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USING DESIGN INSIGHTS FROM CUSTOMER FEEDBACK TO ADVANCE DESIGN FOR REPAIRABILITY

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ABSTRACT

Design for repairability is an important design practice to increase the useful life of consumer products and decrease environmental impact. Current design for repairability guidelines include general practices that can be applied to a range of products across industries. However, these guidelines lack device-specific insights. This research proposes a methodology for extracting repairability design insights from customer feedback. This would help repair-conscious designers identify device components that may need redesign and/or prioritize components to offer as replacement parts. In this research, standalone computer keyboards are examined as a case study. This approach includes a repairability keyword list to extract repairability-related phrases from Amazon product reviews. Topic modeling is performed with Non-Negative Matrix Factorization and BERTopic to assess device failure modes for computer keyboards. The repairability-related phrases are used to manually compare the repairability of three different keyboards. The proposed method identifies several failure modes for computer keyboards, such as sticky keys, Bluetooth disconnection, keyboard leg breakage, and instability in the keyboard base. This research indicates that topic modeling is a promising approach for obtaining repairability-related design leads from customer feedback.

Keywords: design-for-repairability, data-driven design, online reviews, customer feedback, topic modeling, product sustainability

1. INTRODUCTION

Electronic waste is environmentally costly for multiple reasons. The materials and manufacturing processes used to make consumer electronics have a significant carbon footprint. This comes from the CO_2 emitted throughout the product life cycle, from mineral mining to end-of-life recycling. This results in embodied carbon in consumer electronics like laptops, cell phones, and tablets [1]. In 2020, an estimated 580 million metric tons of greenhouse gas emissions were from information and communications technology (ICT) devices, which was a 53% increase from the emissions in 2014. Another 50% increase is predicted by 2030 if current trends continue [2]. Additionally, 80% of e-waste ends up in landfills, forming mountains of hazardous waste where toxins pollute both soil and drinking water [3, 4].

The United States commonly exports this waste to developing countries, many of which do not have the necessary facilities or labor to extract value from these products. This poses a burden to the developing world, further widening the environmental inequality gap [2, 4]. Additionally, the metals required for electronics manufacturing (such as tin, cobalt, and gold) often come from mines in developing countries that offer workers (including children) inhumane conditions in exchange for less than a living wage [5]. This reality paints a gloomy picture of a complex problem that requires global collaboration across industries. This paper will present one of the primary ways designers can make a difference: designing products to be easily repairable, referred to as design for repairability [4].

The best way to keep electronics out of landfills is to continue using them. For consumers, this means repairing the devices they already own instead of replacing them. For designers, this means avoiding planned obsolescence and opting instead for designs that prioritize modularity, ease of disassembly, and the availability of replacement parts and device documentation [6]. Many principles of design for repairability can be widely applied to almost all devices (as discussed in the following section), but device-specific insights would further help designers. For example, it may be difficult to anticipate the common failure modes for a device or the most necessary replacement parts.

The right-to-repair movement aims to make repairable design practices commonplace, empowering consumers to fix their own devices instead of being forced to send them in for service or buy new ones altogether [7]. As of the beginning of 2024, twenty-seven U.S. states have some form of right-to-repair legislation [8]. In 2023, California, home to Silicon Valley, enacted legislation that requires manufacturers to "provide the means to diagnose, maintain or repair for seven years for products with a price point more than $100; three years for products under $100" [9]. The increasing prevalence of legislation such as this and growing momentum for the right-to-repair movement makes design tools for repairability even more desirable.

The goal of this research is to examine if customer feedback can help identify target areas for product redesign to improve device repairability and/or indicate components to prioritize as available replacement parts. To achieve this, topic modeling is applied to Amazon product reviews to identify repairability-related issues linked to specific electronic devices. Standalone computer keyboards are examined in this research as a case study. The main contributions of this work include:

- Methodology for retrieving and examining repairability-related product reviews to identify failure mode trends across consumer electronics.
- Illustration of the proposed method's application in supporting design-for-repairability in the early stage of product design.

2. BACKGROUND

2.1 Design for Repairability

The fundamental goal of repairable design is to make it as easy as possible for consumers to fix their own electronics. This requires consideration throughout the product design process, from early design decisions that create modular components all the way to making sure device documentation, repair guides, and replacement parts are available after product launch. According to the repair experts at iFixit, "highly repairable devices" should be designed to 1) "disassemble and reassemble, nondestructively and reversibly," 2) involve only easily available tools for repair, and 3) prioritize access and repair of components that are either critical for device functionality or most likely to need repair [10].

The third criterion for highly repairable devices often requires specific knowledge about the performance of the device itself or similar existing products. One application of the methodology proposed in this paper is to help designers obtain these insights through customer feedback, so they can identify repair-critical components from similar existing products and improve their own product design. It is true, however, that many aspects of design for repairability can be widely applied across different devices. Design practices to enhance product repairability include, but are not limited to:

- Employ a modular design, allowing for easy component repair, upgrade, and recycling [1, 10-13].
- Use forward-thinking design approaches for components with fast evolutionary speeds (i.e., those that become obsolete the fastest) to enable future upgrades [11, 12].
- Use fasteners or magnets instead of adhesives whenever possible [10, 11, 13].
- Choose standard fasteners that can be removed with common tools [10, 13].
- Prioritize using off-the-shelf components instead of custom parts [10].
- Structure the device to minimize the number of steps it takes to remove critical components such as batteries [10, 13].
- Include identifying marks on devices to indicate key assembly information (such as arrows indicating proper orientation, labels for device make and model to enable online research, etc.) [10, 13].
- Provide a device service manual with replacement instructions for critical components, troubleshooting recommendations, necessary schematics and diagrams, etc. [10, 13].
- Ensure availability of reasonably priced device replacement parts from the original manufacturer or a trusted third party [10, 13].
- Use standard connection ports [11].
- Use separable snap-fits instead of fused plastic [11, 13].
- Design high-quality, durable products that people will *want to repair* and continue using [13].

There have been recent research efforts aimed at promoting product repairability. Repairability is closely linked to disassembly, as the ease of disassembling a product directly influences how easily it can be repaired. For example, with the goal of advancing design for repairability of mechatronic products, [14] and [15] use a case study of electro-mechanical ovens to introduce and apply an eco-design framework. In [14], researchers propose a methodology for establishing eco-design rules based on factors such as disassembly complexity, disassembly time, tooling, fasteners, and connectors.

Efforts to achieve a circular economy (where resources are reused instead of discarded) are closely linked to device repair. The circular economy goal is not only dependent on device repairability, but also on consumer repair practices. