the framework supports more sustainable engineering practices by promoting longer product lifespans, reducing unnecessary resource use, and enhancing consumer trust (Alzaydi, 2024), key concerns in the management of product obsolescence in the digital era. The remainder of the paper is structured as follows: section 2 reviews the relevant literature, section 3 outlines the methodology, section 4 presents the results, section 5 discusses the findings, and section 6 provides a summary of the study's conclusions.

5.2 Literature

5.2.1 Obsolescence

IEC 62402:2019 defines obsolescence as the transition of a product from being available to unavailable by the original equipment manufacturer (OEM) according to its original specification. A product is considered obsolete when it is no longer produced with the components specified in its original design (Vasilev, 2024). Moreover, the AFNOR NF X60-012: 2006 standard defines "obsolete" as a product that is no longer used or outdated, without implying it is necessarily unavailable (Mellal, 2020). Obsolescence occurs when a product loses usability and desirability due to design choices, technological advancements, or evolving societal norms (Alzaydi, 2024; Sierra-Fontalvo et al., 2023). It devalues products both materially and communicatively and can be triggered by the introduction of more energy-efficient alternatives (Guillard et al., 2023; Proske & Jaeger-Erben, 2019b). Understanding obsolescence helps extend product usage, reduce waste, and promote durable products and circular business models (Sierra-Fontalvo et al., 2023). (Alzaydi, 2024) states that longer-lasting products can lower environmental impact by up to 50%, while durability fosters consumer trust and loyalty. A deep understanding of obsolescence enables designers to forecast longevity, assess environmental and socio-economic impacts, and develop sustainable, innovative products (Alzaydi, 2024; Slade, 2007; Tim Cooper, 2004). Therefore, promoting design longevity, modularity, and sustainable consumption patterns are essential for managing and mitigating obsolescence (T. Cooper, 2010).

5.2.2 Obsolescence of EEE products

The obsolescence of non-smart EEE products is one of the contexts that has received specific attention in prior research. (T. Cooper, 2005) identified key reasons for product obsolescence, including ergonomics, sensory quality, changing needs, functional decline, working costs, and wear-out. (Hennies & Stamminger, 2016b) surveyed German households and found that defects, dissatisfaction, inefficiency, loss of appeal, and replacement by gifts contribute to obsolescence in laptops, TVs, washing machines, and hand mixers. (İmir, 2010a) highlighted factors such as operational and maintenance difficulties, poor performance, lifestyle changes, and the appeal of newer models in the obsolescence of kitchen appliances. In addition, (Karagiannopoulos et al., 2024b) identified high energy consumption as a factor making non-smart residential EEE products unusable.

Smartphone is another category of EEE that has drawn attention for research in the context of product obsolescence, due to its high E-waste generation. (Bilici & Özdemir, 2024) examined smartphone obsolescence in Turkey, identifying factors such as shortened lifespans, newer models rendering older ones outdated, and consumer desire for upgrades driven by marketing activities. (Marina Proske et al., 2016) attributed short smartphone lifespans to broken screens and poor battery performance but emphasized the dominant role of new features and subsidized contracts in driving functional and psychological obsolescence. Economic obsolescence also plays a role, as repairs become costly due to product design, such as non-removable batteries. (Kordic et al., 2018) identified four key drivers: socio-demographic factors, rapid innovation, software/hardware limitations, and maintainability issues, along with the influence of trends and subsidized contracts. Moreover, (Oraee et al., 2024) focused on young adults, highlighting battery life, screen durability, and repair costs, lack of repair skills, and peer pressure as contributors to premature obsolescence. (Wieser & Tröger, 2016) also links smartphone obsolescence to perceptions of technological and aesthetic decline, highlighting how rapid technological advancements and fashion trends encourage replacements over repair or reuse.

The aerospace, aviation, and military sectors have also been studied in the context of software obsolescence, particularly in commercial-off-the-shelf (COTS) products, which render associated EEE devices obsolete. (Muñoz et al., 2015) categorized 25 drivers of software obsolescence in aerospace into external constraints, development environment, and operative environment. (Sandborn, 2007) defined three main causes in the COTS industry: functional obsolescence due to unmet new requirements, technological obsolescence from discontinued vendor support, and logistical obsolescence when storage media becomes unusable. (Merola, 2006) highlighted that COTS software is often withdrawn due to technological progress, declining popularity, or market factors, while vendors may discontinue sales or support for older versions (Kern et al., 2018; Sandborn, 2007). Further, ensuring operational availability in cyber-physical systems (CPSs) requires frequent COTS upgrades, and inadequate planning for sustainment, supportability, and costs can lead to software obsolescence of EEE devices (Blackman & Rogowski, 2008; Sandborn, 2007). Rising sustainment costs, evolving requirements, and necessary enhancements further accelerate obsolescence (N. A. Ernst et al., 2015; Ogheneovo, 2014). Additionally, hardware unavailability, outdated development tools, and poor software distribution mechanism contribute to EEE device obsolescence (Bartels et al., 2012). (Rojo et al., 2009) also emphasized that the loss of employees with specialized software knowledge can expedite obsolescence, as remaining staff may lack the necessary expertise.

The literature on EEE product obsolescence has extensively examined various categories, and specialized sectors. However, research on the obsolescence of consumer IoT devices remains limited, despite their growing prevalence in daily life (Poppe et al., 2021). Furthermore, previous studies have primarily relied on traditional data collection methods, overlooking the potential of online consumer reviews as a valuable source of insight. This study addresses these gaps by utilizing online consumer reviews to identify key factors influencing the obsolescence of consumer IoT devices.

5.2.3 Large language models

Conventional natural language processing (NLP) models remain relevant in certain contexts but require manual feature engineering and struggle with complex linguistic patterns compared to deep learning-based LLMs (Falatouri et al., 2024). These models rely on rule-based systems and statistical techniques for text correction and analysis (Yao et al., 2019; F. Zhou et al., 2020), using linguistic knowledge and heuristic rules such as regular expressions (Garofalakis et al., 2002). While rule-based models effectively handle domain-specific tasks like event detection and named entity recognition, they are limited by a fixed knowledge base (Pustejovsky & Stubbs, 2012). Statistical methods, including term frequency-inverse document frequency (TF-IDF) and vector space models, play a crucial role in document retrieval and search engine indexing (Barkha, 2018). However, LLMs are advanced AI system designed for high-level language interpretation with human-like fluency (Devlin et al., 2018). Models such as BERT (George & Sumathy, 2023) and RoBERTa (Y. Liu, Ott, et al., 2019b) are effective for topic modeling and classification but require careful hyperparameter tuning, have context limitations, and demand human effort for interpretation (Rao et al., 2024). Advancements in pre-trained LLMs and prompt engineering have improved large-scale text analysis (Deng et al., 2023; Pham et al., 2023). For example, ChatGPT, a pre-trained LLM model with billions of parameters, has been trained on diverse internet text and literature (Brown et al., 2020). Such pre-trained LLMs exhibit emergent capabilities in machine translation, text summarization, NLP, ideological scaling, and text annotation (Gilardi et al., 2023; Leippold, 2023; P. Y. Wu et al., 2023; W. X. Zhao et al., 2023). While these models are designed for general applications, they outperform traditional computational methods in detecting irony, sarcasm, and nuanced subjective interpretations (Törnberg, 2023).

5.2.4 Multicriteria decision-making

Multicriteria decision-making (MCDM) emerged in the 1970s, with over 70 techniques developed, each with distinct models, assumptions, and methods (Ghaleb et al., 2020). Selecting an appropriate method is essential for accurate assessment. Commonly used techniques for determining criterion weights and ranking alternatives includes analytic network process (ANP), višekriterijumsko kompromisno rangiranje (VIKOR), technique for order of preference by similarity to ideal solution (TOPSIS), and AHP. ANP evaluates interactions and interdependencies among factors without requiring a hierarchical structure (Kheybari et al., 2020). TOPSIS ranks alternatives by selecting the option closest to the ideal solution and farthest from the negative ideal (Papathanasiou & Ploskas, 2018). VIKOR is designed for discrete decision problems involving conflicting and noncommensurable criteria (Opricovic & Tzeng, 2004). This study employs AHP, introduced by (T. L. Saaty, 2008), due to its ability to handle both weighting and ranking simultaneously, a feature less common in other MCDM methods (Dagtekin et al., 2022). AHP is straightforward to apply, involves a simple calculation process, and uses a hierarchical structure to systematically evaluate all criteria and present alternatives transparently. It also structures decision problems hierarchically to align with research goals (Forman & Gass, 2001), integrates decision-maker input, incorporates a consistency ratio for reliable weighting, and converts subjective judgments into objective numerical values for comparison (Choudhary & Shankar, 2012; Sindhu et al., 2016).

5.3 Methodology

To assess the suitability of pre-trained LLMs in identifying factors influencing consumer IoT devices obsolescence, online obsolescence-related reviews are analyzed. Reviews were selected based on two criteria: (1) The review must explicitly indicate that the product has been removed from use by the consumer or disposed of; (2) The review should convey a definitive intention of discontinuing use or replacing the product with an alternative.

These criteria ensure the study focuses on reviews that provide explicit reasons for product obsolescence. After identifying and labelling these reviews using a pre-trained LLM, UGC time-series-based product obsolescence indexes, were developed to measure and track the impact of each factor, integrating their relative significance as determined by Freq-AHP with their severity influence on consumers, analyzed through RoBERTa, as illustrated in Figure 5.1.

5.3.1 Data preparation

To evaluate the effectiveness of pre-trained LLMs in identifying factors contributing to obsolescence of consumer IoT devices, 47,695 online reviews were collected from Amazon.com and BestBuy.com. The dataset includes reviews of 93 individual products, 20 distinct product types, and 9 different product categories, as detailed in Appendix III. Traditional text mining for text analysis involves tokenization, stop word removal, stemming, or lemmatization, and part-of-speech modification (Bird, 2017). However, pre-trained LLMs streamline this process, reducing the need for manual preprocessing (Nasseri et al., 2023).

5.3.2 Model determination

Three pre-trained LLMs—ChatGPT-4o, Llama 3, and Claude-3 Opus—were evaluated for their effectiveness in extracting factors contributing to obsolescence of consumer IoT devices. ChatGPT-4o was selected for its adaptability and ability to be fine-tuned for NLP tasks, enhancing performance across various domains (X. Liu et al., 2023). To compare results and explore alternatives, Llama 3 by Meta was included, recognized for its advanced reasoning capabilities and strong performance in deep linguistic and cultural tasks (Lu et al., 2024; Meta, 2024). Additionally, Anthropic's Claude-3 Opus was selected as another competitor, with its series offering varying levels of speed and quality (Anthropic, 2024). In this study, the temperature was set to 0.2 to ensure more focused and deterministic outputs, as higher values, such as 0.8, increase diversity and unpredictability (Törnberg, 2023).

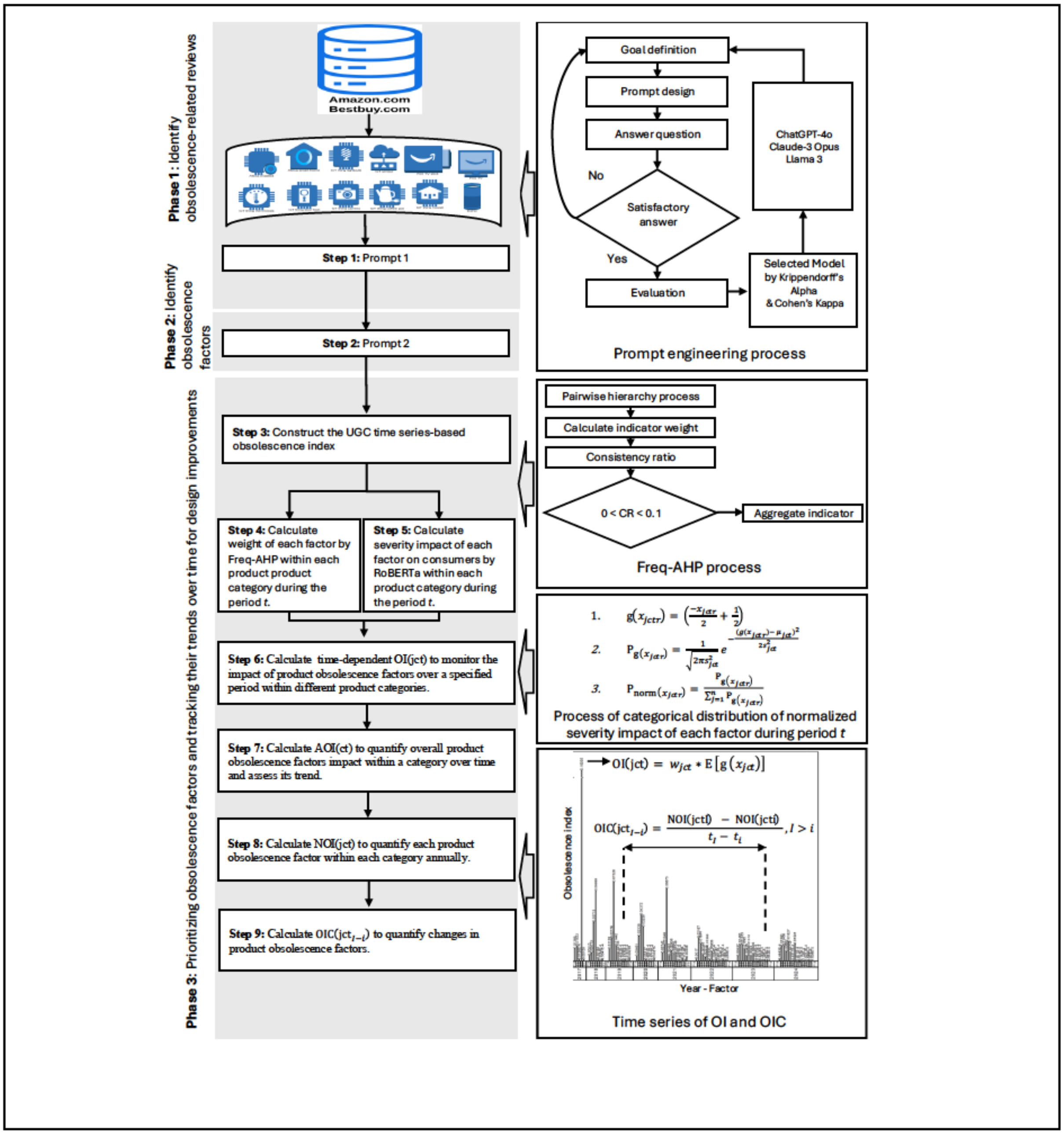


Figure 5.1 Data processing framework for calculation of product obsolescence factors

5.3.3 Prompt engineering

A prompt is a textual instruction that enhances a GPT model's functionality (P. Liu et al., 2023), but crafting effective prompts requires creativity, intuition, and iterative refinement (Lo, 2023). Poorly designed prompts can lead to vague, inaccurate, or contextually inappropriate responses (White et al., 2023). To address this, the GPEI framework (Velásquez-Henao et al., 2023) is applied, consisting of four steps: defining a goal, designing the prompt, evaluating the response, and iterating. Two prompts are used in this study: the first instructs the model to classify reviews as relevant or irrelevant to product obsolescence, ensuring that only meaningful online reviews are analyzed. The second prompt directs the model to extract product obsolescence factor from the relevant reviews, providing insights into why products have been considered obsolete based on consumer feedback. These prompts serve distinct purposes – classification and factor analysis – outlined in Table 5.1 and Table 5.2.

Table 5.1 Prompt 1 for identifying obsolescence-related reviews

```
def  classify_review (review_text, product_name):
    prompt = f"""
    I am analyzing a dataset of customer reviews and need your assistance in classifying these
    reviews. Specifically, classify each review as "related" to product obsolescence based on
    the following criteria: First, the review must explicitly indicate that the product has been
    removed from use by the consumer or disposed of. Second, the review should express a
    clear intention of discontinuing use or replacing the product with an alternative. If either
    condition is met, respond only with 'related'. Otherwise, respond only with 'unrelated'.
    Review: "{review_text}"
       Classification (related / unrelated):
       """
```

Table 5.2 Prompt 2 for identifying the factors of product obsolescence

```
def  generate_text_for_review(review_text):
    prompt = f"""
    I am analyzing a dataset that includes customer reviews for smart products. You are my
    assistant in reviewing each customer feedback entry to identify the major problem causing
    consumers to stop using the product. If a customer feedback entry mentions more than
    one major problem, list them using this format: Reason / Reason. Provide just a single
    comprehensive word to represent each problem without explanation.
    Review: "{review_text}"
```

5.3.4 Evaluation

To ensure the reliability of pre-trained LLM-generated outputs, rigorous evaluation routines are implemented before interpretation and comparison (Törnberg, 2023). First, a randomly selected subsample was assessed by three independent researchers based on predefined criteria.

Online reviews were included only if they clearly explained product obsolescence. Only reviews with consensus among reviewers were considered (Falatouri et al., 2024), leading to a final sample of 1,000 reviews used to assess pre-trained LLMs reliability in identifying obsolescence-related reviews. Then, Krippendorff's alpha (De Swert, 2012) and Cohen's Kappa index metric (Wongpakaran et al., 2013) were used to assess the alignment between model results and validation data. These metrics measure how much the model and validation data agree while also adjusting for any agreement that might have occurred due to random coincidence. Scores range from 0 to 1, with higher values indicating stronger consensus. The model with highest agreement is selected for the next phase, which involves extracting product obsolescence factors from the dataset.

5.3.5 Prioritizing obsolescence factors for design improvement

5.3.5.1 Obsolescence index (OI)

OI is a quantitative measure that captures the impact of factors contributing to product obsolescence within each product category in this study. It helps prioritize critical factors driving product obsolescence, enabling targeted improvements to enhance product longevity. The calculation of OI is designed to accommodate different purposes, following a three-step approach. In the first approach, OI is introduced as a time-dependent function, $OI_{(jct)}$, to monitor the impact of product obsolescence factors over a specified period within different product categories. The calculation of $OI_{(jct)}$ involves two steps: (1) determining the relative importance of each product obsolescence factor using Freq-AHP, which assigns weights based on factor frequency within each product category over a specific period of time, and (2) quantifying the expected severity impact of each product obsolescence factor using RoBERTa to analyze sentiment intensity in online consumer reviews. Since dissatisfaction can drive obsolescence even when a product remains functional (Hou et al., 2020; van den Berge et al., 2021), it serves as a critical component of the analysis. The severity of a product issue is closely linked to the intensity of negative emotions, as more severe problems elicit stronger negative responses (Catenazzo & Paulssen, 2023; Wei et al., 2023). By integrating these dimensions, $OI_{(jct)}$ provides a dynamic, consumer-driven assessment of product obsolescence factors across different product categories. $OI_{(jct)}$ is defined as follows:

$$OI_{(jct)} = w_{jct} * E\left[g\left(x_{jct}\right)\right], \ \forall t, t = 1, 2, \ldots, k; \ \forall c, c = 1, 2, \ldots, n; \ \forall j, j = 1, 2, \ldots., m. \quad (5.1)$$

Here:

- w_{jct} represents the relative importance of an obsolescence factor within a product category over a defined period.
- $E\left[g\left(x_{jct}\right)\right]$ denotes the sum of the expected values of the emotional impact of an obsolescence factor, reflecting the severity of consumer dissatisfaction associated with each factor within a product category over a defined period.
- j represents an obsolescence factor.
- c signifies a product category.
- t indicates a period.

To determine the relative importance of each product obsolescence factor within each product category over a defined period (w_{jct}), the Freq-AHP is applied. Traditional AHP relies on expert grading to assign wights, which can introduce subjectivity due to reliance on expert opinion. To enhance objectivity, this study employs the Freq-AHP method established by (Liang et al., 2021), which replaces expert grading with frequency-based pairwise comparison matrices, ensuring a more data-driven and unbiased weighting process. The process involves the following steps:

1.1. Frequency vector $F = (f_1, f_2, \ldots., f_m)$ is derived, where f_j represents the frequency of the j-th obsolescence factor.
1.2. Pairwise comparison matrix: the relative importance of obsolescence factor a_j compared to obsolescence factor a_i is calculated as:

$$a_{ji} = {}^{f_j}\!/_{f_i} \quad (5.2)$$

and the pairwise comparison matrix A is constructed as:

$$A = \begin{bmatrix} a_{11} & a_{12} \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} \cdots & a_{nn} \end{bmatrix} \tag{5.3}$$

Here

- $a_{ji} = {f_j}/{f_i}$ represents the relative importance of factor a_j to factor a_i.
- f_j and f_i denote the frequency of obsolescence factors a_j and a_i, respectively.
- $a_{j\,i}$= 1: Since the importance of an obsolescence factor relative to itself is always 1.

After building the paired comparison matrix A, the relative importance of various indexes is computed using the geometric mean normalization technique. w_{jct} symbolizes the degree of importance for the j-th index:

$$w_{jct} = \frac{(\prod_{i=1}^{n} a_{ji})^{1/n}}{\sum_{j=1}^{n}(\prod_{i=1}^{n} a_{ji})^{1/n}}, j = 1, 2, \ldots, m; t = 1, 2, \ldots, k; c = 1, 2, \ldots, n. \tag{5.4}$$

To confirm that pairwise comparison is rational and suitable, a consistency test must be carried out as:

$$C = A * w_{ct}^{T} \tag{5.5}$$

Where:

$$w_{ct}^{T} = [w_{1ct}, w_{2ct}, \ldots, w_{mct}]^{T}, \text{(T denotes the transpose operation)} \tag{5.6}$$

Here:

- A is the pairwise comparison matrix ($n * n$).
- w_{ct}^{T} is the weight vector of all factors in category c at period t, structured as an $n * 1$ column vector.
- Each value in w_{ct}^{T} represents the weight of factor j-th (where j = 1, 2, …, m) in category c at time t, calculated using formula (4).

Then, the consistency values for each factor within each product category over a defined period can be computed as:

$$CV_{jct} = \frac{c_{jct}}{w_{jct}}, j = 1, 2, \ldots, m; t = 1, 2, \ldots, k; c = 1, 2, \ldots, n. \tag{5.7}$$

Here:

- c_{jct} is the consistency vector value for factor *j* in category *c* at time *t*.

  Where:

  $$c_{jct} = a_{j1}w_{1ct} + a_{j2}w_{2ct} + \cdots + a_{ji}w_{mct}\ , j = 1, 2, \ldots, m; t = 1, 2, \ldots, k; c = 1, 2, \ldots, n \tag{5.8}$$

  Here:

  i. a_{ji} is obtained as per formula (5.2).

  ii. $w_{1ct}, w_{2ct}, \ldots, w_{mct}$ are the corresponding factor weights from the weight vector w_{ct}^{T}.

- w_{jct} follows the calculation outlined in equation (5.4).

To avoid any inconsistency due to diversified measurement scales in the assessment process, R. W. Saaty (1987) recommended application of maximal eigenvalue λ_{max} to assess the validity of measurements. The maximal eigenvalue can be determined using the following equation:

$$\lambda_{max} = \frac{\sum_{j=1}^{n} cv_{jct}}{n} \quad j = 1, 2, \ldots, n. \tag{5.9}$$

Using λ_{max}, a consistency index (CI) can be calculated as follows:

$$\text{CI} = \frac{\lambda_{max} - n}{n-1} \tag{5.10}$$

The value of CI = 0, suggesting that the pairwise comparison is entirely consistent. Note that the closer the maximal eigenvalue is to *n*, the more consistent assessment is. Typically, a consistency ratio (CR) (R. W. Saaty, 1987) can be used as a guidance value to check for conformity :

$$\text{CR} = {}^{CI}\!/_{RI} \tag{5.11}$$

RI represents the average random consistency index (Franek & Kresta, 2014) with the value that is estimated using different orders at the pairwise matrices of comparison as presented in Table 5.3. If the CR value is less than 0.1, then the importance degree evaluation of criteria is assumed to be rational.

TABLE 5.3 The value of random consistency index RI

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.46	1.58	1.48	1.56	1.57	1.59

After determining the relative importance of each product obsolescence factor, the sum of the expected values of their severity impact within each product category over a defined period is calculated. This begins with applying RoBERTa to analyze the sentiment intensity in each online review, assigning values from -1 (negative) to 1 (positive) (Penmetsa et al., 2021). RoBERTa, an improved adaptation of BERT, is fine-tuned to address BERT's training complexity and missing hyperparameters (Y. Liu, Ott, et al., 2019a). Since the severity level must be represented on a 0 (positive) to 1 (negative) scale – where 0 indicates the lowest and 1 the highest intensity – to ensure $OI_{(jct)}$ remains within this ranges, sentiment intensity results are normalized. This normalization adjusts sentiment scores from the original -1 to 1 scale to align with the required format. Thus, g (x_{jctr}) represents the normalized sentiment intensity of each online review associated with product obsolescence factor j within product category c over a defined period t, ensuring consistency in measuring impact. Let g (x_{jctr}) be:

$$g(x_{jctr}) = \left(\frac{-x_{jctr}}{2} + \frac{1}{2}\right), j = 1, 2, \ldots, m; t = 1, 2, \ldots, k; c = 1, 2, \ldots, n; r = 1, 2, \ldots, y. \quad (5.12)$$

Where:

- x_{jctr} denotes the sentiment intensity of a single review r (where r = 1, 2, …, y), associated with obsolescence factor j within product category c over a defined period t, as calculated by RoBERTa.

Next, to ensure that the normalized intensity of each online review r contributes proportionally and fairly to the overall calculation, the expected value is used. This method effectively addresses the non-uniform distribution of sentiment data by incorporating probability distribution, which accounts for the relative likelihood of each normalized sentiment intensity g (x_{jctr}). By weighing frequent values more heavily and minimizing the influence of anomalies, this approach provides a more accurate representation of overall behavior. To do so, first probability distribution is defined as:

$$\mathrm{P}_{\mathrm{g}\,(x_{jctr})} = \frac{1}{\sqrt{2\pi s_{jct}^2}} e^{-\frac{(g(x_{jctr}) - \mu_{jct})^2}{2s_{jct}^2}}, j = 1, 2, \dots, m; t = 1, 2, \dots, k; c = 1, 2, \dots, n; r = 1, 2, \dots, \mathrm{y}. \quad (5.13)$$

Where:

- $\mathrm{P}_{\mathrm{g}\,(x_{jctr})}$ is probability distribution of $\mathrm{g}\,(x_{jctr})$.
- $\mathrm{g}\,(x_{jctr})$ is the normalized sentiment intensity of review *r*, associated with factor *j*, in product category *c*, during period *t*.
- μ_{jct} is mean of the normalized sentiment intensity of reviews, associated with factor *j*, in product category *c*, during period *t*.
- s_{jct}^2 is sample variance of the normalized sentiment intensity of reviews, associated with factor *j*, in product category *c*, during period *t*: $s_{jct}^2 = \frac{\Sigma(\mathrm{g}\,(x_{jctr}) - \mu_{jct})^2}{n_{jct} - 1}$.
- n_{jct} is the number of reviews mentioning factor *j* in category *c* over period *t*.

After computing the probability distribution of $\mathrm{g}\,(x_{jctr})$, normalization is applied to ensure that the sum of all probabilities equals 1, which is a fundamental property of valid probability distributions. So let $\mathrm{P}_{\mathrm{norm}\,(x_{jctr})}$ be:

$$\mathrm{P}_{\mathrm{norm}\,(x_{jctr})} = \frac{\mathrm{P}_{\mathrm{g}\,(x_{jctr})}}{\sum_{j=1}^{n} \mathrm{P}_{\mathrm{g}\,(x_{jctr})}}, j = 1, 2, \dots, m; t = 1, 2, \dots, k; c = 1, 2, \dots, n; r = 1, 2, \dots, \mathrm{y}. \quad (5.14)$$

Subsequently, to calculate expected value of $\mathrm{g}\,(x_{jctr})$, $\mathrm{E}\,[\mathrm{g}\,(x_{jctr})]$ is defined as:

$$\mathrm{E}\,[\mathrm{g}\,(x_{jctr})] = \mathrm{P}_{\mathrm{norm}\,(x_{jctr})} * \mathrm{g}\,(x_{jctr}),, j = 1, 2, \dots, m; t = 1, 2, \dots, k; c = 1, 2, \dots, n; r = 1, 2, \dots, \mathrm{y}. \quad (5.15)$$

To compute the overall expected value of emotional impact of each factor j within product category c over period t, we sum $\mathrm{E}\left[\mathrm{g}\left(x_{jctr}\right)\right]$ as:

$$\mathrm{E}\left[\mathrm{g}\left(x_{jct}\right)\right] = \sum_{r=1}^{n_{jct}} \mathrm{P}_{\mathbf{norm}\,(x_{jctr})} * \mathrm{g}\left(x_{jctr}\right), \forall t, t = 1, 2, \dots, k;\ \forall c, c = 1, 2, \dots, n;\ \forall j, j = 1, 2, \dots, m. \quad (5.16)$$

In the second approach, the aggregated product obsolescence index ($\mathrm{AOI}_{(ct)}$) was computed to quantify overall product obsolescence factors impact within a category over time and assess its trend. This index was derived by summing $\mathrm{OI}_{(jct)}$ for each product category annually, weighted by the proportion of online obsolescence-related reviews in that year relative to the total across all years. This normalization accounts for fluctuations in review volume, ensuring that observed trends reflect actual shifts in product obsolescence factors impact rather than inconsistencies in data availability, providing a more reliable basis for longitudinal analysis. Let $\mathrm{AOI}_{(ct)}$ be:

$$\mathrm{AOI}_{(\mathrm{ct})} = \left(\frac{NR_{ct}}{\sum_{t=1}^{T} NR_{ct}}\right) * OI(ct), \forall t, t = 1, 2, \dots, k;\ \forall c, c = 1, 2, \dots, n. \quad (5.17)$$

Where:

- NR_{ct} is the number of online obsolescence-related reviews for product category c in period t.
- $\sum_{t=1}^{T} NR_{ct}$ is the total number of online obsolescence-related reviews for category c across all time periods.
- $OI_{(\mathrm{ct})}$ is sum of all $\mathrm{OI}_{(jct)}$ within category c in period t: $OI_{(\mathrm{ct})} = \sum_{j=1}^{m} OI_{jct}$.

In the final approach, the product obsolescence index change ($OIC_{(\mathrm{jct}_{I-i})}$) was introduced to track how the impact of an obsolescence factor evolves within a category over time. By calculating $OIC_{(\mathrm{jct}_{I-i})}$, trends in product obsolescence factors can be observed, indicating whether their influence is increasing or decreasing. This dynamic analysis provides a deeper understanding of temporal shifts in factor impact, allowing for the identification of critical periods where product improvements are most needed to mitigate obsolescence risk. So, to ensure accurate trend analysis, the normalized product obsolescence index ($NOI_{(jct)}$) was first calculated for each factor within each category annually, offering a standardized assessment. Since $OI_{(jct)}$ reflects the impact of factor *j* in category *c* over period *t*, direct comparisons across years can be misleading if fluctuations in factor identification are not considered. Normalization is essential to prevent misinterpretation, ensuring that observed changes in $OIC_{(\mathrm{jct}_{I-i})}$ reflects actual shifts in obsolescence factor impact rather than inconsistencies in factor identification. Let $NOI_{(jct)}$ be:

$$\mathrm{NOI}_{(\mathrm{jct})}= \left(\frac{NF_{(jct)}}{\sum_{t=1}^{T} NF_{(jct)}}\right) * OIC_{(\mathrm{jct})}, \forall t, t = 1, 2, \dots, k;\ \forall c, c = 1, 2, \dots, n;\ \forall j, j = 1, 2, \dots., m. \tag{5.18}$$

Where:

- $NF_{(jct)}$ is the number of product obsolescence factor *j* within category *c* over period *t*.
- $\sum_{t=1}^{T} NF_{(jct)}$ is the total number of product obsolescence factor *j* within category *c* across all years.
- $OI_{(jct)}$ is obtained as per equation (5.1).

Then to calculate $OIC_{(\mathrm{jct}_{I-i})}$, it is defined as:

$$OIC_{(\mathrm{jct}_{I-i})} = \frac{NOI_{(\mathrm{jctI})} - NOI_{(\mathrm{jcti})}}{t_I - t_i}, \forall t, t = 1, 2, \dots, k; I > i;\ \forall c, c = 1, 2, \dots, n;\ \forall j, j = 1, 2, \dots., m. \tag{5.19}$$

Where:

- $NOI_{(\mathrm{jctI})}$ is $NOI_{(\mathrm{jct})}$ of factor *j* within category *c* at t_I.
- $NOI_{(\mathrm{jcti})}$ is $NOI_{(\mathrm{jct})}$ of factor *j* within category *c* at t_i.
- $t_I - t_i$ is the time interval between the two measurements of the $NOI_{(\mathrm{jct})}$ while $I > i$.

5.4 Result

5.4.1 Extraction of obsolescence-related reviews and associated factors to obsolescence

To determine the most accurate LLM before applying prompt 1 to the full dataset of 47,695 reviews, a randomly selected subsample of 1,000 reviews was independently evaluated by three researchers based on predefined criteria. After labeling, prompt 1 was tested on this subsample to assess each LLM's ability to identify obsolescence-related reviews. As shown in Table 5.4, ChatGPT-4o outperformed Claude-3 Opus and Llama 3. Consequently, ChatGPT-4o was used to process the entire dataset, identifying 4,771 obsolescence-related reviews. Prompt 2 was then applied to these reviews to analyze and assign labels to the specific factors leading consumers to discontinue product use.

Table 5.4 Comparison of LLMs in identifying obsolescence-related reviews

	ChatGPT-4o	**Claude-3 Opus**	**Llama 3**
Krippendorff's alpha	0.529	0.504	-0.190
Cohen's Kappa	0.531	0.507	-0.059

ChatGPT-4o assigned multiple labels to the reviews, which were later grouped into 19 broader categories by researchers, as outlined in Appendix IV. Key obsolescence factors common to all product categories are malfunction, durability, design flaws, connectivity issue, incompatibility, inaccuracy, latency issue, controllability issue, and poor user interface, as shown in Figure 5.2.

