A Consumer-Centric Framework for Measuring Product Obsolescence Using User-Generated Content and Large Language Models: Evidence From IoT Devices

Mohamadreza Azar Nasrabadi, Yvan Beauregard, and Amir Ekhlassi

***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. First, ChatGPT-4o, an advanced pretrained large language model, 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 engineering managers 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 the robustly optimized bidirectional encoder representations from transformers approach. This is further supported by a robustness check, where small perturbations were applied to sentiment intensities and all indices recalculated, confirming the aggregated obsolescence index remained stable across all product categories. This study focuses on consumer Internet of Things (IoT) devices, an area underexplored in existing literature, analyzing 47 695 online consumer reviews across nine product categories and selecting 4771 online obsolescence-related reviews for detailed analysis. Findings reveal 19 key factors and demonstrate a fundamental shift in obsolescence, indicating that product obsolescence of consumer IoT devices is increasingly driven by adaptability, interoperability, and digital resilience rather than physical durability. These insights demonstrate the potential of the proposed approach to inform product obsolescence mitigation strategies and guide more resilient, user-centered design in IoT ecosystems.**

***Managerial Relevance Statement*—This study provides engineering managers and policymakers with a practical, data-driven framework to address product obsolescence in consumer IoT devices by leveraging user-generated content and analyzing it with large language models. They can detect emerging obsolescence drivers, assess and prioritize their impact, and translate these insights into evidence-based design improvements. A major contribution is the creation of dynamic product obsolescence indexes that enable engineering managers to continuously monitor 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, allowing for more precise and context-aware strategies. Findings also reveal overlooked drivers associated with user experience and business models that extend beyond technical specifications, indicating that obsolescence is shifting from being primarily determined by physical durability toward factors related to a device's capacity to integrate with evolving technologies, maintain compatibility across platforms, and sustain reliable performance. This broader understanding enables policymakers to develop more adaptive and forward-looking policy responses. This article also contributes to the following sustainable development goal (SDG): SDG 12.**

***Index Terms*—Internet-of-Things (IoT), large language models (LLMS), online consumer review, product obsolescence, user-generated content (UGC).**

I. Introduction

PRODUCT obsolescence poses environmental and social challenges by depleting nonrenewable resources and increasing waste from production and disposal [1], [2]. Obsolescence can be understood as the point at which a product no longer offers sufficient usability or appeal, whether due to design decisions, rapid technological shifts, or changing social expectations, ultimately leading users to abandon it prematurely [2], [3]. While manufacturers once prioritized high-quality and durable products [4], technological advancements now drive them to introduce feature-enhanced models to boost sales and meet consumer requirements [5], [6]. This shift has shortened product lifespans, rendering products obsolete through mass production, even when they remain functional [7].

The rapidly growing electrical and electronic equipment (EEE) sector shows this problem clearly. Although electronic devices play a vital role in modern society, the processes associated with their production, consumption, and disposal are environmentally unsustainable and contribute significantly to ecological degradation [8], [9]. Rapid technological advancements [10], a competitive market [11], and evolving consumer preferences drive frequent replacement of EEE devices with newer models

Received 26 May 2025; revised 7 August 2025, 19 October 2025, and 18 November 2025; accepted 29 November 2025. Date of publication 4 December 2025; date of current version 22 December 2025. This work was supported by École de Technologie Supérieure (ÉTS) under Grant 102729. Review of this article was arranged by Department Editor R. Beise-Zee. *(Corresponding author: Mohamadreza Azar Nasrabadi.)*

Mohamadreza Azar Nasrabadi and Yvan Beauregard are with the Department of Mechanical Engineering, École de Technologie Supérieure, Montreal, QC H3C 1K3, Canada (e-mail: mohamadreza.azarnasrabadi.1@ens.etsmtl.ca).

Amir Ekhlassi is with the Department of Management, University of Niagara Falls Canada (UNF), Niagara Falls, ON L2E 7J7, Canada.

This article has supplementary downloadable material available at https://doi.org/10.1109/TEM.2025.3640012, provided by the authors.

Digital Object Identifier 10.1109/TEM.2025.3640012

[2], [12]. 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 [13]. In 2019, E-waste totaled 53.6 million tonnes (Mt), a 21% rise over five years, and is projected to reach 74.7 Mt by 2030 [14]. 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 [15].

Existing research on EEE product obsolescence has mainly focused on specific contexts, such as smartphones [16], [17], [18], laptops, and nonsmart home appliances [6], [19], [20], and also applications in aviation, aerospace, and military sectors [21], [22], [23]. 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 drivers has become critical, as these devices provide a suitable context to investigate whether obsolescence is caused solely by physical failures or by broader functional and ecosystem-level factors. Instead of relying on time-consuming and costly methods [24] such as consumer interviews [25], [26], expert interviews [27], and surveys [28], [29], this study analyzes 47 695 online reviews of consumer IoT devices collected from Amazon.com and BestBuy.com. These reviews are categorized 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 pretrained large language model (LLM) ChatGPT-4o, which outperformed Claude-3 Opus and Llama 3 in detecting product obsolescence-related reviews in this study, is employed to analyze 4771 online reviews. The study then defines user-generated content (UGC) time-series-based product obsolescence indexes to quantify the impact and shifts of each factor across product categories. Unlike previous studies where [30] constructed an obsolescence index (OI) based on product performance data and [31] used expert assessments and system architecture models for the obsolescence criticality index, this research aligns with Industry 4.0 by leveraging real-time UGC data to develop time-series-based product obsolescence indexes [32]. 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 the robustly optimized bidirectional encoder representations from transformers approach (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 [33], [34], [35].

While this study adopts a management engineering perspective by engineering the analytical processes underlying managerial decision-making, it remains firmly situated within the broader engineering management discipline. As emphasized by Elia et al. [36], management engineering operates as an integrative stream within engineering management, uniting technical, analytical, and managerial knowledge to address complex socio-technical challenges. Accordingly, this research contributes to engineering management theory and practice by introducing a data-driven framework that enables engineering managers to monitor and manage product obsolescence in dynamic technological environments.

From a theoretical perspective, this study extends the body of knowledge in technology and innovation management and engineering systems management, two established domains within engineering management. It reconceptualizes product obsolescence not merely as a technical endpoint but as a dynamic managerial process influenced by the interaction between technological evolution, user adaptation, and ecosystem interdependencies. By integrating UGC analytics with product lifecycle modeling, the study advances a socio-technical understanding of obsolescence that complements traditional models grounded in performance degradation or expert assessment. This reconceptualization expands engineering management theory by emphasizing the role of real-time consumer feedback in technology lifecycle analysis and by demonstrating how analytical tools such as LLMs, multicriteria decision frameworks, and sentiment analysis, can augment managerial cognition and foresight in engineering contexts. In doing so, the study aligns with the ongoing evolution of engineering management toward data-intensive, evidence-based approaches for decision support in complex systems.

From a practical perspective, the proposed framework contributes to project and operations management, technology strategy, and sustainability management, core areas of engineering management practice. It provides engineering managers with a robust, scalable mechanism for identifying, quantifying, and tracking obsolescence factors using user-generated data streams. The framework supports real-time managerial interventions in design prioritization, technology lifecycle extension, and sustainability planning. It equips managers to make informed decisions regarding software support, hardware upgrades, and interoperability improvements, thereby enhancing organizational agility and reducing E-waste. Moreover, by operationalizing consumer insights into quantitative indicators, the framework strengthens feedback loops between user experience and engineering design, fostering more resilient and adaptive product development processes consistent with Industry 4.0 principles. Ultimately, the study supports more sustainable engineering practices by promoting longer product lifespans, reducing unnecessary resource use, and enhancing consumer trust [3], key concerns in the management of product obsolescence in the digital era. The remainder of this article is structured as follows: Section II reviews the relevant literature. Section III outlines the methodology. Section IV presents the results. Section V discusses the findings. Section VI provides a summary of the study's conclusions.

II. Literature Review

A. Obsolescence

Obsolescence has been defined from multiple perspectives in the literature. The IEC 62402:2019 defines obsolescence as the transition of a product from being available to unavailable by the original equipment manufacturer according to its original specification. A product is considered obsolete when it is no longer produced with the components specified in its original design [37]. 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 [38]. Finally, some scholars emphasize user perception, defining obsolescence as the loss of usability or desirability due to design choices, technological progress, or changing societal norms, even when the product remains functional [2], [3]. While the first two definitions are valuable, they do not fully capture user-driven premature discontinuation, central to this study. Therefore, the latter is adopted, user-centered definition and operationalize obsolescence as occurring when a consumer stops using or discards a product before its expected end of life, driven by perceived loss of usability or desirability.

Obsolescence devalues products both materially and communicatively and can be triggered by the introduction of more energy-efficient alternatives [17], [39]. Understanding obsolescence helps extend product usage, reduce waste, and promote durable products and circular business models [2]. Alzaydi [3] 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 [3], [6], [40]. Therefore, promoting design longevity, modularity, and sustainable consumption patterns is essential for managing and mitigating obsolescence [41].

B. Obsolescence of EEE Products

Prior research on product obsolescence has predominantly focused on non-IoT EEE products across several contexts. In household appliances such as washing machines, TVs, and kitchen devices, studies including [42], [19], [20], and [25] have consistently identified factors like functional decline, defects, high energy consumption, changing consumer needs, and the appeal of newer models as key drivers of obsolescence. Smartphones, due to their rapid turnover and significant contribution to E-waste, have also received extensive attention. Research by the authors [18], [26], [43], [44], and [45] highlight factors such as rapid technological innovation, marketing-induced psychological obsolescence, high repair costs, design limitations like nonremovable batteries, and social pressures that encourage premature replacement. In addition, obsolescence in aerospace, aviation, and military sectors primarily stems from software-related issues, particularly involving commercial-off-the-shelf components. Key studies [27], [46], [48], [49], [50], [51], [52], [53], [54] have identified discontinued vendor support, evolving operational requirements, rising sustainment costs, hardware unavailability, and the loss of specialized expertise as major contributors. The details of the reviewed studies and their identified factors are detailed in Table I to highlight existing research trends and contextual differences.

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 [47]. Furthermore, previous studies have primarily relied on traditional data collection methods, overlooking the potential of online consumer reviews as a valuable source of insight. Thus, this study aims to address the following questions: 1) How can obsolescence factors affecting consumer IoT devices be identified and quantified through UGC analysis? And 2) Are consumer IoT devices rendered obsolete solely due to physical failures, or do broader system-level attributes play a critical role in driving obsolescence? These system-level attributes include adaptability, interoperability, and digital resilience [48], [49], [50]. Specifically, adaptability refers to a device's ability to adjust its structure, behavior, or operations in response to evolving technological conditions or user requirements [49], [50]; interoperability denotes the capacity of devices and platforms to communicate, exchange data, and function cohesively within a connected ecosystem [48]; and digital resilience reflects the ability of devices, users, and supporting systems to maintain reliable performance and recover from disruptions [49], [50]. These functional and ecosystem-related drivers are largely neglected in prior studies, which focus primarily on hardware failures, highlighting the need for a structured approach to capture the complex determinants of IoT device obsolescence. Prior studies have largely neglected these functional and ecosystem-related drivers, focusing instead on physical or technical failures in the EEE products listed in Table I. This gap underscores the need for a structured framework to capture the complex drivers of IoT device obsolescence. By framing obsolescence in terms of both functional and ecosystem-related factors and systematically leveraging insights from online consumer experiences, this study advances the engineering management literature in two interrelated ways. First, it extends the domain of technology and lifecycle management by proposing a systematic, data-driven method to identify and quantify obsolescence drivers that influence product replacement cycles, resource allocation, and long-term platform sustainability. This contribution enhances managerial understanding of technology lifecycle dynamics and supports evidence-based decision-making in engineering contexts. Second, it contributes to design and innovation management by revealing how consumer-perceived ecosystem dependencies, interoperability issues, and functional limitations shape product longevity and user retention. These insights enable the development of more resilient, user-centered, and sustainable design strategies that align with engineering management objectives of innovation performance, technology integration, and lifecycle optimization.

C. 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 [58]. These models rely on rule-based systems and statistical techniques for text correction and analysis [59], [60], using linguistic knowledge and heuristic rules such as regular expressions [61]. While

TABLE I
LITERATURE ON FACTORS CONTRIBUTING TO NON-IOT EEE DEVICE OBSOLESCENCE

Context	Identified factors	Reference
Non-smart EEE products	Ergonomics, Sensor quality, Changing needs, Functional decline, Working costs, Wear-out	[42]
	Defects, Dissatisfaction, Inefficiency, Loss of appeal, Replacement by gifts	[19]
	Operational and maintenance difficulties, Poor performance, Lifestyle changes, The appeal of newer models	[25]
	Energy consumption	[20]
Smartphones	Shortened lifespans, Newer models rendering older ones outdated, Consumer desire for upgrades	[43]
	Broken screen, Poor battery performance, Emerging new features, Subsidized contracts, Repair cost	[44]
	Socio-demographic factors, Rapid innovation, Software/hardware limitations, Maintainability issues, Trends, Subsidized contracts	[45]
	Battery life, Screen durability, Repair cost, lack of repair skills, Peer pressure	[26]
	Technological advancements, Fashion trends	[18]
Aerospace, aviation, and military	External constraints, Development environment, Operative environment	[27]
	Unmet new requirements, Discontinued vendor support, Logistical	[51]
	Technological progress, Declining popularity, Market upgrades	[52]
	Discontinued sale and support	[51], [53]
	Frequent upgrades, Inadequate planning for sustainment, Supportability, Sustainment cost	[51], [54]
	Sustainment cost	[55], [56]
	Hardware unavailability, Outdated development tools, Poor software distribution mechanisms	[57]
	Loss of employees with specialized software knowledge	[46]

rule-based models effectively handle domain-specific tasks like event detection and named entity recognition, they are limited by a fixed knowledge base [62]. Statistical methods, including term frequency-inverse document frequency and vector space models, play a crucial role in document retrieval and search engine indexing [63]. However, LLMs are advanced AI systems designed for high-level language interpretation with human-like fluency [64]. Models such as BERT [65] and RoBERTa [66] are effective for topic modeling and classification but require careful hyperparameter tuning, have context limitations, and demand human effort for interpretation [67]. Advancements in pretrained LLMs and prompt engineering have improved large-scale text analysis [68], [69]. For example, ChatGPT, a pretrained LLM with billions of parameters, has been trained on diverse internet text and literature [70]. Such pretrained LLMs exhibit emergent capabilities in machine translation, text summarization, NLP, ideological scaling, and text annotation [71], [72], [73], [74]. While these models are designed for general applications, they outperform traditional computational methods in detecting irony, sarcasm, and nuanced subjective interpretations [75].

D. Multicriteria Decision-Making

Multicriteria decision-making (MCDM) emerged in the 1970s, with over 70 techniques developed, each with distinct models, assumptions, and methods [76]. Selecting an appropriate method is essential for accurate assessment. Commonly used techniques for determining criterion weights and ranking alternatives include 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 [77]. TOPSIS ranks alternatives by selecting the option closest to the ideal solution and farthest from the negative ideal [78]. VIKOR is designed for discrete decision problems involving conflicting and noncommensurable criteria [79]. This study employs AHP, introduced by Saaty [80], due to its ability to handle both weighting and ranking simultaneously, a feature less common in other MCDM methods [81]. AHP is straightforward to apply, involves a simple calculation process, and uses a hierarchical structure to systematically evaluate all criteria and present alternatives

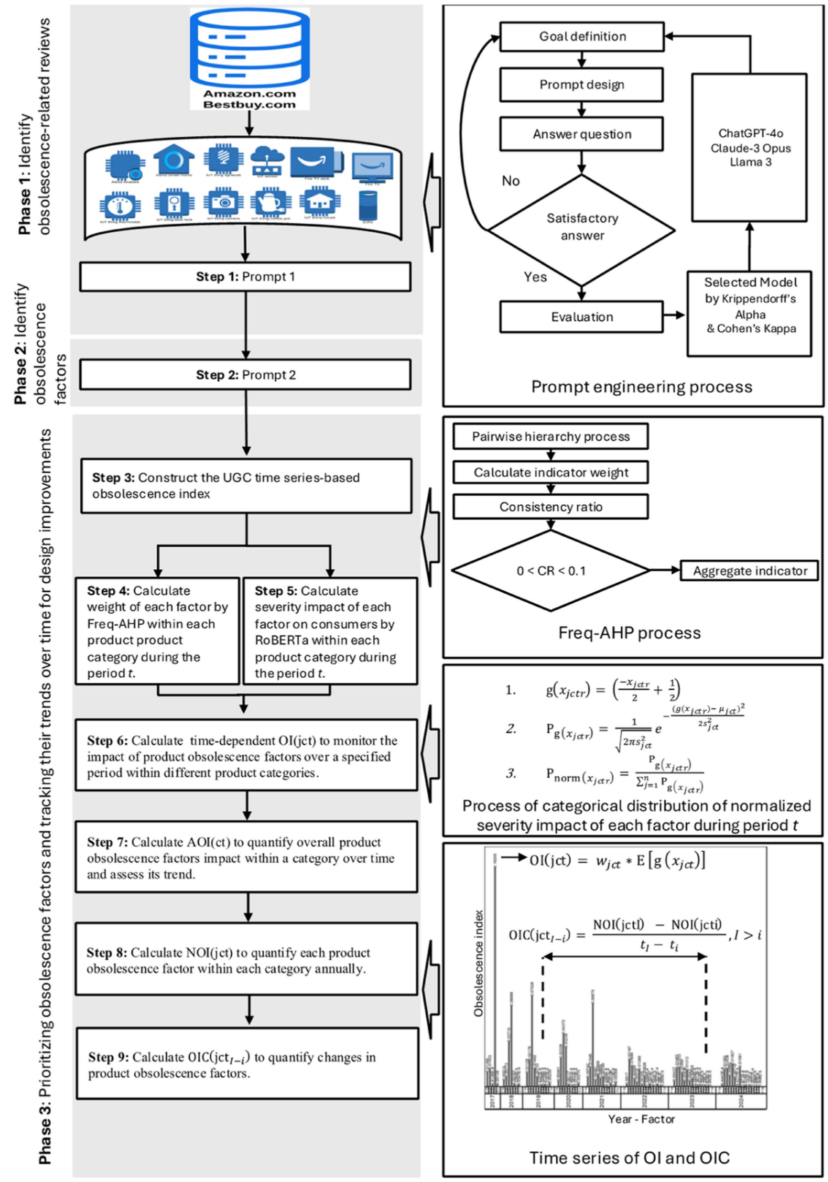

Fig. 1. Data processing framework for calculation of product obsolescence factors.

transparently. It also structures decision problems hierarchically to align with research goals [82], integrates decision-maker input, incorporates a consistency ratio for reliable weighting, and converts subjective judgments into objective numerical values for comparison [83], [84].

III. Methodology

To assess the suitability of pretrained LLMs in identifying factors influencing consumer IoT device 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; and 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 labeling these reviews using a pretrained 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 Fig. 1.

A. Data Preparation

To evaluate the effectiveness of pretrained LLMs in identifying factors contributing to the 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 1 (see Supplementary Material).

Traditional text mining approaches for text analysis involves tokenization, stopword removal, stemming or lemmatization, and part-of-speech tagging modification [85]. However, pretrained LLMs streamline this process, reducing the need for manual preprocessing [86].

B. Model Determination

Three pretrained LLMs—ChatGPT-4o, Llama 3, and Claude-3 Opus—were evaluated for their effectiveness in extracting factors contributing to the obsolescence of consumer IoT devices. ChatGPT-4o was selected for its adaptability and ability to be finetuned (i.e., further trained on domain-specific data to improve task performance) for NLP tasks, which enhances performance across various domains [87]. To compare results and explore alternatives, Llama 3 by Meta was included, recognized for its advanced reasoning capabilities and strong performance in complex linguistic and cultural tasks [88], [89]. In addition, Anthropic's Claude-3 Opus was selected as another competitor, with its different series offering varying levels of speed and quality [90]. 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 [75].

C. Prompt Engineering

A prompt is a textual instruction that enhances a GPT model's functionality [91], but crafting effective prompts requires creativity, intuition, and iterative refinement [92]. Poorly designed prompts can lead to vague, inaccurate, or contextually inappropriate responses [93]. To address this, the goal, prompt, evaluation, and iteration framework [94] 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 factors from the relevant reviews, providing insights into why products have been considered obsolete based on consumer feedback. Further details of these prompts are provided in Appendix 2 (see Supplementary Material).

D. Evaluation

To ensure the reliability of pretrained LLM-generated outputs, rigorous evaluation routines are implemented before interpretation and comparison [75]. First, a randomly selected subsample was assessed by three independent researchers based on predefined criteria described in the methodology section. Online reviews were included only if they clearly explained reasons for product obsolescence. Only reviews with consensus among the reviewers were retained [58], leading to a final sample of 1000 reviews used to assess pretrained LLMs reliability in identifying obsolescence-related reviews. Then, Krippendorff's alpha [95] and Cohen's Kappa index metric [96] were used to assess the alignment between model results and validation data. These metrics quantify agreement while adjusting for chance, with scores ranging from 0 to 1, where higher values indicate stronger consensus. The model with the highest agreement score was then selected to extract product obsolescence factors.

E. Prioritizing Product Obsolescence Factors for Design Improvement

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 the OI follows a three-step approach, designed to be adaptable to different analytical purposes. In the first approach, OI is introduced as a time-dependent function, $\mathrm{OI}_{(jct)}$, to monitor the impact of product obsolescence factors over a specified period within different product categories. The calculation of $\mathrm{OI}_{(jct)}$ 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 [97], [98], 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 [99], [100]. By integrating these dimensions, $\mathrm{OI}_{(\mathrm{jct})}$ provides a dynamic, consumer-driven assessment of product obsolescence factors across different product categories. $\mathrm{OI}_{(\mathrm{jct})}$ is defined as follows:

$$\mathrm{O\,I}_{(\mathrm{jct})} = w_{jct} * \mathrm{E}\left[\mathrm{g}\left(x_{jct}\right)\right], \forall t,\ t = 1, 2, \ldots, k; \forall c,\ c = 1, 2, \ldots, n; \forall j,\ j = 1, 2, \ldots., m. \tag{1}$$

Here

1) w_{jct} represents the relative importance of an obsolescence factor within a product category over a defined period.
2) $\mathrm{E}\left[\mathrm{g}\left(x_{jct}\right)\right]$ 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.
3) j represents an obsolescence factor.
4) c signifies a product category.
5) 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 weights, 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. [101], which replaces expert grading with frequency-based pairwise comparison matrices, ensuring a more data-driven and unbiased weighting process. A detailed description of the Freq-AHP procedure is presented in Appendix 3 (see Supplementary Material).

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) [102]. RoBERTa, an improved adaptation of BERT, is finetuned (i.e., trained on specific tasks with optimized hyperparameters) to address BERT's training complexity and missing hyperparameters [103], [104]. 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 $\mathrm{OI}_{(\mathrm{jct})}$ 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

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

where x_{jctr} denotes the sentiment intensity of a single online review *r* (where $r = 1, 2, \ldots, y$), associated with product 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 nonuniform 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. After computing the probability distribution of 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. Subsequently, the expected value of g (x_{jctr}) is defined. The equations used to calculate these steps are comprehensively presented in Appendix 4 (see Supplementary Material). Then to compute the overall expected value of severity impact of each factor *j* within product category *c* over period *t*, we sum E [g (x_{jctr})] as follows:

$$\mathrm{E}\ [\mathrm{g}\ (x_{jct})] = \sum_{r=1}^{n_{jct}} \mathrm{P}_{\mathrm{norm}\ (x_{jctr})} * \mathrm{g}\ (x_{jctr}),\ \forall t,\ t = 1, 2, \ldots, k;\ \forall c,\ c = 1, 2, \ldots, n;\ \forall j,\ j = 1, 2, \ldots, m. \quad (3)$$

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 $\mathrm{OI}_{(\mathrm{jct})}$ 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 $\mathrm{AOI}_{(\mathrm{ct})}$ be

$$\mathrm{AOI}_{(\mathrm{ct})} = \left(\frac{NR_{ct}}{\sum_{t=1}^{T} NR_{ct}}\right) * \mathrm{OI}\,(ct),\ \forall t,\ t = 1, 2, \ldots, k;\ \forall c,\ c = 1, 2, \ldots, n \quad (4)$$

where

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

In the final approach, the product obsolescence index change ($\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$) was introduced to track how the impact of an obsolescence factor evolves within a category over time. By calculating $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$, 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 ($\mathrm{NOI}_{(\mathrm{jct})}$) was first calculated for each factor within each category annually, offering a standardized assessment. Since $\mathrm{OI}_{(\mathrm{jct})}$ 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 $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$ reflects actual shifts in obsolescence factor impact rather than inconsistencies in factor identification. Let $\mathrm{NOI}_{(jct)}$ be

$$\mathrm{NOI}_{(\mathrm{jct})} = \left(\frac{NF_{(jct)}}{\sum_{t=1}^{T} NF_{(jct)}}\right) * \mathrm{OIC}_{(\mathrm{jct})},\ \forall t,\ t = 1, 2, \ldots, k;\ \forall c,\ c = 1, 2, \ldots, n;\ \forall j,\ j = 1, 2, \ldots, m \quad (5)$$

where

1) $NF_{(jct)}$ is the number of product obsolescence factor *j* within category *c* over period *t*;
2) $\sum_{t=1}^{T} NF_{(jct)}$ is the total number of product obsolescence factor *j* within category *c* across all years;
3) $\mathrm{OI}_{(\mathrm{jct})}$ is obtained as per (1).

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

$$\mathrm{OIC}_{(jct_{I-i})} = \frac{\mathrm{NOI}_{(\mathrm{jctI})} - \mathrm{NOI}_{(\mathrm{jcti})}}{t_I - t_i},\ \forall t,\ t = 1, 2, \ldots, k; I > i;\ \forall c,\ c = 1, 2, \ldots, n;\ \forall j,\ j = 1, 2, \ldots, m \quad (6)$$

where

1) $\mathrm{NOI}_{(jctI)}$ is $\mathrm{NOI}_{(jct)}$ of factor *j* within category *c* at t_{I};
2) $\mathrm{NOI}_{(jcti)}$ is $\mathrm{NOI}_{(\mathrm{jct})}$ of factor *j* within category *c* at t_i;

TABLE II
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

3) $t_I - t_i$ is the time interval between the two measurements of the $\text{NOI}_{(jct)}$ while $I >$ i.

After computing the obsolescence indices, small random perturbations with assessed variance is introduced to the dataset to ensure the robustness of our framework. To empirically determine an evidence-based variance, a sample review is first selected, and then ChatGPT is used to generate three paraphrased versions with slightly different wording (Appendix 7, see Supplementary Material). After that, the sentiment intensities of all reviews (a sample review + generated reviews) are calculated by RoBERTa. Using all four sentiment values, the sample variance is computed as follows:

$$S^2 = \frac{1}{n-1} \sum_{r=1}^{n} (gx_{jctr}) - g(x_{jct}))^2, \; n = 4, \; r = 1, \, 2, \, 3, \, 4 \quad (7)$$

where

1) r: indexes the original and generated reviews;
2) n: the total number of reviews;
3) $g(x_{jct})$: is the mean of sentiment intensities of all reviews $\frac{1}{4}\sum_{r=1}^{4} g(x_{jctr})$.

The resulting variance ($S^2 = \;\; X$) quantifies the empirical fluctuation in sentiment intensity caused by paraphrasing. Using this evidence-based estimate, small random noise with variance X was subsequently added to all sentiment intensities in the dataset to simulate model uncertainty and subtle textual variation. The OI and AOI are then recalculated using these perturbed sentiment values. Such controlled perturbations are consistent with prior research showing that transformer-based sentiment models exhibit only small performance changes (typically within a few percentage points) under minor textual and model variations [105], [106], [107], [108]. By propagating these empirically grounded variations through the full computational pipeline, it is demonstrated that the derived obsolescence metrics preserve their trend, providing an evidence-based robustness validation of the proposed framework.

IV. RESULT

A. Extraction of Online 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 1000 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 II, ChatGPT-4o outperformed Claude-3 Opus and Llama 3. Consequently, ChatGPT-4o was used to process the entire dataset, identifying 4771 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 III
KEY OBSOLESCENCE FACTORS COMMON TO ALL PRODUCT CATEGORIES

- Malfunction
- Durability
- Design flaws
- Connectivity issue
- Incompatibility
- Inaccuracy
- Latency issue
- Controllability issue
- Poor user interface

ChatGPT-4o assigned multiple labels to the reviews, which were later grouped into 19 broader categories by researchers, as outlined in Appendix 5 (see Supplementary Material). 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 Table III.

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 Table IV.

B. Factors Influencing Obsolescence of Consumer IoT Devices

The Freq-AHP method, as detailed in equations A3.1 to A3.10, 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 (3). With both the weight and dissatisfaction level of each factor established, $\text{OI}_{(\text{jct})}$ was then calculated using (1) to quantify the impact of each obsolescence factor within its respective category over a defined period, as illustrated in Fig. 2. To further analyze obsolescence factor trends, (5) was applied to compute $\text{NOI}_{(\text{jct})}$, enabling an assessment of factor variations

TABLE IV
FACTORS INFLUENCING OBSOLESCENCE IN SOME PRODUCT CATEGORIES

Category-specific factor	**Product category**
Image quality degradation	• Smart entertainment system • Smart health device • Smart security system • Smart speaker and display
Storage limitation	• Smart entertainment system
Battery drain	• Smart blind • Smart entertainment system • Smart health device • Smart security system • Smart thermostat
Privacy	• Smart entertainment system • Smart health device • Smart lighting • Smart security system • Smart speaker and display • Smart thermostat
Updateability issue	• Smart entertainment system • Smart health device • Smart lighting • Smart speaker and display
Security	• Smart entertainment system • Smart lighting • Smart security system • Smart speaker and display
Subscription-based access	• Smart entertainment system • Smart health device • Smart lighting • Smart security system • Smart speaker and display
Working cost	• Smart climate control • Smart entertainment system • Smart health device • Smart lighting • Smart security system • Smart speaker and display • Smart thermostat
Advertising-based interruption	• Smart entertainment system • Smart health device • Smart lighting • Smart speaker and display
Audio quality degradation	• Smart entertainment system • Smart health device • Smart security system • Smart speaker and display

across product categories over time. Appendix 6 (see Supplementary Material) highlights shift in obsolescence factors that exhibited notable changes. In addition, obsolescence factors with the most substantial $\mathrm{OIC}_{(jct_{I-i})}$ values were identified, providing insights into how their influence evolved over time. The discussions and insights presented in the following sections align with Fig. 2 and Appendix 6, offering a comprehensive visual representation of both static and dynamic trends in obsolescence factors across different product categories. In addition, the stability of the derived obsolescence metrics was assessed by introducing small random noise with a variance of 8×10^{-6}, calculated using (7), to all sentiment intensities. The indices OI and AOI were then recalculated with these perturbed values. The comparison between the original AOI and the AOI computed with noise, provided in Appendix 8 (see Supplementary Material), shows minimal deviations, confirming that the framework's outputs are robust under minor perturbations.

Malfunction is a key driver of product replacement [18], as it diminishes consumer satisfaction and fosters the desire to replace products [109]. Its prevalence has increased across most categories, with notable positive $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$ values for smart climate control (0.02 from 2019 to 2024) and smart entertainment systems (0.03 from 2022 to 2024), indicating a

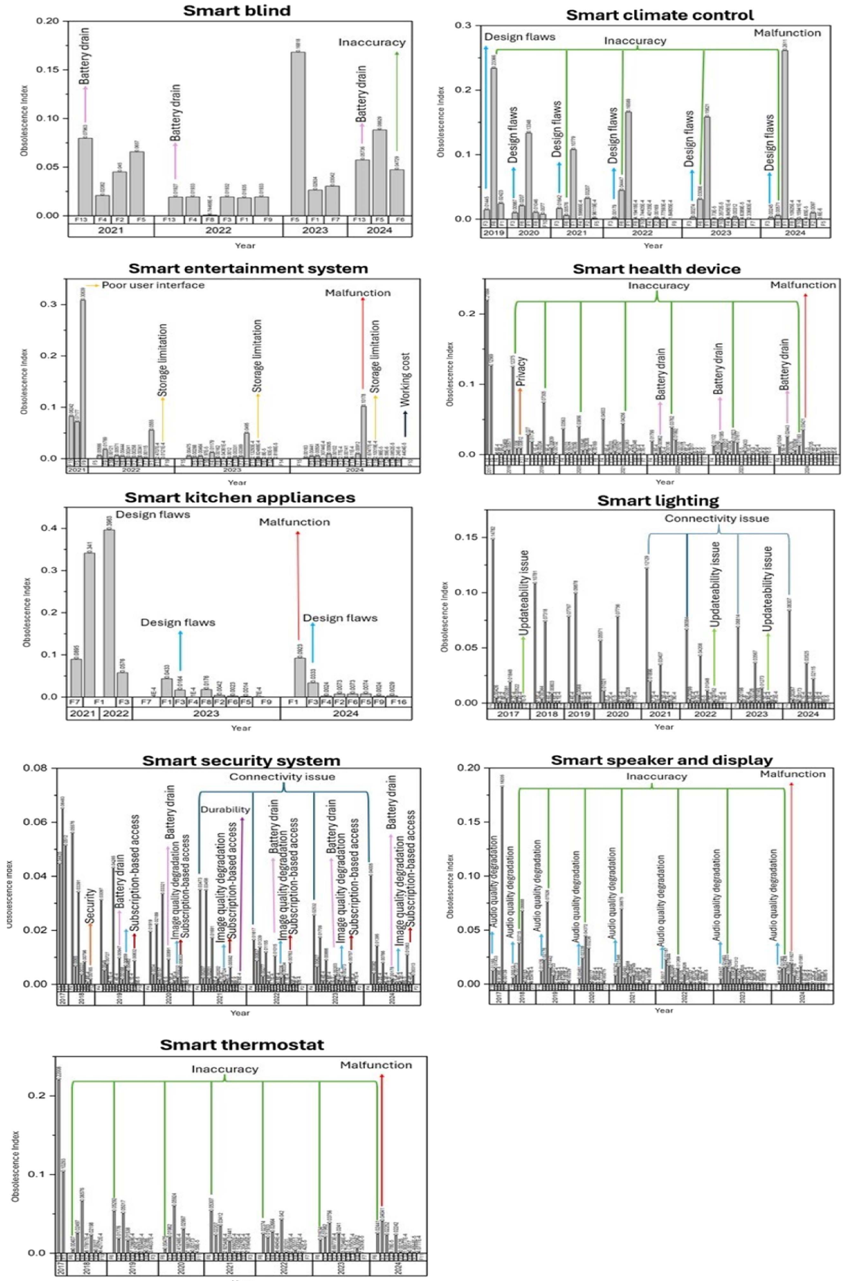

Fig. 2. Annual $\mathrm{OI}_{(\mathrm{jct})}$ across IoT product categories.
Note: The acronyms referenced in Fig. 2 are clarified as follows: F1: Malfunction, F2: Durability, F3:Design flaws, F4: Connectivity issue, F5: Incompatibility, F6: Inaccuracy, F7: Latency issue, F8: Controllability issue, F9: Poor user interface, F10: Working costs, F11: Privacy, F12: Security, F13: Battery drain, F14: Subscription-based access, F15: Advertising-based interruption, F16: Audio quality degradation, F17: Image quality degradation, F18: Updeateability issue, F19: Storage limitation.

rising impact in these categories. In 2024, malfunction recorded the highest $\mathrm{OI}_{(\mathrm{jct})}$ across six product categories, as shown in Fig. 2, 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 V. Connectivity issues 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. [110], and Touqeer et al. [111], 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 $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$ (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 issues include Wi-Fi or Bluetooth disruptions, signaling and bandwidth constraints, presence detection failures, and inference, all of which significantly impair device functionality [112], [113].

Inaccuracy became a notable concern for smart blinds in 2024 and remained a persistent issue in smart climate control,

TABLE V
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 <u>now a second (different) unit is clicking</u>. 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. <u>During a movie, after maybe 2-3 hours of playing, the screen goes dark and the G logo starts up again</u>. 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. <u>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</u>. 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. <u>This is the most recent one. I purchased it on July 11, 2023, and on June 30, 2024, it quit working</u>. 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. <u>I am not going to buy any more Fitbit devices</u>. Also, FYI, the iPhone app is very slow to sync with the Fitbit device.

despite claims of high accuracy in this category [114], [115]. 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 [116], with an increasing trend. In smart speaker and display, inaccuracy has been a critical factor of obsolescence, primarily due to speech recognition errors [117], resulting in consistently high $\mathrm{OI}_{(\mathrm{jct})}$ levels, a trend that has been increasing since 2022. In contrast, while inaccuracy has had a substantial $\mathrm{OI}_{(\mathrm{jct})}$ in smart thermostat over multiple periods, it has declined since 2021, likely due to advancements in occupancy detection technology [118]. A similar decline has been observed in smart security systems since 2020, attributed to the integration of advanced technologies [119]. 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 [120], [121], it has increased in others, likely due to the absence or 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 [120].

Controllability refers to the ability to remotely and automatically manage devices while allowing users to customize functions to their preferences [122], [123], as shown in Table V. 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 [122], [124]. In addition, improvements in balancing automation with meaningful user interaction and increasing user agency have contributed to this decline [123], [125]. Conversely, it has increased in smart thermostats after 2021, an example illustrated in Table V. This rise is attributed to design limitations, including reliance on single-point temperature readings, standard comfort models, and inaccurate user mental models [126], [127]. 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 [126], [127], [128]. Another important factor to consider is durability, defined as a product's ability to maintain functionality and performance over its expected lifespan [129]. 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 [3]. Short-lived products harm brand reputation and deter future purchases, as reflected in Table V. 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 [130], [131].

Poor user interface, though having a low impact on eight product categories, emerged as an obsolescence factor, with the highest $\mathrm{OI}_{(\mathrm{jct})}$ 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 [132], [133]. To address these challenges, solutions such as user surveys, intuitive interfaces, personalized experiences, and context-aware applications should be implemented [133], [134] to enhance usability and mitigate interface-related obsolescence in consumer IoT devices. Design flaws, encompassing aesthetics [135], [136], ergonomics [137], [138], shape and color [139], and material [140], [141] contribute to obsolescence. While aesthetics and ergonomics are widely recognized as critical factors [6], this study emphasizes material-related issues as equally significant. For example, one consumer review explained: "*…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 $\mathrm{OI}_{(\mathrm{jct})}$ was notably higher. These two categories also experienced the most significant increase in $\mathrm{NOI}_{(\mathrm{jct})}$, 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 [142], 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 250 ms degrade quality [143]. 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.

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 Table IV. Although these factors have a minimal impact, as indicated by the low $\mathrm{OI}_{(\mathrm{jct})}$ in Fig. 2, 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 [144]. This study confirms that high operation and maintenance costs can lead to product obsolescence, aligning with [6], who identified these costs as contributors to obsolescence. A customer review 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 the 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 [145]. Privacy concerns peaked in smart health devices in 2018, while security reached its highest $\mathrm{OI}_{(\mathrm{jct})}$ in smart security systems the same year. However, both factors showed a steady decline from 2022 to 2024, as shown in Appendix 6. 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 [146]. In addition to previous studies have identified battery drain as an obsolescence factor in smartphones [26], [44], this study confirms its impact on consumer IoT devices as well. Battery drain exhibited high $OI_{(jct)}$ during certain periods in smart blinds, 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 6.

Audio and image quality degradation contribute to functional obsolescence by diminishing user experience over time, ultimately driving product obsolescence [3]. 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 durable goods [147]. While its impact remained low across most product categories, smart security systems experienced a notable $OI_{(jct)}$ over the years, with a positive $OIC_{(jct_{I-i})}$ (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 [148]. Although subscription models enhance customer retention by fostering long-term relationships through customization and continuous improvements [148], 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 [149]. 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 [150], 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 [151]. 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 [151], [152]. Finally, storage limitations that was previously identified as a driver of obsolescence in mobile devices [153], can also impact obsolescence of smart entertainment systems, underscoring its broader impact on consumer technology.

V. Discussion

A. Using Pretrained LLMs for Identifying Product Obsolescence Factors

Pretrained LLMs, such as ChatGPT-4o, provide an efficient tool to extract obsolescence-related factors from large volumes of consumer feedback. By categorizing reviews and identifying multiple obsolescence drivers, the LLMs enable the creation of structured datasets that capture both general and category-specific contributors to obsolescence. Beyond merely detecting explicit mentions of hardware failures, LLMs demonstrate the capability to infer latent drivers related to system functionality and user experience from nuanced consumer narratives. This allows the extraction of insights about devices' ability to adjust to technological advancements, maintain interoperability with connected devices, and ensure consistent functionality over time, offering a deeper and more holistic understanding of the factors influencing premature replacement. By leveraging these capabilities, LLMs provide a bridge between observable product issues and broader ecosystem and experiential considerations, allowing researchers and practitioners to identify obsolescence drivers. Consequently, this approach supports a richer, user-centered perspective on consumer IoT device longevity, highlighting the multidimensional nature of obsolescence in modern technological environments.

B. Leveraging User-Generated Content for Product Obsolescence Analysis

UGC provides a rich, real-time perspective on how consumers experience product lifespan, functionality, and interaction with IoT devices. Beyond capturing explicit references to hardware failures, UGC reflects obsolescence drivers emerging from broader system-level attributes, including a device's capacity to evolve with technological changes, maintain interoperability across platforms, and sustain reliable performance under varying conditions. Analysis of these consumer narratives reveals that product replacement decisions are increasingly shaped by operational, and experiential factors, rather than solely by physical durability or technical faults. By tracking these patterns over time, manufacturers and designers can anticipate emerging consumer expectations, assess real-world performance, and prioritize improvements that enhance long-term usability and satisfaction. In this way, UGC analysis not only provides a practical source of information for monitoring product obsolescence but also confirms the theoretical proposition that consumer IoT device longevity depends on both hardware integrity and system-level functional capabilities, thereby supporting more resilient, user-centered design and informing proactive lifecycle management strategies.

C. Factors and Theoretical Perspectives Shaping Obsolescence in Consumer IoT Devices

As illustrated in Fig. 3, the study reveals that $AOI_{(ct)}$, calculated using (4), has exhibited 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

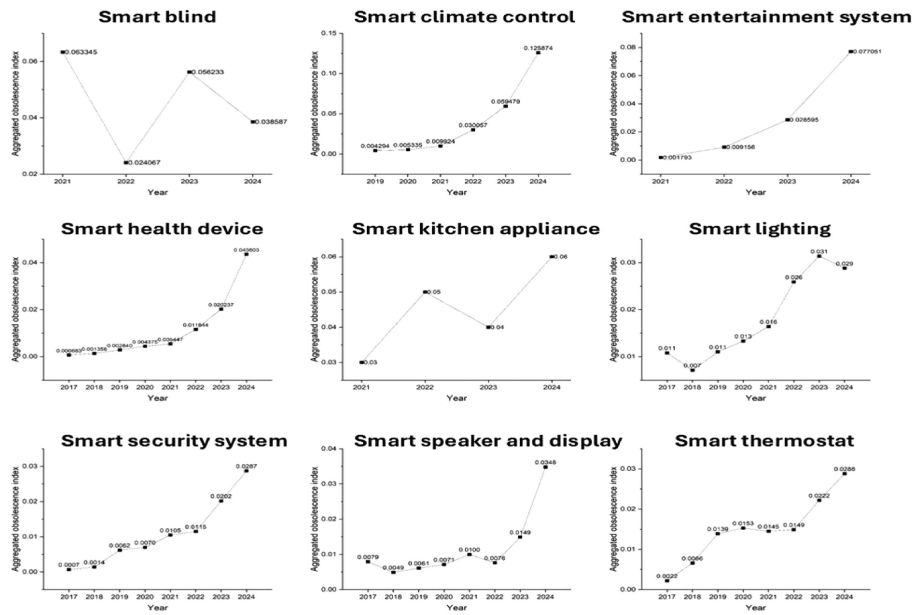

Fig. 3. Trend analysis of $AOI_{(ct)}$ across IoT product categories.

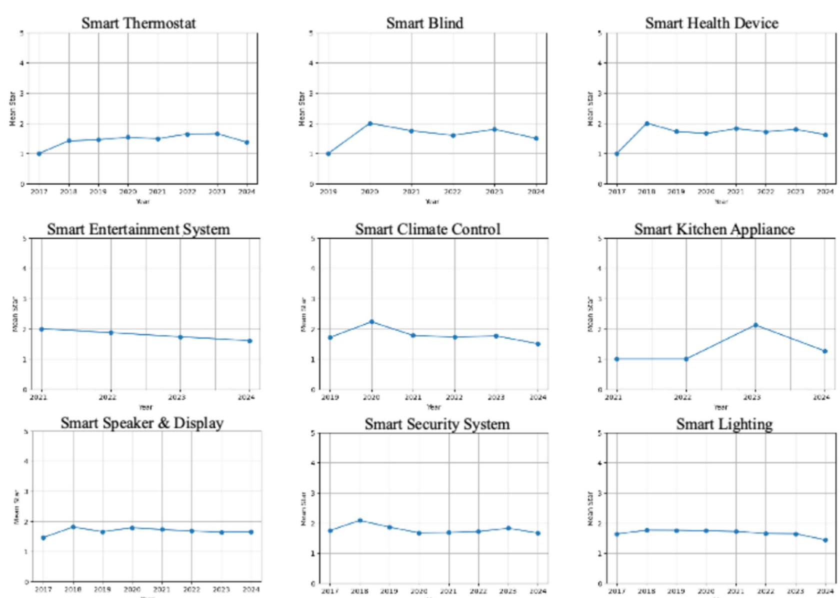

Fig. 4. Consumer dissatisfaction trends by product category based on star ratings.

longevity. The rising $AOI_{(ct)}$ in most categories indicates that product obsolescence-related issues are becoming more prevalent, which aligns 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 [15].

This study has identified a diverse and nuanced set of 19 product obsolescence factors spanning multiple consumer IoT device categories. This breadth of factors highlights a far more intricate and context-dependent landscape of consumer decision-making than is typically assumed. While nine product obsolescence factors emerge consistently across all product categories, others are distinctly category-specific. This differentiation challenges the conventional one-size-fits-all approach to product design and provide actionable insights for product managers aiming to develop more targeted, category-specific strategies. By addressing these design-driven challenges, they can help counteract the "throwaway culture" and foster a more sustainable, user-centric, and ethically responsible approach to product development [7], [154].

Our findings point to a broader structural shift in the nature of product obsolescence: it is increasingly driven less by physical wear and failure, and more by complex ecosystem-level and socio-technical dynamics. This shift can be understood through sociotechnical systems theory [155], which emphasizes that products exist within interconnected systems of technologies, standards, organizational practices, and user behaviors. Consistent with this perspective, our observation that indirect software-induced issues, such as incompatibility, connectivity problems, and latency, have a more persistent impact than direct technical faults highlights that devices become obsolete not only due to internal flaws but also because of changes or fragmentation in the surrounding technical and institutional context. Even industry-wide efforts like the Matter and Lumos standards [120], [121], aimed at enhancing interoperability, have limited impact due to uneven adoption and structural differences across competing ecosystems [156]. This theoretical lens clarifies why technical improvements alone may fail to significantly extend product life when systemic factors remain unaddressed.

In addition, platform theory [157] and servitization theory [158] provide complementary insights. Platform theory emphasizes that digital platforms act as intermediaries controlling software updates, data flows, and access to core features, while servitization highlights the transformation of products into service-oriented offerings to extend value over time. Our findings indicate that platform governance and service-based business models increasingly shape obsolescence: consumers often abandon devices when rising service costs, intrusive advertising, or feature restrictions degrade user experience, even if the physical product remains functional. This demonstrates that obsolescence emerges as an outcome of strategic platform decisions rather than purely technical decline, showing how ecosystem design, platform control, and service models interact to influence product longevity.

Lastly, the persistence of consumer dissatisfaction, even as absolute product performance improves, is well accounted for by expectation-disconfirmation theory [159]. To quantify dissatisfaction, we analyzed mean star ratings for each product category over time, following established practice [160], [161]. Each consumer can assign a star rating to indicate their satisfaction with the product on platforms like Amazon or BestBuy, where lower ratings reflect higher dissatisfaction. Fig. 4 shows that, despite technical improvements, dissatisfaction levels remain high across categories. This pattern arises because marketing and engineering increasingly emphasize AI-powered precision and seamless integration, driving consumer expectations beyond what is realistically achievable. When actual device performance (e.g., accuracy) falls short of these heightened expectations, users experience greater dissatisfaction and may replace products prematurely.

Thus, even with technical gains, dissatisfaction persists because expectations escalate faster than systemic or technological capabilities. By linking these empirical findings to theoretical frameworks, this study provides a deeper, conceptually grounded understanding of why obsolescence in consumer IoT devices is shifting from being driven primarily by physical durability toward issues related to system-level attributes such as adaptability, interoperability, and digital resilience. So, this underscores the need for design and policy strategies that go beyond improving hardware, to also address platform governance, service models, and the broader sociotechnical environment in which these devices operate.

VI. Conclusion

This study advances the understanding of product obsolescence, especially in 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. The stability of the derived obsolescence trends is further supported through an evidence-based robustness check, in which small perturbations were applied to sentiment intensities and all indices were recalculated, confirming consistent trend patterns across product categories. Building on this validated foundation, this research introduces $\mathrm{OI}_{(\mathrm{jct})}$ and $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$, innovative metrics that provide a comprehensive and dynamic framework for understanding and addressing obsolescence. $\mathrm{OI}_{(\mathrm{jct})}$ captures the intensity of obsolescence factors over time, offering a snapshot of the current impact, while the $\mathrm{OIC}_{(\mathrm{jct}_{I-i})}$ 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, By uncovering ecosystem-level and software-induced drivers of obsolescence, these findings challenge traditional durability-focused approaches, revealing that product longevity depends not only on hardware but also on software updates, interoperability, and user experience. This insight enables managers to proactively redesign lifecycle strategies, prioritize software support and platform compatibility, and implement consumer-centered practices that can reduce premature obsolescence and associated economic and environmental costs. 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, several limitations should be acknowledged to guide future research. First, the scope is limited to specific product categories, which may affect the generalizability of the findings to other IoT devices or broader technology ecosystems. Future work could refine the framework using domain-specific datasets and extend it to a wider range of devices for broader applicability. Second, the study relies on UGC from online reviews. Although these reviews offer rich consumer perspectives, they may not fully capture technical aspects of obsolescence, industry-level trends, or objective measures, and they can be biased or unrepresentative. Integrating complementary data sources, such as technical specifications, industry reports, or structured surveys, could help mitigate these limitations. Third, this work does not explore the role of customer service and warranty policies in shaping product longevity. Investigating how these factors influence user retention, repair practices, and satisfaction could provide actionable insights for manufacturers and policymakers. Fourth, while the obsolescence indexes have been rigorously developed and statistically validated using large-scale UGC, real-world application in organizational case studies remains a future step to further demonstrate practical utility. Fifth, while the analysis emphasizes consumer dissatisfaction as a signal of obsolescence, it may overlook objective drivers such as manufacturing defects, design limitations, or regulatory shifts. Incorporating objective product data and expert assessments could help develop a more holistic view. Sixth, users might not be entirely aware of their reasons for stopping use of a device or may avoid mentioning issues such as their own competencies in UGC, so UGC may not capture all causes of obsolescence. Future research could address this by combining UGC analysis with interviews to capture unreported factors and better understand the drivers of obsolescence. Finally, the dataset is sourced from Amazon.com and BestBuy.com, which may introduce data bias and limit representativeness of global consumer perspectives. Expanding the analysis to include other platforms and regions could enhance the generalizability of findings. By addressing these limitations, future research can develop a more comprehensive and validated understanding of IoT device obsolescence, ultimately contributing to strategies that enhance product lifespans and align with sustainability objectives.

References

[1] M. Proske, "How to address obsolescence in LCA studies – Perspectives on product use-time for a smartphone case study," *J. Cleaner Prod.*, vol. 376, Nov. 2022, Art. no. 134283, doi: 10.1016/j.jclepro.2022.134283.

[2] L. Sierra-Fontalvo, A. Gonzalez-Quiroga, and J. A. Mesa, "A deep dive into addressing obsolescence in product design: A review," *Heliyon*, vol. 9, no. 11, Nov. 2023, Art. no. e21856, doi: 10.1016/j.heliyon.2023.e21856.

[3] A. Alzaydi, "Balancing creativity and longevity: The ambiguous role of obsolescence in product design," *J. Cleaner Prod.*, vol. 445, Mar. 2024, Art. no. 141239, doi: 10.1016/j.jclepro.2024.141239.

[4] Y. Su and J.-S. Hwang, "Integration of customer satisfaction and sustained use of a product for value assessment," *Total Qual. Manage. Bus. Excellence*, vol. 31, no. 15/16, pp. 1760–1773, 2020.

[5] P. Munten, J. Vanhamme, and V. Swaen, "Reducing obsolescence practices from a product-oriented PSS perspective: A research agenda," *Recherche et Appl. en Marketing*, vol. 36, no. 2, pp. 42–74, Jun. 2021, doi: 10.1177/2051570720980004.

[6] T. Cooper, "Inadequate life? evidence of consumer attitudes to product obsolescence," *J. Consum. Policy*, vol. 27, pp. 421–449, 2004.

[7] J. L. Rivera and A. Lallmahomed, "Environmental implications of planned obsolescence and product lifetime: A literature review," *Int. J. Sustain. Eng.*, vol. 9, pp. 119–129, Mar. 2016, doi: 10.1080/19397038.2015.1099757.

[8] H. Habib, M. Wagner, C. P. Baldé, L. H. Martínez, J. Huisman, and J. Dewulf, "What gets measured gets managed – does it? Uncovering the waste electrical and electronic equipment flows in the European Union," *Resour., Conservation Recycling*, vol. 181, Jun. 2022, Art. no. 106222, doi: 10.1016/j.resconrec.2022.106222.

[9] K. Mathiyazhagan, A. Gnanavelbabu, N. Kumar, and V. Agarwal, "A framework for implementing sustainable lean manufacturing in the electrical and electronics component manufacturing industry: An emerging economies country perspective," *J. Cleaner Prod.*, vol. 334, Feb. 2022, Art. no. 130169, doi: 10.1016/j.jclepro.2021.130169.

[10] N. Singh, H. Duan, O. A. Ogunseitan, J. Li, and Y. Tang, "Toxicity trends in E-waste: A comparative analysis of metals in discarded mobile phones," *J. Hazardous Mater.*, vol. 380, Dec. 2019, Art. no. 120898, doi: 10.1016/j.jhazmat.2019.120898.

[11] M. Chen, O. A. Ogunseitan, J. Wang, H. Chen, B. Wang, and S. Chen, "Evolution of electronic waste toxicity: Trends in innovation and regulation," *Environ. Int.*, vol. 89–90, pp. 147–154, Apr. 2016, doi: 10.1016/j.envint.2016.01.022.

[12] T. Lyu, H. Chen, and Y. Guo, "Investigating innovation diffusion, social influence, and personal inner forces to understand people's participation in online e-waste recycling," *J. Retailing Consum. Serv.*, vol. 73, Jul. 2023, Art. no. 103366, doi: 10.1016/j.jretconser.2023.103366.

[13] H. T. T. Nguyen, R. J. Hung, C. H. Lee, and H. T. T. Nguyen, "Determinants of residents' E-waste recycling behavioral intention: A case study from Vietnam," *Sustainability (Switzerland)*, vol. 11, no. 1, Jan. 2019, Art. no. 164, doi: 10.3390/su11010164.

[14] F. Vanessa, C. P. Balde, R Kuehr, and G. Bel, "The Global E-waste Monitor 2020: Quantities, flows and the circular economy potential" 2020.

[15] M. Sharma, D. Kaushal, S. Joshi, A. Kumar, and S. Luthra, "Electronic waste disposal behavioral intention of millennials: A moderating role of electronic word of mouth (eWOM) and perceived usage of online collection portal," *J. Cleaner Prod.*, vol. 447, Apr. 2024, Art. no. 141121, doi: 10.1016/j.jclepro.2024.141121.

[16] T. Makov and C. Fitzpatrick, "Is repairability enough? Big Data insights into smartphone obsolescence and consumer interest in repair," *J. Cleaner Prod.*, vol. 313, 2021, Art. no. 127561.

[17] M. Proske and M. Jaeger-Erben, "Decreasing obsolescence with modular smartphones?–An interdisciplinary perspective on lifecycles," *J. Cleaner Prod.*, vol. 223, pp. 57–66, 2019.

[18] H. Wieser and N. Tröger, "Exploring the inner loops of the circular economy: Replacement, repair, and reuse of mobile phones in Austria," *J. Cleaner Prod.*, vol. 172, pp. 3042–3055, Oct. 2016, doi: 10.1016/j.jclepro.2017.11.106.

[19] L. Hennies and R. Stamminger, "An empirical survey on the obsolescence of appliances in German households," *Resour., Conservation Recycling*, vol. 112, pp. 73–82, Sep. 2016, doi: 10.1016/j.resconrec.2016.04.013.

[20] P. S. Karagiannopoulos, N. M. Manousakis, K. Kalkanis, and C. S. Psomopoulos, "Investigation of home appliances industry and devices obsolescence considering energy consumption," *Sci. Rep.*, vol. 14, no. 1, Dec. 2024, Art. no. 18096, doi: 10.1038/s41598-024-68982-8.

[21] T. F. Bowlds, J. M. Fossaceca, and R. Iammartino, "Software obsolescence risk assessment approach using multicriteria decision-making," *Syst. Eng.*, vol. 21, no. 5, pp. 455–465, Sep. 2018, doi: 10.1002/sys.21446.

[22] B. J. Giovannoni and C. Boyles, "Hidden costs of unsupported software, obsolescence and non standards; the importance and value of a multi-mission software program," in *Proc. 14th Int. Conf. Space Operations*, 2016, p. 2499.

[23] S. Rajagopal, J. A. Erkoyuncu, and R. Roy, "Impact of software obsolescence in defence manufacturing sectors," *Procedia CIRP*, vol. 28, pp. 197–201, 2015, doi: 10.1016/j.procir.2015.04.034.

[24] A. Timoshenko and J. R. Hauser, "Identifying customer needs from user-generated content," *Marketing Sci.*, vol. 38, no. 1, pp. 1–20, 2018, doi: 10.1287/mksc.2018.1123.

[25] I. Ö. İmir, "Progressive obsolescence and product non-use in electrical kitchen appliances," Master's thesis, Middle East Technical Univ., 2010.

[26] A. Oraee, L. Pohl, D. Geurts, and M. Reichel, "Overcoming premature smartphone obsolescence amongst young adults," *Cleaner Responsible Consumption*, vol. 12, Mar. 2024, Art. no. 100174, doi: 10.1016/j.clrc.2024.100174.

[27] R. G. Muñoz et al., "Key challenges in software application complexity and obsolescence management within aerospace industry," *Procedia CIRP*, vol. 37, pp. 24–29, 2015, doi: 10.1016/j.procir.2015.08.013.

[28] M. A. Pardo-Vicente, P. Camacho-Magriñan, and P. Pavon-Dominguez, "Influence of technology on perceived obsolescence though product design properties," *Sustainability (Switzerland)*, vol. 14, no. 21, Nov. 2022, Art. no. 14555, doi: 10.3390/su142114555.

[29] L. Magnier and R. Mugge, "Replaced too soon? An exploration of Western European consumers' replacement of electronic products," *Resour., Conservation Recycling*, vol. 185, Oct. 2022, Art. no. 106448, doi: 10.1016/j.resconrec.2022.106448.

[30] Z. Zhao, Y. Li, and X. Chu, "Data-driven approach to identify obsolete functions of products for design improvements," *J. Intell. Fuzzy Syst.*, vol. 40, no. 3, pp. 5369–5382, 2021, doi: 10.3233/JIFS-202144.

[31] S. S. Cordero, M. Zolghadri, R. Vingerhoeds, and C. Baron, "Identification and assessment of obsolescence in the early stages of system design," *J. Integr. Des. Process Sci.*, vol. 24, no. 3/4, pp. 15–33, 2022.

[32] H. M. Naeem and E. Di Maria, "Customer participation in new product development: An Industry 4.0 perspective," *Eur. J. Innov. Manage.*, vol. 25, no. 6, pp. 637–655, 2020, doi: 10.1108/EJIM-01-2021-0036.

[33] M. P. Couper, "Web surveys: A review of issues and approaches," *Public Opin. Quart.*, vol. 64, no. 4, pp. 464–494, 2000.

[34] Y. Zhang and B. M. Wildemuth, *Unstructured Interviews: Appl. of Social Res. Methods to Questions in Inf. Library Sci.*, vol. 2, Exeter, U.K.: Libraries Unlimited, pp. 222–231, 2009.

[35] A. Bryman, *Social Research Methods*. London, U.K.: Oxford Univ. Press, 2016.

[36] G. Elia, A. Margherita, and G. Passiante, "Management engineering: A new perspective on the integration of engineering and management knowledge," *IEEE Trans. Eng. Manage.*, vol. 68, no. 3, pp. 881–893, Jun. 2021, doi: 10.1109/TEM.2020.2992911.

[37] I. Vasilev, "Business process engineering (BPE) in the context of dual training in telecommunications university," 2024. [Online]. Available: https://www.researchgate.net/publication/387191554

[38] M. A. Mellal, "Obsolescence – A review of the literature," *Technol. Soc.*, vol. 63, Nov. 2020, Art. no. 101347, doi: 10.1016/j.techsoc.2020.101347.

[39] V. Guillard, E. L. Nagard, and G. de Campos Ribeiro, "A typology of consumers regarding perceived obsolescence: The paradox of eco-conscious consumers," *J. Cleaner Prod.*, vol. 412, Aug. 2023, Art. no. 137202, doi: 10.1016/j.jclepro.2023.137202.

[40] G. Slade, *Made to Break: Technology and Obsolescence in America*. Cambridge, MA, USA: Harvard Univ. Press, 2007.

[41] T. Cooper, *Longer Lasting Products: Alternatives to the Throwaway Society*. Surrey, U.K.: Gower Publishing, 2010.

[42] T. Cooper, "Slower consumption: Reflections on product life spans and the 'throwaway society," *J. Ind. Ecol.*, vol. 9, no. 1/2, pp. 51–67, Dec. 2005, doi: 10.1162/1088198054084671.

[43] F. Bilici and E. Özdemir, "Consumer perception of planned obsolescence: A research on smartphone owners," *J. Bus. Res.*, vol. 16, no. 1, pp. 244–261, Mar. 2024, doi: 10.20491/isarder.2024.1788.

[44] M. Proske, J. Winzer, M. Marwede, N. F. Nissen, and K.-D. Lang, "Obsolescence of electronics - the example of smartphones," in *Proc. Electron. Goes Green 2016+*, 2016, pp. 1–8.

[45] G. Kordic, I. Grgurevic, and S. Husnjak, "Identification of factors relevant for the estimation of smartphone life cycle," in *Proc. 25th Telecommun. Forum*, 2017, pp. 1–4. doi: 10.1109/TELFOR.2017.8249276.

[46] F. J. R. Rojo, R. Roy, E. Shehab, and P. J. Wardle, "Obsolescence challenges for product-service systems in aerospace and defence industry," in *Proc. CIRP Ind. Product-Service Syst. Conf.*, 2009, p. 255.

[47] E. Poppe, E. Wagner, M. Jaeger-Erben, J. Druschke, and M. Köhn, "Is it a bug or a feature? The concept of software obsolescence Is it a bug or a feature?," 2021. [Online]. Available: https://hdl.handle.net/10344/10242

[48] R. Gonzalez-Usach, D. Yacchirema, M. Julian, and C. E. Palau, "Interoperability in IOT," in *Handbook of Research On Big Data and the IoT*. Hershey, PA, USA: IGI Global, 2019, pp. 149–173.

[49] D. Bianculli et al., *Software Architecture. ECSA 2025 Tracks and Workshops*. Limassol, Cyprus: Springer, 2025.

[50] Y. Tim and D. E. Leidner, "Digital resilience: A conceptual framework for information systems research," *J. Assoc. Inf. Syst.*, vol. 24, no. 5, pp. 1184–1198, Sep. 2023, doi: 10.17705/1jais.00842.

[51] P. Sandborn, "Software obsolescence-complicating the part and technology obsolescence management problem," *IEEE Trans. Compon. Packag. Technol.*, vol. 30, no. 4, pp. 886–8888, 2007.

[52] L. Merola, "The COTS software obsolescence threat," in *Proc. 5th Int. Conf. Commercial-off–Shelf-Based Softw. Syst.*, 2006, p. 7.

[53] E. Kern et al., "Sustainable software products—Towards assessment criteria for resource and energy efficiency," *Future Gener. Comput. Syst.*, vol. 86, pp. 199–210, Sep. 2018, doi: 10.1016/j.future.2018.02.044.

[54] I. Blackman and R. Rogowski, "The obsolescence tools minefield: A guide to availability monitoring," COG Intl. Ltd., U.K., 2008.

[55] E. E. Ogheneovo, "On the relationship between software complexity and maintenance costs," *J. Comput. Commun.*, vol. 2, no. 14, pp. 1–16, 2014, doi: 10.4236/jcc.2014.214001.

[56] N. A. Ernst et al., "Estimating the Breaking Point for Technical Debt.," in *Proc. 7th Int. Workshop Manag. Tech. Debt.*, 2015, pp. 53–56.

[57] B. Bartels, U. Ermel, P. Sandborn, and M. G. Pecht, *Strategies to the Prediction, Mitigation and Management of Product Obsolescence*. Hoboken, NJ, USA: Wiley, 2012.

[58] T. Falatouri, D. Hrušecká, and T. Fischer, "Harnessing the power of LLMs for service quality assessment from user-generated content; harnessing the power of LLMs for service quality assessment from user-generated content," *IEEE Access*, vol. 12, pp. 99755–99767, 2024, doi: 10.1109/ACCESS.

[59] L. Yao, C. Mao, and Y. Luo, "Clinical text classification with rule-based features and knowledge-guided convolutional neural networks," *BMC Med. Informat. Decis. Mak.*, vol. 19, Apr. 2019, pp. 70–71, doi: 10.1186/s12911-019-0781-4.

[60] F. Zhou, J. Ayoub, Q. Xu, and X. J. Yang, "A machine learning approach to customer needs analysis for product ecosystems," *J. Mech. Des., Trans. ASME*, vol. 142, no. 1, pp. 1–13, 2020, doi: 10.1115/1.4044435.

[61] M. Garofalakis, R. Rastogi, and K. Shim, "Mining sequential patterns with regular expression constraints," 2002. [Online]. Available: www.yahoo.com

[62] J. Pustejovsky and A. Stubbs, *Natural Language Annotation for Machine Learning: A Guide to Corpus-Building for Applications*. Sebastopol, CA, USA: O'Reilly Media, Inc., 2012.

[63] B. Barkha, "Sentiment classification of online consumer reviews using word vector representations," *Procedia Comput. Sci.*, vol. 132, 2018, Art. no. 1147.

[64] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics: Hum. Lang. Technol.*, vol. 1, 2019, pp. 4171–4186.

[65] L. George and P. Sumathy, "An integrated clustering and BERT framework for improved topic modeling," *Int. J. Inf. Technol. (Singapore)*, vol. 15, no. 4, pp. 2187–2195, Apr. 2023, doi: 10.1007/s41870-023-01268-w.

[66] Y. Liu et al., "RoBERTa: A robustly optimized BERT pretraining approach," Jul. 2019.[Online]. Available: arxiv.org/abs/1907.11692

[67] V. N. Rao, E. Agarwal, S. Dalal, D. Calacci, and A. Monroy-Hernández, "QuaLLM: An LLM-based framework to extract quantitative insights from online forums," May 2024.[Online]. Available: v.org/abs/2405.05345

[68] C. M. Pham, A. Hoyle, S. Sun, P. Resnik, and M. Iyyer, "TopicGPT: A prompt-based topic modeling framework," Nov. 2023.[Online]. Available: arxiv.org/abs/2311.01449

[69] X. Deng, V. Bashlovkina, F. Han, S. Baumgartner, and M. Bendersky, "LLMs to the Moon? Reddit market sentiment analysis with large language models," in *Proc. ACM Web Conf. Companion World Wide Web Conf.*, Apr. 2023, pp. 1014–1019. doi: 10.1145/3543873.3587605.

[70] T. B. Brown et al., "Language models are few-shot learners," 2020. [Online]. Available: https://commoncrawl.org/the-data/

[71] M. Leippold, "Thus spoke GPT-3: Interviewing a large-language model on climate finance," *Finance Res. Lett.*, vol. 53, May 2023, Art. no. 103617, doi: 10.1016/j.frl.2022.103617.