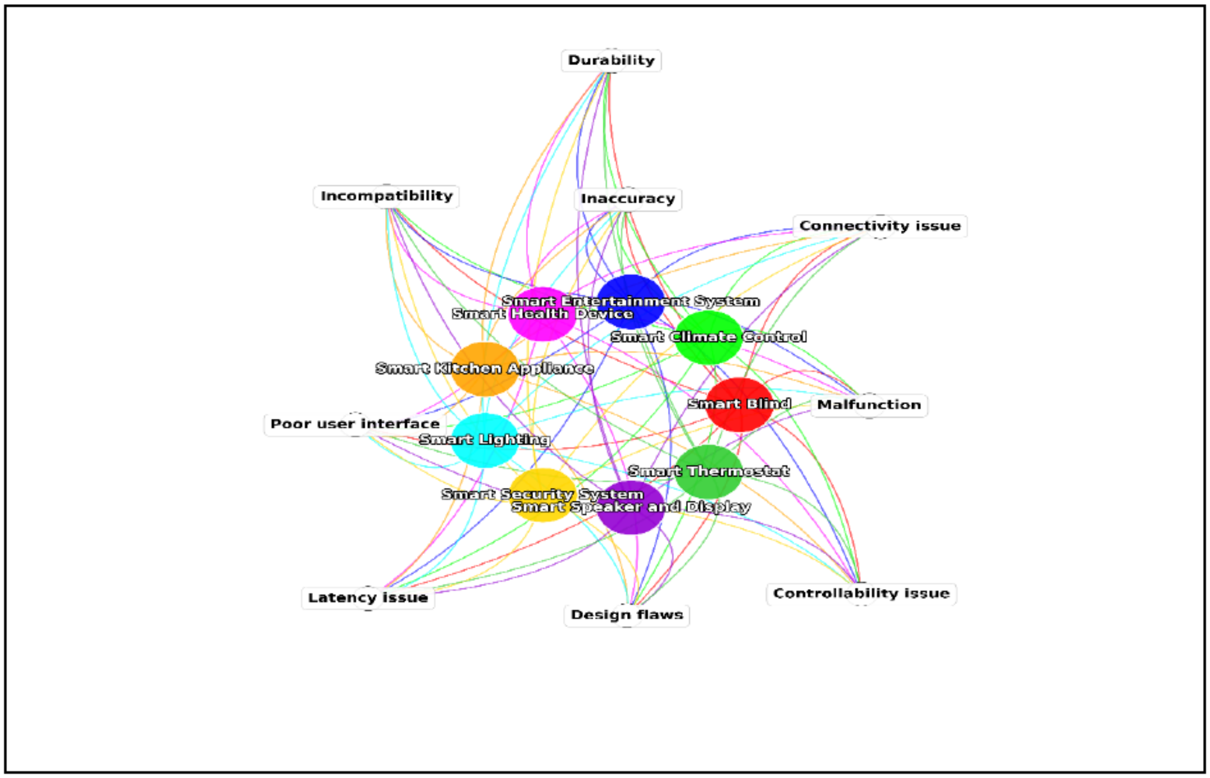


Figure 5.2 Smart product category networks with their associated obsolescence factors

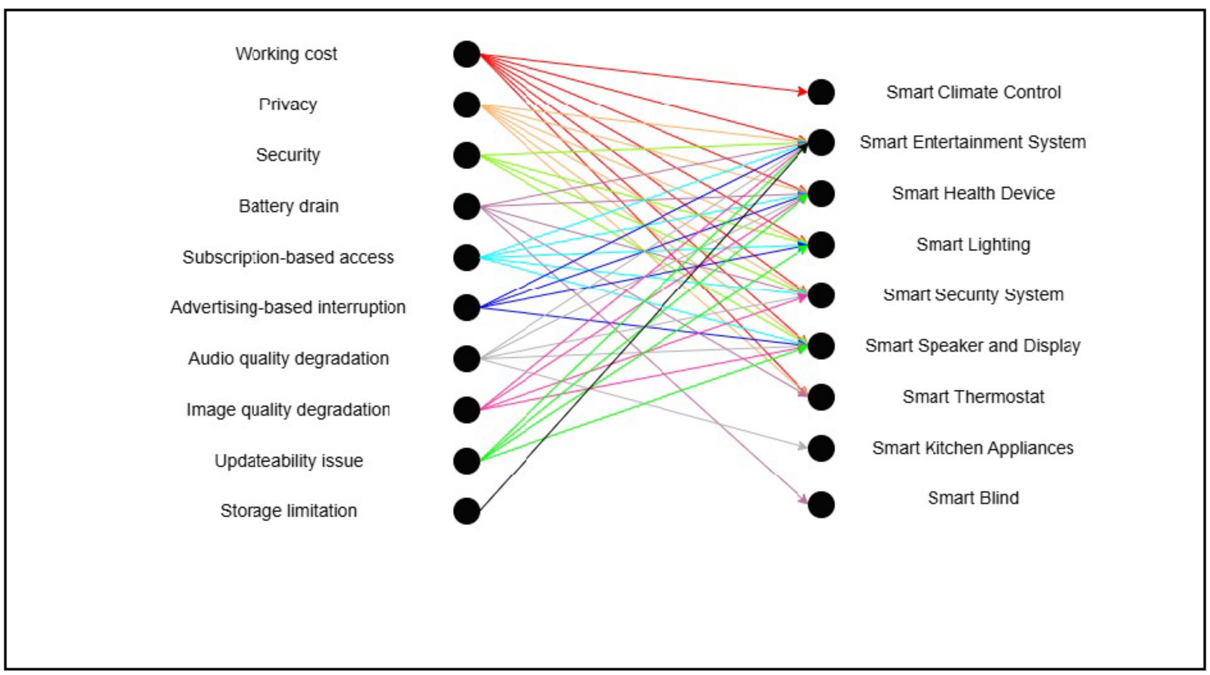


Figure 5.3 Factors influencing obsolescence in some product categories

However, ten factors: working costs, privacy, security, battery drain, subscription-based access, advertising-based interruption, audio quality degradation, image quality degradation, updateability issue, and storage limitation – contribute to obsolescence in specific product categories rather than all, as shown in Figure 5.3.

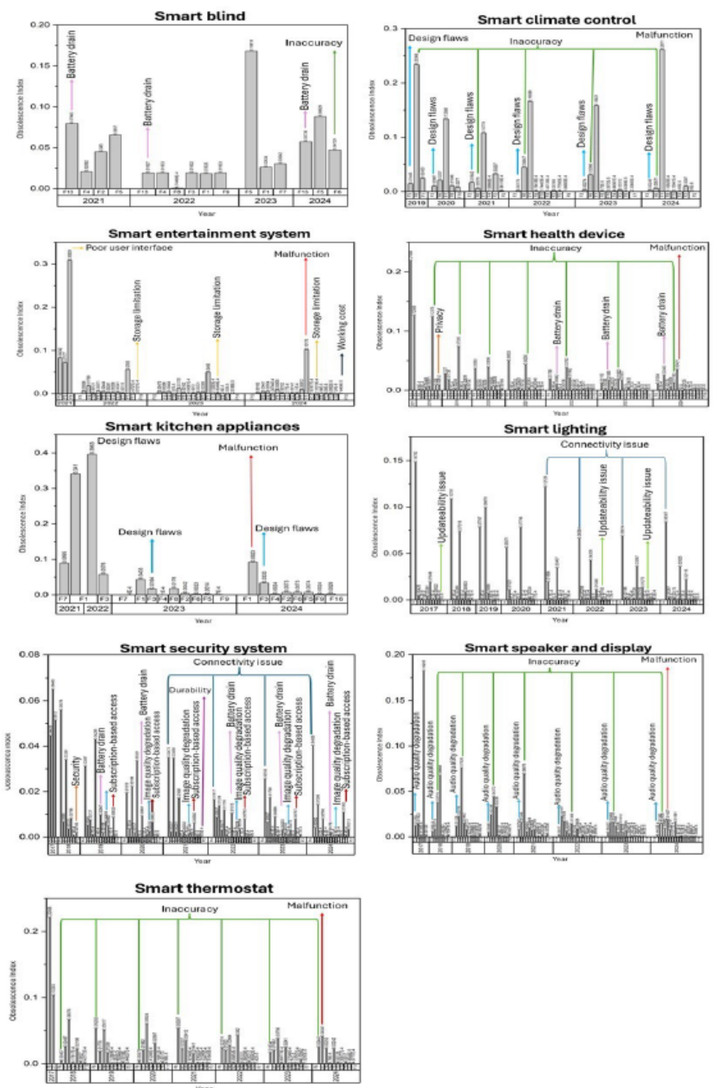
5.4.2 Factors influencing obsolescence of consumer IoT devices

The Freq-AHP method, as detailed in Formulas 4 to 11, was employed to assign weights to product obsolescence factors across all product categories and time periods. The CI was 0, and the CR was below 0.1, ensuring a reliable and consistent weighting process. Following this, the dissatisfaction levels associated with each obsolescence factor were computed using Formula 16. With both the weight and dissatisfaction level of each factor established, $OI_{(jct)}$ was then calculated using Formula 1 to quantify the impact of each obsolescence factor within its respective category over a defined period, as illustrated in Figure 5.4. To further analyze obsolescence factor trends, Formula 18 was applied to compute $NOI_{(jct)}$, enabling an assessment of factor variations across product categories over time. Appendix V highlights shift in obsolescence factors that exhibited notable changes. Additionally, obsolescence factors with the most substantial $OIC_{(\mathrm{jct}_{I-i})}$ values were identified, providing insights into how their influence evolved over time. The discussions and insights presented in the following sections align with Figures 5.4 and Appendix V, offering a comprehensive visual representation of both static and dynamic trends in obsolescence factors across different product categories.

Malfunction is a key driver of product replacement (Wieser & Tröger, 2016), as it diminishes consumer satisfaction and fosters the desire to replace products (Brigden & Häubl, 2020). Its prevalence has increased across most categories, with notable positive $OIC_{(\mathrm{jct}_{I-i})}$ values for smart climate control (0.02 from 2019 to 2024) and smart entertainment system (0.03 from 2022 to 2024), indicating a rising impact in these categories. In 2024, malfunction recorded the highest $OI_{(jct)}$ across six product categories, as shown in Figure 5.4, establishing it as the most significant obsolescence factor. It affects both software and hardware, with software-related issues, such as technical errors, unexpected behavior, and random resets, and hardware problems, including examples like excessive noise and water leakage, as outlined in Table 5.5.

Connectivity issue has had a moderate impact across most product categories but has been particularly significant in smart lighting and smart security systems, especially after 2021. This trend aligns with findings by (Parise et al., 2024; Touqeer et al., 2021), who highlight growing challenge of maintaining stable connectivity as more devices integrate into these networks. Smart security systems have experienced the most significant increase in $OIC_{(\mathrm{jct}_{I-i})}$ (0.002 from 2017 to 2024), while in smart climate control, it has fluctuated but has shown a declining impact since 2023. Key causes of connectivity issue include Wi-Fi or Bluetooth disruptions, signaling and bandwidth constraints, presence detection failures, and inference, all of which significantly impair device functionality (Eltholth, 2023; Petrut & Otesteanu, 2018).

Inaccuracy became a notable concern for smart blind in 2024 and remained a persistent issue in smart climate control, despite claims of high accuracy in this category (Efthakhar Alam et al., 2024; Iessa, 2024). It significantly impacted obsolescence in smart health devices across most periods, particularly for example in smartwatches, where systematic bias affects the measurement of moderate to vigorous physical activity (Degroote et al., 2018), with an increasing trend. In smart speaker and display, inaccuracy has been a critical factor of obsolescence, primarily due to speech recognition errors (Wei et al., 2021), resulting in consistency high $OI_{(\mathrm{jct})}$ levels, a trend that has been increasing since 2022. In contrast, while inaccuracy has had a substantial $OI_{(\mathrm{jct})}$ in smart thermostat over multiple periods, it has declined since 2021, likely due to advancements in occupancy detection technology (Stopps & Touchie, 2021). A similar decline has been observed in smart security systems since 2020, attributed to the integration of advanced technologies (Anoosha Iqtidar et al., 2024). Collectively, these trends highlight the role of technological advancements in mitigating inaccuracy-related obsolescence across diverse product categories. Moreover, incompatibility is a factor contributing to obsolescence, with moderate effects on some smart categories and substantial impacts on others, particularly in earlier years. While its influence has declined in some categories due to initiatives like the Matter standard and emerging framework such as Lumos, which promote interoperability (Gorinsky et al., 2020; Madadi-Barough et al., 2024), it has increased in others, likely due to the absence of slower adoption of such advancements. This trend highlights the ongoing fragmentation of the smart home market, where full interoperability remains unachieved. The persistent challenges associated with incompatibility emphasize the need for comprehensive solutions capable of seamlessly integrating diverse devices across different ecosystems (Gorinsky et al., 2020).



Note: The acronyms referenced in Figure 5.4 are clarified as follows: F1: Malfunction – F2: Durability – F3:Design flaws– F4: Connectivity issue – F5: Incompatibility – F6: Inaccuracy – F7: Latency issue – F8: Controllability issue – F9: Poor user interface – F10: Working cost – F11: Privacy – F12: Security – F13: Battery drain – F14: Subscription-based access – F15: Advertising-based interruption – F16: Audio quality degradation – F17: Image quality degradation – F18: Updateability issue – F19: Storage limitation

Figure 5.4 Annual $OI_{(jct)}$ across IoT product categories

Controllability refers to the ability to remotely and automatically manage devices while allowing users to customize functions to their preferences (Xu et al., 2024; Yar et al., 2021), as shown in Table 5.5. While it had a low impact on some product categories, it has had a moderate effect on smart lighting and smart security systems in previous years. However, this impact has recently declined due to advancements such as naming mechanisms that enable control of multiple appliances with a single command (X. Wang & Qian, 2024; Yar et al., 2021). Additionally, improvements in balancing automation with meaningful user interaction and increasing user agency have contributed to this decline (Geeng & Roesner, 2019; Xu et al., 2024). Conversely, it has increased in smart thermostat after 2021, an example illustrated in Table 5.5. This rise is attributed to design limitations, including reliance on single-point temperature readings, standard comfort models, and inaccurate user mental models (S. Kang et al., 2023; Mulayim et al., 2024). These constraints often lead users to override automated settings to achieve thermal comfort and precise control, underscoring the need for more adaptive, user-centric systems (Kane & Sharma, 2019; S. Kang et al., 2023; Mulayim et al., 2024). Another important factor to consider is durability, defined as a product's ability to maintain functionality and performance over its expected lifespan (Maitre-Ekern & Dalhammar, 2016). While its impact remained low in four product categories and moderate in smart climate control, smart health device, and smart lighting throughout each period, the importance of designing longer-lasting products to meet consumer expectations has gained increasing attention (Alzaydi, 2024). Short-lived products harm brand reputation and deter future purchases, as reflected in Table 5.5. In smart security systems category, durability emerged as an obsolescence factor in 2021 and continued to increase through 2024. This trend is attributed to environmental factors and inconsistent power supply, highlighting the need for more robust designs and regular system updates to enhance longevity (Vardakis et al., 2024; Yuan et al., 2023).

Poor user interface, though having a low impact on eight product categories, emerged as an obsolescence factor, with the highest $OI_{(jct)}$ recorded in 2021 for smart entertainment systems. However, after 2021, its impact declined, largely due to efforts aimed at simplifying complex features, operating systems, and brand-specific interfaces, which previously led to cognitive overload and navigation difficulties (Alam et al., 2019; Faizrakhmanov et al., 2023). To address these challenges, solutions such as user surveys, intuitive interfaces, personalized experiences, and context-aware applications should be implemented (Faizrakhmanov et al., 2023; Srinivasrao et al., 2024) to enhance usability and mitigate interface-related obsolescence in consumer IoT devices. Design flaws, encompassing aesthetics (Folkmann, 2010; A. Zhou et al., 2023), ergonomics (Safin et al., 2020; Sagot et al., 2003), shape and color (Homburg et al., 2015), and material (Ashby & Johnson, 2013; Karana et al., 2008), contribute to obsolescence. While aesthetics and ergonomics are widely recognized as critical factors (Tim Cooper, 2004), this study emphasizes material-related issues as equally significant. For example, one consumer review, "*...the noxious plastic smell emanating from the unit was making me sick.*" Design flaws have had a low impact across most product categories, except for smart climate control and smart kitchen appliances, where $OI_{(jct)}$ was notably higher. These two categories also experienced the most significant increase in $NOI_{(jct)}$, highlighting the growing influence of design-related issues in their obsolescence. Turning to another technical factor, latency, defined as the time taken for data transmission (Abu Bakar, 2020), contributes to product obsolescence by affecting user satisfaction. Different applications have varying latency tolerance: remote control systems require millisecond-level responses, while environmental control systems can accommodate delays of a few seconds. Soft real-time systems, such as light controls, tolerate minor delays, but response times exceeding 250ms degrade quality (Fariza et al., 2016). Latency had a minimal impact on half of the product categories and disappeared in some after 2023. However, it fluctuated in smart lighting, smart speaker and display, and smart security systems, while its effect increased in smart entertainment system. These variations emphasize the need for application-specific latency optimizations to maintain performance and enhance user satisfaction across different product categories.

TABLE 5.5 Examples of customer review comments

Product type	Review
Smart air purifier	**Works well, plagued by "clicking" sound** Reviewed in the United States on August 26, 2024 Style: Small Room - Wifi | Verified Purchase I really like this product and want to give it 5 stars. I immediately noticed a difference in the air quality, smell, and a decrease in the dust/fur/debris in our home. That being said, I have 4 units, two of which have developed an incessant clicking sound. I contacted customer service when one unit began to click, and after a bit of back and forth they sent me a new one. After about 2 weeks the new unit began to click, and now a second (different) unit is clicking. It is so obnoxious that I simply had to stop using it. While I could contact customer support again, I'm chalking these up to sunk costs and waiting for the others to inevitably start clicking and become unusable. It's a shame, because they work well, but this clicking issue renders them unusable.
Smart streaming stick	**I'd love to share the same opinion as the rest, but NO.** Reviewed in the United States on July 29, 2023 Style: Google Chromecast + TV 4K | Verified Purchase I've been using Chromecast devices for many years. I've had no complaints thus far. Better than any other that I've used on the market. If you're tech savvy, you will like it even more. HOWEVER, there is a big BUT! This new Chromecast TV has its flaws. If I wanted to just stick to casting my screens like I always have, I would stick with previous Chromecast models, because this one has a big issue that seems to be overlooked or simply gets left unspoken. It glitches a lot and resets itself during movies. I've replaced it after a few days to make sure that it wasn't simply a defective unit. The second unit, the replacement, has been experiencing the same problem. During a movie, after maybe 2-3 hours of playing, the screen goes dark and the G logo starts up again. These units are resetting themselves and there's nothing indicating whether it's a problem, overheating, or what it may be. I've made sure in every part of the setting that everything is up to date, to no avail. These units have a flaw, and I'll be switching back over to my older devices which have been working perfectly fine until they either fix this issue or come out with an updated model.
Smart thermostat	**The Nest, Not What It's Cracked Up to Be "Version 3"** Reviewed in the United States on October 26, 2020 Color: Stainless Steel One year ago, I purchased the Nest Thermostat as the exterior of the Nest was a good design and I mistakenly thought the expensive Nest would work well for my family in our home. The most important fact about the Nest Thermostat is an understanding and the acceptance, prior to buying, the buyer is not in control of the thermostat. The term "learn" is exactly what the Nest is and that's when all the good stuff will turn sour and in only a day or two. After a day or two, then, let's say, you have a really cold day and it is chilly inside too; you turn the Nest Thermostat up a few degrees, a note will pop up on the face of the Nest and will indicates in 2.5 hours the heat may not even turn on 2.5 hours. The Nest will decide the owner is not being a good steward in our Eco world and decide for you to not turn on and, regardless, of what you try to do, the heat will not come on so your heater may take the chill out of the air. Also, if the home is extra warm in the summer, you'll experience the same delay. The Nest is the boss and it will let you immediately know that fact. Sometimes, the delay is a little less and also a little more but you'll realize, you, the buyer, are not in control of your home's thermostat and your indoor temperatures. The Nest determines what is best for the buyer and the environment and there is no way to change the learning factor and according to the Nest tech's, with whom I spoke, they finally tell me what I have learned is a fact...you are not in control of your thermostat. Now the expensive Nest Thermostat sits in a box in storage and, yesterday, I purchased a simple, logical, programmable thermostat.
Smart fitness tracker	**Didn't last a year...** Reviewed in the United States on June 30, 2024 Color: Black/Morning Glow | Verified Purchase I have had several of the lower-end Fitbit devices. This is the most recent one. I purchased it on July 11, 2023, and on June 30, 2024, it quit working. It didn't even last a year. This is pretty typical of the Fitbits that I have owned. They are not throw-away items; at least, they are not priced like throw-away items. These kinds of electronic devices should last for years. I am not going to buy any more Fitbit devices. Also, FYI, the iPhone app is very slow to sync with the Fitbit device.

Unlike the previously discussed factors that affect all product categories, some factors are specific to certain categories, highlighting their unique contribution to obsolescence within those categories, as shown in Figure 5.3. Although these factors have a minimal impact, as indicated by the low $OI_{(jct)}$ in Figure 5.4, addressing them could significantly enhance product longevity. The explanations of these category-specific factors are as follows:

Working costs incurred throughout a product's lifecycle, including installation, operation, maintenance, revitalization, and disposal, influence consumer decisions (Lapašinskaitė & Boguslauskas, 2005). This study confirms that high operation and maintenance costs can lead to product obsolescence, aligning with (Tim Cooper, 2004), who identified these costs as contributors to obsolescence. A customer reviews illustrates this concern: *"….The filters are $99 a pop which is TOO much to replace more than twice a year. I clean the pre filter every couple weeks and my house is not overly dusty and definitely not dirty. Very disappointed in the expensive filter life which is less than half of what was advertised. will be buying something else."* While working costs emerged as an obsolescence factor in smart entertainment system category in 2024, its impact declined in other associated product categories but increased in smart security systems. Privacy and security are additional factors contributing to obsolescence. Although their overall impact on associated product categories is low, they can significantly influence consumer trust, affect brand reputation, and lead to product replacement decisions (Guhr et al., 2020). Privacy concerns peaked in smart health devices in 2018, while security reached its highest $OI_{(jct)}$ in smart security systems the same year. However, both factors showed a steady decline from 2022 to 2024, as shown in Appendix V. Consumer reviews illustrate these concerns: Privacy: *"...CANNOT install this app unless you buy more products from them and agree to them using your data for marketing. You have to give them ALL YOUR PERSONAL DATA. NO WAY none of their business.";* Security: *"...My camera that was hacked was a newer model, not the one they named in the breach."* Battery drain in IoT devices is mainly due to wireless communication, sleep mode duration, high power consumption during active states, and controller I/O pin leakage (Callebaut et al., 2021). In addition to previous studies have identified battery drain as an obsolescence factor in smartphones (Marina Proske et al., 2016; Oraee et al., 2024), this study confirms its impact on consumer IoT devices as well. Battery drain exhibited high $OI_{(jct)}$ during certain periods in smart blind, smart health device, and smart security systems. Although it followed a fluctuating trend in smart blinds, its $NOI_{(jct)}$ declined compared to its initial year in both categories. Similarly, in smart security systems, battery drain experienced a significant decrease after 2022, with a negative $OIC_{(jct_{I-i})}$ of -0.001, indicating a reduced influence on obsolescence over time. In contrast, its $NOI_{(jct)}$ in smart health devices increased substantially, as shown in Appendix V.