[72] W. X. Zhao et al., "A survey of large language models," Mar. 2023. [Online]. Available: arxiv.org/abs/2303.18223

[73] P. Y. Wu, J. Nagler, J. A. Tucker, and S. Messing, "Large language models can be used to estimate the latent positions of politicians," Mar. 2023.[Online]. Available: arxiv.org/abs/2303.12057

[74] F. Gilardi, M. I. Alizadeh, and M. I. Kubli, "ChatGPT outperforms crowd workers for text-annotation tasks," *Political Sci.*, vol. 120, 2023, Art. no. e2305016120, doi: 10.1073/pnas.

[75] P. Törnberg, "How to use LLMs for text analysis," Jul. 2023.[Online]. Available: arxiv.org/abs/2307.13106

[76] A. M. Ghaleb, H. Kaid, A. Alsamhan, S. H. Mian, and L. Hidri, "Assessment and comparison of various MCDM approaches in the selection of manufacturing process," *Adv. Mater. Sci. Eng.*, vol. 2020, 2020, Art. no. 4039253, doi: 10.1155/2020/4039253.

[77] S. Kheybari, F. M. Rezaie, and H. Farazmand, "Analytic network process: An overview of applications," *Appl. Math. Comput.*, vol. 367, 2020, Art. no. 124780.

[78] J. Papathanasiou and N. Ploskas, "Topsis. Multiple criteria decision aid," in *Springer Optimization and Its Applications*, vol. 136. Cham, Switzerland: Springer, 2018.

[79] S. Opricovic and G.-H. Tzeng, "Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS," *Eur. J. Oper. Res.*, vol. 156, no. 2, pp. 445–455, 2004.

[80] T. L. Saaty, "Decision making with the analytic hierarchy process," *Int. J. Serv. Sci.*, vol. 1, no. 1, pp. 83–98, 2008.

[81] Y. Dagtekin, S. Kaya, and N. Besli, "Distributed energy system selection for a commercial building by using Multi Criteria Decision Making methods," *Int. J. Hydrogen Energy*, vol. 47, no. 86, pp. 36672–36692, Oct. 2022, doi: 10.1016/j.ijhydene.2022.08.208.

[82] E. H. Forman and S. I. Gass, "The analytic hierarchy process—An exposition," *Oper. Res.*, vol. 49, no. 4, pp. 469–486, 2001.

[83] D. Choudhary and R. Shankar, "An STEEP-fuzzy AHP-TOPSIS framework for evaluation and selection of thermal power plant location: A case study from India," *Energy*, vol. 42, no. 1, pp. 510–521, 2012.

[84] S. P. Sindhu, V. Nehra, and S. Luthra, "Recognition and prioritization of challenges in growth of solar energy using analytical hierarchy process: Indian outlook," *Energy*, vol. 100, pp. 332–348, 2016.

[85] S. Bird, "NLTK Documentation Release," Online: accessed: Apr. 2008.

[86] M. Nasseri, P. Brandtner, R. Zimmermann, T. Falatouri, F. Darbanian, and T. Obinwanne, "Applications of large language models (llms) in business analytics–exemplary use cases in data preparation tasks," in *Proc. Int. Conf. Human-Comput. Interaction*, 2023, pp. 182–198.

[87] X. Liu et al., "GPT understands, too," *AI Open*, vol. 5, pp. 208–215, 2024, doi: 10.1016/j.aiopen.2023.08.012.

[88] T. Lu, J. Hu, and P. Chen, "Benchmarking Llama 3 for Chinese news summation: Accuracy, cultural nuance, and societal value alignment," *Authorea Preprints*, 2024.

[89] Meta, "Introducing meta llama 3: The most capable openly available llm to date".

[90] Anthropic, "Introducing the next generation of Claude". [Online]. Available: https://www.anthropic.com/news/claude-3-family

[91] P. Liu, W. Yuan, J. Fu, Z. Jiang, H. Hayashi, and G. Neubig, "Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing," *ACM Comput. Surv.*, vol. 55, no. 9, Jan. 2023, Art. no. 195, doi: 10.1145/3560815.

[92] L. S. Lo, "The art and science of prompt engineering: A new literacy in the information age," *Internet Reference Serv. Quart.*, vol. 27, no. 4, pp. 203–210, 2023.

[93] J. White et al., "A prompt pattern catalog to enhance prompt engineering with ChatGPT," Feb. 2023. [Online]. Available: arxiv.org/abs/2302.11382

[94] J. D. Velásquez-Henao, C. J. Franco-Cardona, and L. Cadavid-Higuita, "Prompt Engineering: A methodology for optimizing interactions with AI-Language Models in the field of engineering," *Dyna (Medellin)*, vol. 90, no. 230, pp. 9–17, Nov. 2023, doi: 10.15446/dyna.v90n230.111700.

[95] K. De Swert, "Calculating inter-coder reliability in media content analysis using Krippendorff's Alpha," *Center Politics Commun.*, vol. 15, no. 1–15, 2012, Art. no. 3.

[96] N. Wongpakaran, T. Wongpakaran, D. Wedding, and K. L. Gwet, "A comparison of Cohen's Kappa and Gwet's AC1 when calculating inter-rater reliability coefficients: A study conducted with personality disorder samples," *BMC Med. Res. Methodol.*, vol. 13, pp. 1–7, 2013.

[97] C. Hou, M. S. Jo, and E. Sarigöllü, "Feelings of satiation as a mediator between a product's perceived value and replacement intentions," *J. Cleaner Prod.*, vol. 258, Jun. 2020, Art. no. 120637, doi: 10.1016/j.jclepro.2020.120637.

[98] R. van den Berge, L. Magnier, and R. Mugge, "Too good to go? Consumers' replacement behaviour and potential strategies for stimulating product retention," *Curr. Opin. Psychol.*, vol. 39, pp. 66–71, Jun. 2021, doi: 10.1016/j.copsyc.2020.07.014.

[99] J. Wei, M. Jiang, Y. N. Li, W. Li, and J. A. Mead, "The impact of product defect severity and product attachment on consumer negative emotions," *Psychol. Marketing*, vol. 40, no. 5, pp. 1026–1042, May 2023, doi: 10.1002/mar.21778.

[100] G. Catenazzo and M. Paulssen, "Experiencing defects: The moderating role of severity and warranty coverage on quality perceptions," *Int. J. Qual. Rel. Manage.*, vol. 40, no. 9, pp. 2205–2221, Oct. 2023, doi: 10.1108/IJQRM-10-2021-0352.

[101] D. Liang, Z. Dai, and M. Wang, "Assessing customer satisfaction of O2O takeaway based on online reviews by integrating fuzzy comprehensive evaluation with AHP and probabilistic linguistic term sets," *Appl. Soft Comput.*, vol. 98, Jan. 2021, Art. no. 106847, doi: 10.1016/j.asoc.2020.106847.

[102] P. Penmetsa, P. Sheinidashtegol, A. Musaev, E. K. Adanu, and M. Hudnall, "Effects of the autonomous vehicle crashes on public perception of the technology," *IATSS Res.*, vol. 45, no. 4, pp. 485–492, Dec. 2021, doi: 10.1016/j.iatssr.2021.04.003.

[103] Y. Liu et al., "RoBERTa: A robustly optimized BERT pretraining approach," Jul. 2019. [Online]. Available: arxiv.org/abs/1907.11692

[104] J. Devlin, M.-W. Chang, K. Lee, K. T. Google, and A. I. Language, "BERT: Pre-training of deep bidirectional transformers for language understanding," 2019. [Online]. Available: https://github.com/tensorflow/tensor2tensor

[105] N. Cassee, A. Agaronian, E. Constantinou, N. Novielli, and A. Serebrenik, "Transformers and meta-tokenization in sentiment analysis for software engineering," *Empirical Softw. Eng.*, vol. 29, no. 4, Jul. 2024, Art. no. 77, doi: 10.1007/s10664-024-10468-2.

[106] X. Gong, W. Ying, S. Zhong, and S. Gong, "Text sentiment analysis based on transformer and augmentation," *Front. Psychol.*, vol. 13, May 2022, Art. no. 906061, doi: 10.3389/fpsyg.2022.906061.

[107] H. Fei, T. S. Chua, C. Li, D. Ji, M. Zhang, and Y. Ren, "On the robustness of aspect-based sentiment analysis: Rethinking model, data, and training," *AACM Trans. Inf. Syst.*, vol. 41, no. 2, Dec. 2022, Art. no. 50, doi: 10.1145/3564281.

[108] T. Ouyang, A. P. MaungMaung, K. Konishi, Y. Seo, and I. Echizen, "Stability analysis of ChatGPT-based sentiment analysis in AI quality assurance," *Electron. (Switzerland)*, vol. 13, no. 24, Dec. 2024, Art. no. 5043, doi: 10.3390/electronics13245043.

[109] N. Brigden and G. Häubl, "Inaction traps in consumer response to product malfunctions," *J. Marketing Res.*, vol. 57, no. 2, pp. 298–314, Apr. 2020, doi: 10.1177/0022243719889336.

[110] G. Parise, G. Zissis, and L. Martirano, "Smart lighting systems, controls, and communication protocols: Introducing open communication protocols," *IEEE Ind. Appl. Mag.*, vol. 31, no. 2, pp. 68–79, Mar./Apr. 2025, doi: 10.1109/MIAS.2024.3482882.

[111] H. Touqeer, S. Zaman, R. Amin, M. Hussain, F. Al-Turjman, and M. Bilal, "Smart home security: Challenges, issues and solutions at different IoT layers," *J. Supercomputing*, vol. 77, no. 12, pp. 14053–14089, Dec. 2021, doi: 10.1007/s11227-021-03825-1.

[112] I. Petrut and M. Otesteanu, "The IoT connectivity challenges," in *Proc. IEEE 12th Int. Symp. Appl. Comput. Intell. Inform.*, 2018, pp. 000385–000388.

[113] A. A. Eltholth, "Improved spectrum coexistence in 2.4 GHz ISM band using optimized chaotic frequency hopping for Wi-Fi and bluetooth signals," *Sensors*, vol. 23, no. 11, Jun. 2023, Art. no. 5183, doi: 10.3390/s23115183.

[114] M. E. Alam, M. R. Amin, and S. Nizam Uddin, "AmbientIQ : A sophisticated smart room ecosystem for ultimate comfort and efficiency," 2024, doi: 10.13140/RG.2.2.21967.09129.

[115] K. R. Iessa, "Smart air humidifier for air-conditioned rooms based on NodeMCU ESP8266," *J. Appropriate Technol. Agriculture, Environ., Develop.*, vol. 1, no. 2, pp. 1–9, Apr. 2024, doi: 10.62671/jataed.v1i2.22.

[116] L. Degroote, I. De Bourdeaudhuij, M. Verloigne, L. Poppe, and G. Crombez, "The accuracy of smart devices for measuring physical activity in daily life: Validation study," *JMIR Mhealth Uhealth*, vol. 6, no. 12, Dec. 2018, Art. no. e10972, doi: 10.2196/10972.

[117] J. Wei, T. Dingler, and V. Kostakos, "Understanding user perceptions of proactive smart speakers," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 5, no. 4, Dec. 2021, Art. no. 185, doi: 10.1145/3494965.

[118] H. Stopps and M. F. Touchie, "Residential smart thermostat use: An exploration of thermostat programming, environmental attitudes, and the influence of smart controls on energy savings," *Energy Buildings*, vol. 238, May 2021, Art. no. 110834, doi: 10.1016/j.enbuild.2021.110834.

[119] S. Anoosha Iqtidar, M. Azhar, M. Shaikh, K. Malik, and M. Ali, "Enhancing home security: A comprehensive approach through machine learning in smart homes," 2024. [Online]. Available: https://www.researchgate.net/publication/384663570

[120] S. Gorinsky, R. Guefin, and P. Steenkiste, in *Proc. 28th IEEE Int. Conf. Netw. Protocol*, 2020, pp. 1–13.