Audio and image quality degradation contribute to functional obsolescence by diminishing user experience over time, ultimately driving product obsolescence (Alzaydi, 2024). Image quality degradation recorded the highest $OI_{(jct)}$ in smart security systems, while audio quality degradation peaked in smart speaker and display. Both factors exhibited fluctuations over time, reflecting their varying impact on product obsolescence. The expansion of the subscription business model now extends to durables goods (Kerschbaumer et al., 2023). While its impact remained low across most product categories, smart security systems experienced a notable $OI_{(jct)}$ over the years, with a positive $OIC_{(\mathrm{jct}_{I-i})}$ (0.0006) from 2019 to 2024. In this category, subscription models typically require users to pay recurring fees for cloud storage, software updates, or continuous monitoring services (Lindström et al., 2024). Although subscription models enhance customer retention by fostering long-term relationships through customization and continuous improvements (Lindström et al., 2024), this study highlights their potential drawbacks. Mandatory subscriptions can negatively affect consumers, leading some to discontinue product use. A consumer review illustrates this issue: *"...I failed to notice that after a three month trial period, you can ONLY store videos on the cloud with a subscription."* Advertising-based interruption is another factor affecting product obsolescence. Surveys indicate that nearly half of U.S. consumers find advertising overly intrusive, and 84% globally consider digital ads too frequent (Vranica, 2016). While its overall impact across product categories remained low, it was notable in certain years for the two categories. In smart entertainment systems, the influence of advertising-based interruption declined from 2021 to 2024. However, as highlighted by (K. Park et al., 2022), the increasing use of advertisements in smart speaker led to a rising trend in this category until 2024.

Smart home IoT devices often rely on proprietary software, making updates difficult and leaving many devices with outdated and vulnerable components. Delays in vendor updates, the absence of silent update mechanisms, and user reluctance to install updates further exacerbate these issues (Prakash et al., 2022). The updateability issue has emerged in recent years across three product categories but has been a persistent challenge in smart lighting. It should be recognized as a growing concern in these categories and urgently addressed in smart lighting to mitigate its impact. The inability to update can result in financial loss, reputational damage, and a degraded user experience, as devices may lack new features, essential bug fixes, and compatibility with updated systems (Ansari et al., 2024; Prakash et al., 2022). Finally, storage limitation that was previously identified as a driver of obsolescence in mobile devices

(Mosesso et al., 2023), can also impact obsolescence of smart entertainment systems, underscoring its broader impact on consumer technology.

5.5 Discussion

5.5.1 Using LLMs for identifying obsolescence factors

Pre-trained LLMs like ChatGPT-4o offer an efficient way to extract product obsolescence-related factors from customer reviews, reducing the manual efforts required in traditional NLP methods. They can quickly categorize text and generate labels similar to human-created ones. However, pre-trained LLMs outputs do not always align perfectly with human understanding or established theories, necessitating human oversight to refine and interpret classifications. While pre-trained LLMs enhance efficiency, their results must be validated to ensure accuracy. Overall, pre-trained LLMs serve as a valuable tool for extracting insights, improving product design, and enabling data-driven decision-making to enhance customer experience. As pre-trained LLMs technology evolves, its influence on business practices and innovation will continue to expand.

5.5.2 Leveraging user-generated content for obsolescence analysis

This study advances engineering management practice by introducing a novel method for integrating UGC into product obsolescence analysis, a key concern in technology lifecycle management. Unlike previous studies that relied on resource-intensive methods such as interviews, surveys, and focus groups to identify product obsolescence factors, this study highlights the value of UGC, as an efficient, scalable, and real-time source of consumer insight. UGC reduces the time and cost associated with conventional consumer insight-gathering methods and has been widely used to detect product flaws and understand consumer needs (Nasrabadi et al., 2024). This enables engineering managers to make faster, data-informed decisions about product improvements and lifecycle strategies.

By leveraging UGC, this study introduces the consumer-based, time-series different product obsolescence indexes, providing a dynamic framework to track and analyze how key factors influence product obsolescence over time. While previous research has primarily focused on objective product performance metrics, this approach captures subjective user dissatisfaction and emerging behavioral trends, offering engineering leaders a deeper, demand-side perspective on product obsolescence. Furthermore, while the $OI_{(jct)}$ offers a nuanced understanding of product obsolescence factors, $OIC_{(jct_{I-i})}$ and $NOI_{(jct)}$ tracks shifts in these factors, enabling the proactive identification of emerging risks and trends. These contributions are particularly valuable for engineering management decision-making as they support data-driven product design, agile responsiveness to user concerns, and strategic planning to mitigate early product obsolescence. By closing the gap between technical performance measures and consumer experience, this approach facilitates more sustainable, adaptable, and user-centric product development. In doing so, it enhances not only product longevity but also consumer trust, critical to competitive advantage and responsible innovation in engineering-driven organizations.

5.5.3 Factors affecting obsolescence in consumer IoT devices

As illustrated in Figure 5.5, the study reveals that $AOI_{(ct)}$, calculated using Formula 17, has shown an increasing trend across most smart product categories. The only exception is smart blinds, where $AOI_{(ct)}$ fluctuates rather than following a clear upward trend, potentially reflecting differences in product longevity. The rising $AOI_{(ct)}$ in most categories indicates that product obsolescence-related issues are becoming more prevalent, aligning with predictions of increasing E-waste production. These findings support existing research emphasizing the rapid annual growth of E-waste, driven by rising consumer electronics consumption and shorter product lifecycles (Sharma et al., 2024).

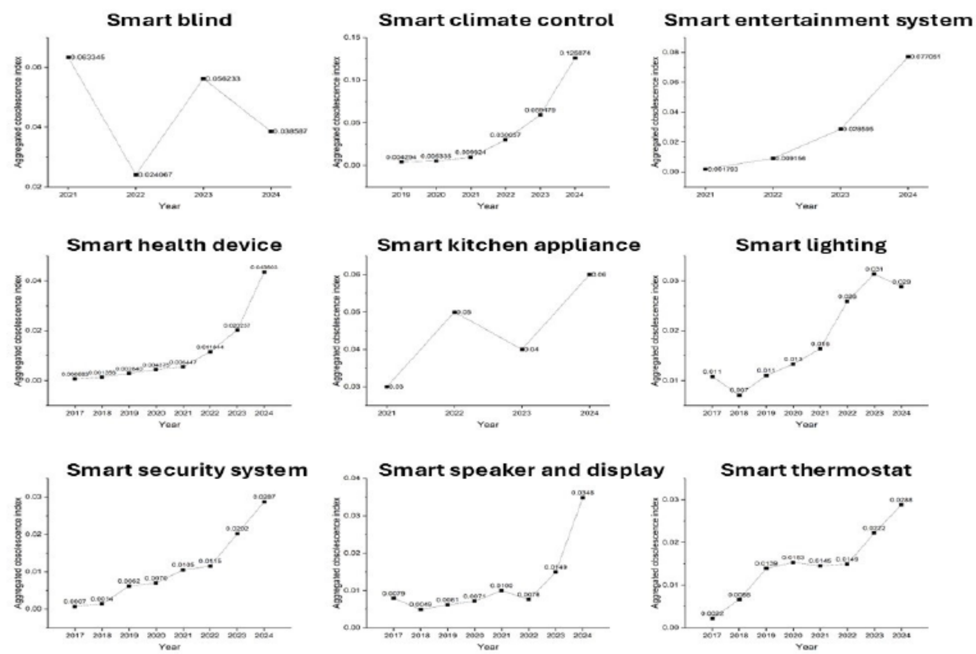


Figure 5.5 Trend analysis of $AOI_{(ct)}$ across IoT product categories

This study has identified a diverse and nuanced range of product obsolescence factors, 19 in total, across various consumer IoT device categories. This breadth of factors reveals a far more intricate and context-dependent landscape of consumer decision-making than is typically assumed. While nine product obsolescence factors appear consistently across all product categories, others are distinctly category-specific. This differentiation challenges the conventional one-size-fits-all approach to product design, offering actionable insights for product managers seeking to develop targeted strategies.

Although familiar issues such as malfunction, durability, design flaws, working costs, battery drain, performance degradation, and storage limitation are well-documented in existing literature, this study contributes novel insights by identifying previously overlooked factors. These newly recognized dimensions of product obsolescence enrich our understanding of consumer dissatisfaction and device discontinuation, while also establishing a foundation for future investigations into the longevity of smart products. Moreover, the findings indicate that indirect software-induced factors, such as incompatibility, connectivity issue, privacy, security, updateability issue, and latency exert a more profound long-term influence on product obsolescence than direct software issues like kill switches or bloatware. So, it is no longer sufficient to evaluate smart products solely on their physical durability or software completeness. Instead, the long-term sustainability of a product increasingly hinges on its adaptability, interoperability, and digital resilience.

Malfunction remains the most prevalent and intensifying product obsolescence factor across nearly all product categories. Its continued presence, even amid technological advancements, highlights ongoing reliability challenges in newer devices. Compounding this software incompatibility and inaccurate system performance frequently drive consumers to abandon products prematurely. Even with the advent of interoperability standards like Matter and Lumos, compatibility issue remains or even worsen in some product categories. This pattern suggests deeper structural limitations within ecosystems and uneven industry adoption, undermining the promise of seamless integration. Furthermore, the study reveals growing consumer expectations regarding accuracy, often fueled by marketing claims about AI-powered precision. However, reported dissatisfaction in this area continues to rise, directly contradicting such promises. Meanwhile, connectivity and latency issues degrade user experience, driving product discontinuation. Poor design in aesthetics, ergonomics, and materials reduces market viability, while durability concerns damage brand reputation. Restrictions on user control such as locked features or limited customization encourage migration to more flexible alternatives, and unintuitive interfaces drive users toward more accessible competitors.

Beyond these general factors, category-specific challenges underscore the need for tailored design and policy responses. High working costs, including operation and maintenance, necessitate cost-effective designs. Privacy and security vulnerabilities demand robust protection, while persistent battery drain highlights the need for energy efficiency. In product categories where audio and image quality are central, degradation in these areas highlights the importance of using high-quality components. Business models also play a critical role, subscription-based services often accelerate product obsolescence when locked features deter long-term engagement, and frequent in-app advertising prompts users to seek less intrusive alternatives. Updateability issues, particularly in smart devices, arise when hardware and software are misaligned, limiting longevity. Additionally, storage limitations, especially in smart entertainment systems, hinder functionality as media files and software updates increase in size, further contributing to product obsolescence.

These challenges stem from design decisions that accelerate product obsolescence, contributing to unsustainable consumption patterns. Product design plays a crucial role in determining the rate and nature of obsolescence, with the potential to either extend or shorten a product's lifespan. Designers must consider the long-term impact of their choices and prioritize factors identified in this study, along with repairability and upgradeability. By addressing these design-driven challenges, they can counteract the "throwaway culture" and promote a more sustainable and ethically responsible approach to product development (Rivera & Lallmahomed, 2016; Sierra-Fontalvo et al., 2024).

5.6 Conclusion

This study advances the understanding of product obsolescence, particularly in the context of consumer IoT devices, a domain that has been largely overlooked in existing literature. By introducing a novel framework that integrates online reviews, LLMs, Freq-AHP, and RoBERTa, the research provides broader perspectives and deeper insights into obsolescence drivers based on real public opinion, contrasting traditional methods reliant on limited consumer insights. Building on the analysis of UGC, this research introduces $OI_{(jct)}$ and $OIC_{(\mathrm{jct}_{I-i})}$, innovative metrics that provide a comprehensive and dynamic framework for understanding and addressing obsolescence. $OI_{(jct)}$ captures the intensity of obsolescence factors over time, offering a snapshot of the current impact, while the $OIC_{(\mathrm{jct}_{I-i})}$ tracks changes in these factors, enabling the identification of emerging trends and shifts. Together, these metrics empower designers and manufacturers to proactively address critical challenges, prioritize improvements, and extend product lifespans. By integrating UGC with advanced analytical tools, this study not only enhances the understanding of obsolescence but also provides a scalable and consumer-focused approach to promoting sustainability and innovation in the IoT ecosystem. Furthermore, it uncovers novel indirect software-induced factors that develop gradually but significantly outweigh direct impacts, alongside newly identified factors that enrich the understanding of obsolescence dynamics across product categories. These contributions offer a robust foundation for future research into other smart device ecosystems and practical guidance for manufacturers to enhance product design, foster consumer loyalty, and mitigate environmental and economic impacts associated with premature obsolescence. While this study provides valuable insights into consumer IoT device obsolescence, its scope is limited to specific product categories. Future research could refine the framework using domain-specific datasets and extend it to a broader range of IoT devices, providing a more comprehensive understanding of obsolescence drivers. Additionally, exploring the role of customer service and warranty policies in shaping consumer experiences and product longevity offers a promising avenue for further investigation. Such research could uncover how these factors influence user retention, repair practices, and overall satisfaction, ultimately contributing to strategies that enhance product lifespans and align with sustainability objectives.

CHAPTER 6

DISCUSSION

The SLR provided a comprehensive overview of the current state of UGC research within the context of NPD. It identified four main themes: the impact 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. This review highlighted the increasing scholarly interest in the subject matter, with the majority of research conducted in recent years. The study underscored the potential of UGC to augment the NPD process by providing valuable customer insights in a timely and cost-effective manner, contrasting it with traditional methods. The identified research gaps within each theme and the proposed future research directions emphasize the evolving nature of this field and the need for further scholarly investigation into the real implications of UGC in NPD process. The theoretical and managerial implications suggest that organizations can leverage UGC to speed up product development, enhance competitiveness by aligning products with user needs, and inform product improvements through the analysis of social media discussions.

Building on this foundation, chapter 4 introduced a framework for assessing consumer acceptance of new products using UGC analysis, specifically applied to ChatGPT, this research addresses the limitations of traditional survey-based methods, which can be time-consuming, costly, and prone to biases. The study demonstrated the significant influence of performance expectancy and trust on users' attitude toward ChatGPT, which in turn affects their behavioral intention to adopt the technology. The proposed UGC-based framework offers a more dynamic and representative way to capture consumer perceptions, moving beyond outdated survey techniques. The successful implementation of this framework highlights the potential of UGC analysis for quantitatively evaluating consumer acceptance of emerging technologies.

Expanding the scope of UGC's utility beyond product acceptance, chapter 5 proposed UGC-based product obsolescence indexes, utilizing online reviews, LLMs, Freq-AHP, and sentiment analysis. This research addressed the scarcity of studies on obsolescence factors in consumer IoT devices. The study demonstrated the effectiveness of LLMs in identifying obsolescence-related reviews and extracting key factors influencing product discontinuation from a consumer perspective. By employing a rigorous evaluation process for LLM-generated outputs and incorporating metrics to track the evolution of obsolescence factors over time, this framework provides actionable insights for improving product longevity and guiding sustainable design practices. The findings emphasize the value of leveraging unsolicited consumer feedback for understanding product lifespan and informing design decisions that mitigate premature obsolescence.

Collectively, the findings of this thesis offer a significant contribution to the scholarly understanding of how UGC can be systematically leveraged across multiple stages of NPD process. From the identification of customer needs and the generation of innovative product ideas to the assessment of consumer acceptance and the analysis of product obsolescence, this research demonstrates the versatility and strategic value of UGC as a data-rich, timely, and cost-effective resource. The application of advanced analytical methodologies, including LLMs, sentiment analysis, and MCDM techniques, illustrates the potential of data-driven approaches in capturing consumer insights from unstructured online content. In terms of generalizability, although each study is grounded in a specific empirical context, such as AI-based technologies in the consumer acceptance study or consumer IoT devices in the product obsolescence analysis, the proposed frameworks and methods were designed to be adaptable across diverse product categories. The conceptual and analytical models are not inherently limited to the examined cases; rather, they offer a foundation that can be extended to other domains where UGC is prevalent, and consumer feedback is critical.

However, several limitations should be considered when interpreting these findings. The literature review was confined to specific databases, subject areas, and English-language peer-reviewed journals, potentially excluding relevant studies from other disciplines, languages, or less traditional publication sources. The consumer acceptance study drew data primarily form a single platform (X, formerly twitter) , which may introduce demographic bias and lacked multilingual or culturally diverse perspectives. It also faced methodological constraints in accurately detecting nuanced sentiments such as sarcasm or irony. The obsolescence framework focused narrowly on certain categories of IoT procures and did not explore the influence of external factors such as customer service, warranties, or repair policies. Acknowledging these limitations not only contextualizes the scope of this thesis but also provides important directions for future research. By expanding empirical coverage, enhancing linguistic and platform diversity, and refining analytical methods, future studies can build upon these contributions to develop more generalizable UGC-based approaches for innovation and product development in an increasingly digital and consumer-driven world.

CONCLUSION

This thesis has explored the significant role of UGC in NPD through three distinct yet interconnected studies. Together, these chapters provide a comprehensive, data-driven approach to leveraging consumer insights derived from online platforms to enhance product innovation, consumer acceptance, and lifecycle management.

Chapter 3 presented the first SLR specifically focused on the role of UGC in NPD process. This study mapped the state of existing research between 2012 and 2023 and identified four major thematic areas: the impact of UGC on innovation, mining UGC for product ideas, deriving features from UGC, and understanding customer requirements through UGC analysis. Beyond synthesizing current knowledge, the study proposed novel research directions and highlighted important gaps, offering a structured agenda for future interdisciplinary exploration into the integration of UGC in product innovation.

Chapter 4 built upon the insights from the SLR and introduced a novel framework for assessing consumer acceptance of new products using UGC analysis. Applying this framework to the case of ChatGPT and utilizing a dataset of tweets, the study employed advanced techniques including topic modeling, clustering, and sentiment analysis, coupled with PLS-SEM. It identified key constructs such as performance expectancy, effort expectancy, and trust, demonstrating their influence on user attitudes and behavioral intention. This chapter provides a scalable and domain-transferable methodology for real-time, data-driven evaluation of emerging technologies, offering a timely and cost-effective alternative to traditional survey-based approaches.

In addition, chapter 5 extended the utility of UGC analysis to the underexplored area of product obsolescence in consumer IoT devices. It developed a dynamic framework that combines online consumer reviews with pre-trained LLMs, Freq-AHP, RoBERTa to identify and track product obsolescence factors over time. The study introduced four time-series indexes that measure the evolution of obsolescence based on consumer feedback., uncovering both direct and indirect factors. This approach provides product designers and manufacturers with actionable insights to proactively address obsolescence, support sustainable product design, and foster consumer trust by extending product lifespans.

In conclusion, this thesis underscores the versality and importance of UGC as a rich source of consumer insights for NPD. The three studies collectively demonstrate how UGC can be systematically analyzed to understand the current research landscape, assess consumer acceptance of novel technologies, and identify factors contributing to product obsolescence. The findings offer significant theoretical and managerial implications. Academically, this work contributes to the growing body of knowledge on UGC in NPD by providing a comprehensive review and introducing innovative frameworks and methodologies. From a managerial perspective, this research offers actionable insights for businesses to harness customer feedback for more effective product development, successful market introduction, and the creation of more sustainable products, ultimately enhancing competitiveness in a dynamic global market.

APPENDIX I

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
	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 II

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	Event study methodology	The utilization of user innovation communities found online enables the invention,

	user innovation communities		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	Machine learning & natural language processing techniques	This study shows that sentiment analysis and NLP methods are useful for product or

	multi-task deep neural networks		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.
Wang et al (2018)	Extracting and summarizing affective features and responses from online product descriptions and	Text mining & kansei engineering	The study shows successful information extraction with high recall and precision, emphasizing the

	reviews: a kansei text mining approach		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 & 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	Sentiment analysis & analogical reasoning	The latent customer needs elicited by the proposed method will delight the customers if

	of online product reviews		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.
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.

APPENDIX III

List of products analyzed in this study

Category	Product type	Model name
Smart Speaker and display	Smart speaker	Echo Dot (1st Gen); Echo Dot (3rd Gen); Echo Dot (4th Gen); Echo Dot (5th Gen); Echo Dot (5th Gen) with Clock; Echo Pop (1st Gen); Echo Studio Hi-Res; Echo Plus (2nd Gen); HomePod (2nd Gen)
	Smart display	Nest Hub (2nd Gen); Nest Hub Max; Echo Show 10 (3rd Gen); Echo Show 10 (3rd Gen); Echo Show 5 (3rd Gen)
Smart lighting	Smart bulbs	Philips Hue White and Color Ambiance; Philips Hue White Ambiance; LIFX A19; Wyze Bulbs; Kasa Smart Light Bulbs; Nanoleaf Essentials Smart Bulbs
	Smart switches	Lutron Caseta Smart; Kasa Smart Light Switch
	Smart plugs	Kasa Smart plug; Govee Smart plug; Wemo mini smart plug
Smart thermostat	Smart thermostat	Google Nest Learning Thermostat (3rd Gen); Google Nest Thermostat; Sensi Smart Thermostat; Sensi EMERSON Sensi Touch; Ecobee 3 Lite Smart Thermostat; Ecobee New Smart Thermostat Enhanced; Honeywell Home T9
Smart security system	Smart doorbells	Ring Video Doorbell Pro 2; Ring Alarm 8-Piece Kit(2nd Gen) with Ring Video Doorbell; Google Nest Doorbell (Wired, 2nd |Gen); Arlo Essential Wired Video Doorbell
	Smart cameras	Arlo VMS5240-100NAS Ultra; Arlo Pro 4 Spotlight Camera; Ring Stick Up Cam Solar; Ring Spotlight Cam Pro; Google indoor Nest security Cam 1080p(Wired- 2nd Gen); Wyze Cam v3; Wyze Cam v3 with Color Night Vision
	Smart locks	August Home Smart lock 3rd Gen; ULTRAOQ U-Bolt Pro with Wi-Fi Bridge; Schlage Encode Smart Wi-Fi; Yale Assure Deadbolt Lock SL

Smart kitchen appliances	Smart coffee maker	Keurig K-Supreme Plus Smart
	Smart refrigerator	Samsung; LG
	Smart oven	GE profile
Smart climate control	Smart air purifier	Dyson Purifier Cool™ TP07; Dyson Purifier Hot+|Cool HP07; AIRDOCTOR 3500i Smart Air Purifier; BLUEAIR Air Purifier; LEVOIT Air Purifier
	Smart dehumidifier	Frigidaire; Dura; GoveeLife; LG
Smart entertainment	Smart TV	Samsung; LG; Sony; TCL; Amazon Fire TV 32; Amazon Fire TV 55; Roku
	Streaming stick	Amazon; Google; Apple
Smart blind	Automated blind	Yoolax; CITOLEN
Smart health device	Smart scale	Fitbit; Wyze; GE; WITHINGS; Runstar
	Smart fitness tracker	Fitbit Charge 5 advanced fitness & health; Fitbit Charge 5 advanced health & fitness; Fitbit Inspire 3; Garmin vívoactive 5; Garmin vívoactive 4; Apple watch series 5; Apple watch series 7; Apple watch series 9; Apple Watch SE; Apple watch series 6; Apple watch series 4; Apple watch series 8; Samsung Galaxy Watch 4 40mm; Samsung galaxy Watch 6 44mm
	Smart sleep monitor	Withings Sleep Tracking Pad; Philips SmartSleep