[121] S. Madadi-Barough, P. Ruiz-Blanco, J. Lin, R. Vidal, and C. Gomez, "Matter: IoT Interoperability for Smart Homes," *IEEE Commun. Mag.*, vol. 63, no. 4, pp. 106–112, Apr. 2025.

[122] H. Yar, A. S. Imran, Z. A. Khan, M. Sajjad, and Z. Kastrati, "Towards smart home automation using IoT-enabled edge-computing paradigm," *Sensors*, vol. 21, no. 14, Jul. 2021, Art. no. 4932, doi: 10.3390/s21144932.

[123] H. Xu, H. Lee, W. Ling, and Y. Pan, "How to keep balance between interaction and automation? toward user overall positive experience of IoT-based smart home design," *Electron. (Switzerland)*, vol. 13, no. 7, Apr. 2024, Art. no. 1375, doi: 10.3390/electronics13071375.

[124] X. Wang and X. Qian, "Information-centric IoT based Smart Home Control and Monitoring System," *IEEE Sens. J.*, vol. 24, no. 21, pp. 35722–35729, Nov. 2024, doi: 10.1109/JSEN.2024.3462929.

[125] C. Geeng and F. Roesner, "Who's in control?: Interactions in multi-user smart homes," in *Proc. Conf. Hum. Factors Comput. Syst.*, May 2019, pp. 1–13, doi: 10.1145/3290605.3300498.

[126] S. Kang et al., "Toward a dynamic comfort model for human-building interaction in grid-interactive efficient buildings: Supported by field data," 2023, *arXiv:2303.07206*.

[127] O. B. Mulayim, E. Severnini, and M. Bergés, "Unmasking the role of remote sensors in comfort, energy, and demand response," *Data-Centric Eng.*, vol. 5, Nov. 2024, Art. no. e28, doi: 10.1017/dce.2024.25.

[128] M. Kane and K. Sharma, "Data-driven identification of occupant thermostat-behavior dynamics," 2019, *arXiv:1912.06705*.

[129] E. Maitre-Ekern and C. Dalhammar, "Regulating planned obsolescence: A review of legal approaches to increase product durability and reparability in Europe," *Rev. Eur., Comp. Int. Environ. Law*, vol. 25, no. 3, pp. 378–394, Nov. 2016, doi: 10.1111/reel.12182.

[130] B. Yuan, J. Wan, Y. H. Wu, D. Q. Zou, and H. Jin, "On the security of smart home systems: A survey," *J. Comput. Sci. Technol.*, vol. 38, no. 2, pp. 228–247, Apr. 2023, doi: 10.1007/s11390-023-2488-3.

[131] G. Vardakis, G. Hatzivasilis, E. Koutsaki, and N. Papadakis, "Review of smart-home security using the Internet of Things," *Electronics*, vol. 13, no. 16, 2024, Art. no. 3343, doi: 10.3390/electronics13163343.

[132] I. Alam, S. Khusro, and M. Khan, "Usability barriers in smart TV user interfaces: A review and recommendations," in *Proc. Int. Conf. Front. Inf. Technol.*, Dec. 2019, pp. 334–3344. doi: 10.1109/FIT47737.2019.00069.

[133] R. Faizrakhmanov, A. Platunov, and M. Bahrami, "Smart home user interface: Development and comparison," in *Proc. Int. Conf. Ind. Eng., Appl. Manuf.*, 2023, pp. 531–536, doi: 10.1109/ICIEAM57311.2023.10139022.

[134] K. Srinivasrao, S. R. K. Joga, A. P. Kumar, O. P. Hemanth, K. L. V. Lavanya, and D. Yaswanth, "User Experience design for IoT-Driven Smart Home Automation interfaces," in *Proc. 3rd Int. Conf. Artif. Intell. Internet Things*, 2024, vol. 2024, pp. 1–6. doi: 10.1109/AI-IoT58432.2024.10574764.

[135] M. N. Folkmann, "Evaluating aesthetics in design: A phenomenological approach," *Des. Issues*, vol. 26, no. 1, pp. 40–53, 2010.

[136] A. Zhou, J. Ma, S. Zhang, and J. Ouyang, "Optimal design of product form for aesthetics and ergonomics," *Comput.-Aided Des. Appl.*, vol. 20, no. 1, pp. 1–27, 2023, doi: 10.14733/cadaps.2023.1-27.

[137] S. Safin, P. Pintus, and C. Elsen, "Ergonomics in design and design in ergonomics: Issues and experience in education," *Work*, vol. 66, no. 4, pp. 917–931, 2020, doi: 10.3233/WOR-203237.

[138] J.-C. Sagot, V. Gouin, and S. Gomes, "Ergonomics in product design: Safety factor," 2003. [Online]. Available: www.elsevier.com/locate/ssci

[139] C. Homburg, M. Schwemmle, and C. Kuehnl, "New product design: Concept, measurement, and consequences," *J. Marketing*, vol. 79, no. 3, pp. 41–56, May 2015, doi: 10.1509/jm.14.0199.

[140] M. F. Ashby and K. Johnson, *Materials and Design: The Art and Science of Material Selection in Product Design*. Oxford, U.K.: Butterworth-Heinemann, 2013.

[141] E. Karana, P. Hekkert, and P. Kandachar, "Material considerations in product design: A survey on crucial material aspects used by product designers," *Mater. Des.*, vol. 29, no. 6, pp. 1081–1089, 2008, doi: 10.1016/j.matdes.2007.06.002.

[142] M. T. Abu Bakar, "Latency issues in Internet of Things: A review of literature and solution," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 9, no. 1–3, pp. 83–91, Jun. 2020, doi: 10.30534/ijatcse/2020/1291.32020.

[143] W. Fariza, W. A. Rahman, A. Hassan, and A. Hashim, "Delay contributing factors and strategies towards its minimization in IoT," *J. Telecommun. Electron. Comput. Eng.*, vol. 8, no. 3, pp. 149–153, 2016.

[144] R. Lapašinskaitė and V. Boguslauskas, "The maintenance cost allocation in product life cycle," *Eng. Econ.*, vol. 44, no. 4, pp. 17–23, 2005.

[145] N. Guhr, O. Werth, P. P. H. Blacha, and M. H. Breitner, "Privacy concerns in the smart home context," *SN Appl. Sci.*, vol. 2, no. 2, Feb. 2020, Art. no. 247, doi: 10.1007/s42452-020-2025-8.

[146] G. Callebaut, G. Leenders, J. Van Mulders, G. Ottoy, L. De Strycker, and L. Van der Perre, "The art of designing remote IoT devices—Technologies and strategies for a long battery life," *Sensors*, vol. 21, no. 3, 2021, Art. no. 913, doi: 10.3390/s21030913.

[147] R. H. Kerschbaumer, D. Kreimer, T. Foscht, and A. B. Eisingerich, "Subscription commerce: An attachment theory perspective," *Int. Rev. Retail, Distrib. Consum. Res.*, vol. 33, no. 1, pp. 92–115, 2023, doi: 10.1080/09593969.2022.2134173.

[148] C. W. J. Lindström, B. Maleki Vishkaei, and P. De Giovanni, "Subscription-based business models in the context of tech firms: Theory and applications," *Int. J. Ind. Eng. Operations Manage.*, vol. 6, no. 3, pp. 256–274, Jul. 2024, doi: 10.1108/ijieom-06-2023-0054.

[149] S. Vranica, "Advertisers try new tactics to break through to consumers," *Wall Street J.*, Jun. 19, 2016.

[150] K. Park, Y. Park, J. Lee, J. H. Ahn, and D. Kim, "Alexa, tell me more! the effectiveness of advertisements through smart speakers," *Int. J. Electron. Commerce*, vol. 26, no. 1, pp. 3–24, 2022, doi: 10.1080/10864415.2021.2010003.

[151] V. Prakash, S. Xie, and D. Y. Huang, "Software update practices on smart home IoT devices," Aug. 2022. [Online]. Available: arxiv.org/abs/2208.14367

[152] A. M. Ansari, M. Nazir, and K. Mustafa, "Smart homes app vulnerabilities, threats, and solutions: A systematic literature review," *J. Netw. Syst. Manage.*, vol. 32, no. 2, Apr. 2024, Art. no. 29, doi: 10.1007/s10922-024-09803-1.

[153] L. Mosesso, M. Nolwenn, N. Edlira, T. Thomas, and T Aurélien, "Obsolescence Paths: living with aging devices," in *Proc. Int. Conf. ICT Sustainability*, Oct. 2023, pp. 13–23.

[154] L. Sierra-Fontalvo, L. Ruiz-Pastor, A. Gonzalez-Quiroga, and J. A. Mesa, "Decoding product obsolescence: A taxonomic approach from product design attributes," *J. Cleaner Prod.*, vol. 475, Oct. 2024, Art. no. 143635, doi: 10.1016/j.jclepro.2024.143635.

[155] F. W. Geels, "From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory," *Res. Policy*, vol. 33, no. 6/7, pp. 897–920, 2004.

[156] R. Bolton and M. Hannon, "Governing sustainability transitions through business model innovation: Towards a systems understanding," *Res. Policy*, vol. 45, no. 9, pp. 1731–1742, 2016.

[157] A. Gawer and M. A. Cusumano, "Industry platforms and ecosystem innovation," *J. Product Innov. Manage.*, vol. 31, no. 3, pp. 417–433, 2014.

[158] T. Baines, A. Ziaee Bigdeli, O. F. Bustinza, V. G. Shi, J. Baldwin, and K. Ridgway, "Servitization: Revisiting the state-of-the-art and research priorities," *Int. J. Operations Prod. Manage.*, vol. 37, no. 2, pp. 256–278, 2017.

[159] R. L. Oliver, "A cognitive model of the antecedents and consequences of satisfaction decisions," *J. Marketing Res.*, vol. 17, no. 4, pp. 460–469, 1980.

[160] R. Aralikatte, G. Sridhara, N. Gantayat, and S. Mani, "Fault in your stars: An analysis of android app reviews," in *Proc. ACM Int. Conf. Proc. Ser.*, Jan. 2018, pp. 57–66, doi: 10.1145/3152494.3152500.

[161] R. Bharati, C. Hill, and J. Fresneda, "From orders to opinions: What consumer reviews reveal about their online grocery shopping experience during the pandemic," *Electron. Commerce Res.*, pp. 1–35, 2025, doi: 10.1007/s10660-025-10036-w.

Mohamadreza Azar Nasrabadi received the Ph.D. degree in engineering from École de Technologie Supérieure, Montreal, QC, Canada. His research interests include operations management and innovation management.

Yvan Beauregard received the Ph.D. degree in mechanical engineering from Concordia University, Montreal, QC, USA, in 2010. He has more than 30 years of industry experience, having worked at companies such as Pratt and Whitney Canada and IBM and over a decade in academia as a Lecturer with Concordia University, Montreal, QC, Canada, and Full Professor with the École de Technologie Supérieure from the University of Quebec, Quebec City, QC, Canada. He is a leading expert in lean engineering and has also been contributing to obsolescence management.

Amir Ekhlassi received the Ph.D. degree in marketing management from the University of Tehran, Tehran, Iran, in 2012. He is an Associate Professor of Marketing with the University of Niagara Falls, Niagara Falls, ON, Canada. Over the past 20 years, he has worked extensively in both academia and the field of marketing. Previously, he served as an Adjunct Professor with the ESB Business School, Reutlingen University, Germany, and as an Assistant Professor of marketing with the Prague University of Economics & Business (VSE). After these roles, he was a Lecturer (Assistant Professor of marketing) with Teesside University, U.K. He has also been a faculty member and Dean of the MBA Executive Program with the University of Tehran for seven years. In addition to his academic career, he has several years of experience in marketing and branding, including running his own branding agency. His recent research focuses on extracting insights from user-generated content using machine learning methods to address marketing challenges.