APPENDIX IV

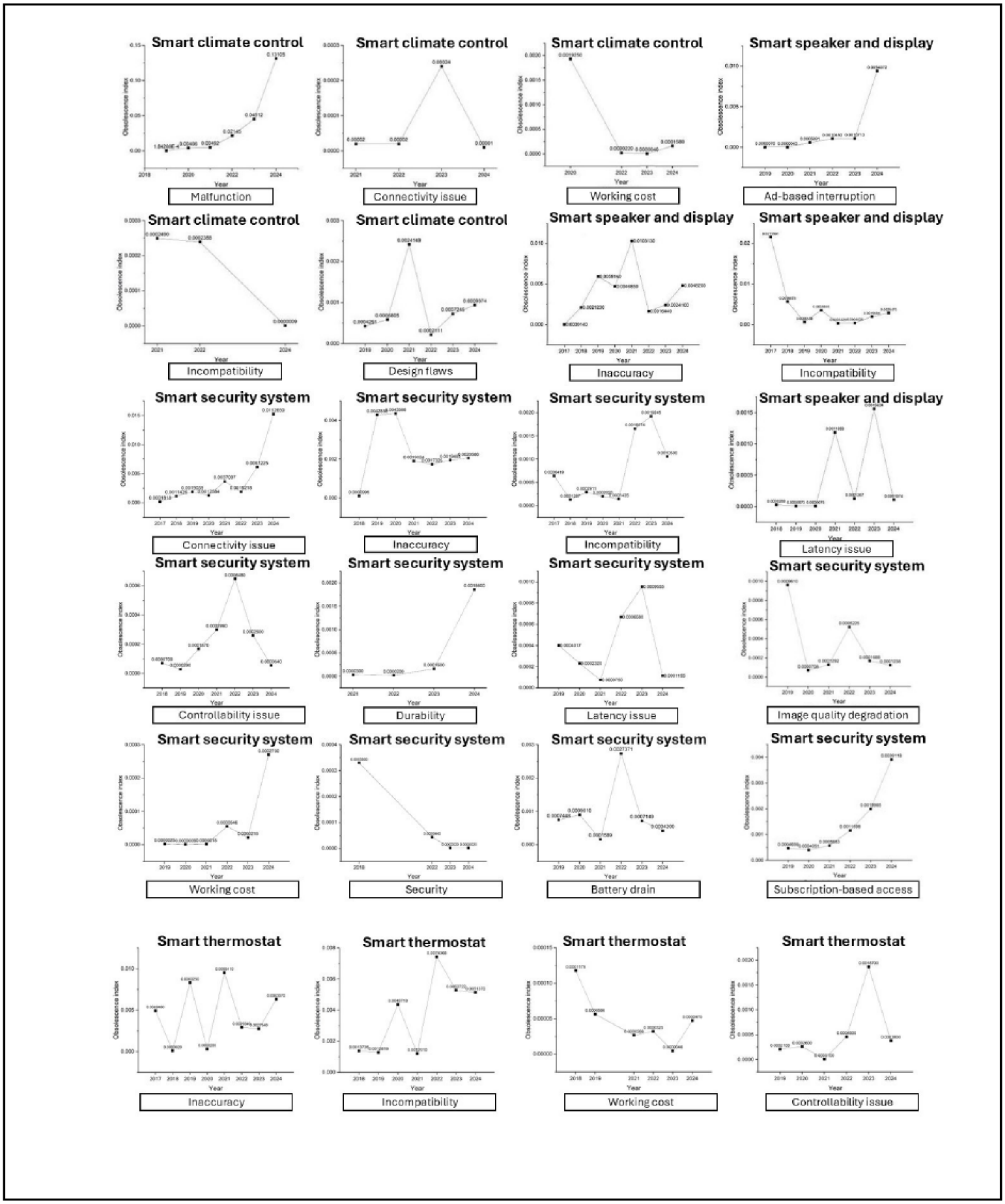
Categorization of labels generated by ChatGPT-4o

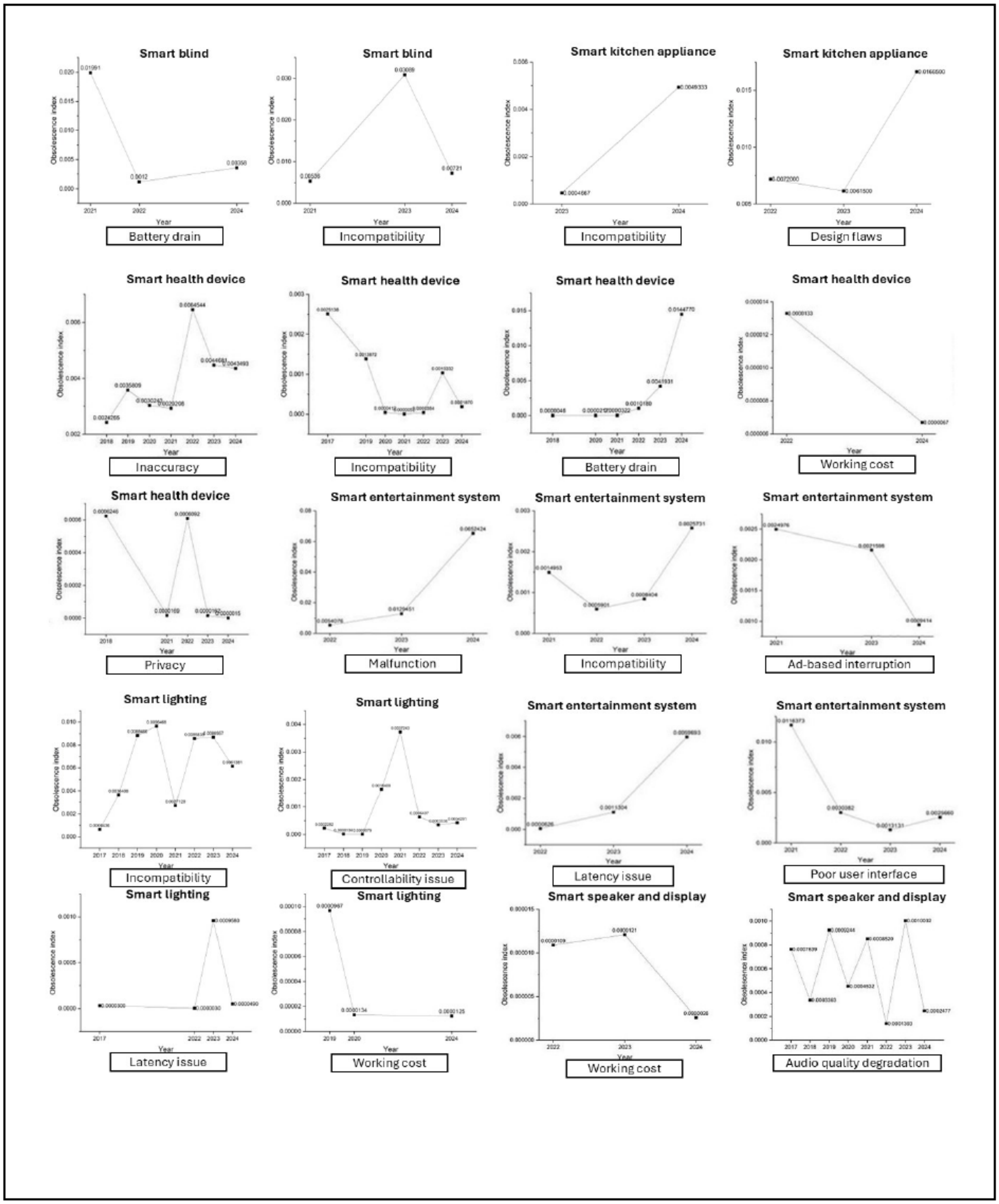
Broader Category	Common labels generated by ChatGPT-4o
Malfunction	(Malfunction, Malfunctioning, Defective, Defectiveness, Defect, Broken, Missing parts, Missing, Damage, Nonfunctional, E3 error, Error, EC error, Freezing, Icing, Frozen, Leakage, Leaking, Breakage, Glitches, Glitching, Unrepairable, Irreparable, Crashes, Crashing, Technical issue, Outdated, Inoperable, Noise, Noisy, Buzzing, Rattling, Squeak, Overheating, Fire, Burning)
Durability	(Durability)
Connectivity issue	(Connectivity, Disconnecting, Disconnection, Dysconnectivity, Discontinuation Stability, Bluetooth, Wi-Fi, Bandwidth, Signal, HDMI, Server)
Inaccuracy	(Inaccuracy, Accuracy, Detection, Sensitivity, responsiveness, Unresponsiveness, Tracking, Inconsistency, Non-responsiveness, Unresponsive, Fingerprint, Auto-lock, Recording, Motion, Learning, Automation, Hearing, Voice recognition, Microphone, Short-cycling, Time, Temperature, Learning, Automation)
Incompatibility	(Compatibility, Incompatibility, Integration, Unpairing, Mismatch, Sync, Syncing, Synch, Lip-sync, Voltage, Casting, Bridge, Hub, Wiring, C-wire)
Battery drain	(Battery, Charging, Charger, Power, Longevity, Overheating)
Controllability issue	(Control, Remote, Accessibility, Inaccessibility, Scheduling, Schedule, Programming, Programmability, Auto-adjustment, Dimming, Lack of feature, Flexibility)
Poor user interface	(Interface, UI, Controller, Auto-off, Auto-exit, Navigation, Setting, Menus, Viewing, Searchability, Platform limitation, Keyboard, Touchscreen, App, Scrolling, Customization, Transition, Notification, Usability)
Latency issue	(Latency, Delay, Lag, Lagging, Load, Loading, Upload, Slow, Slowness, Responsiveness, Reception)

Design flaws	(Design, Aesthetics, Ergonomics, Size, Space, Thickness, Irritation, Allergy, Bulkiness, Wristband, Discomfort, Button, Touchscreen, Sizing, Waterproof, Shelves, Ice maker, Discoloration, Smell, Odor)
Subscription-based access	(Paywall, Subscription, Service, Membership, Account, Data limitation, Limitations, Plans, Access, Blocking)
Advertising-based interruption	(Advertisement, Ads, Interruption)
Audio quality degradation	(Sound, Audio, Speaker, Whistling, Bass, Volume)
Privacy	(Privacy, Spam, Spamming, Account requirement)
Working cost	(Cost, Billing, Subscription fee, Pricing, Price, Overpriced)
Image quality degradation	(Display, Resolution, Screen, Picture, Glare, Flickering, Pixel, Backlighting, Image quality, Video quality, Video, Night vision, Glare, Blurriness, Vision, Brightness, Resolution, Image quality, Pixelation)
Updateability issue	(Update, Software, App, Firmware)
Storage limitation	(Storage, Restriction, Memory)
Security	(Security, Fraud, Vulnerability, Unlocking)

APPENDIX V

Trend analysis of NOI$_{(jct)}$ factors across IoT product categories




Smart blind
Battery drain
Smart blind
Incompatibility
Smart kitchen appliance
Incompatibility
Smart kitchen appliance
Design flaws
Smart health device
Inaccuracy
Smart health device
Incompatibility
Smart health device
Battery drain
Smart health device
Working cost
Smart health device
Privacy
Smart entertainment system
Malfunction
Smart entertainment system
Incompatibility
Smart entertainment system
Ad-based interruption
Smart lighting
Incompatibility
Smart lighting
Controllability issue
Smart entertainment system
Latency issue
Smart entertainment system
Poor user interface
Smart lighting
Latency issue
Smart lighting
Working cost
Smart speaker and display
Working cost
Smart speaker and display
Audio quality degradation
Year
Obsolescence index

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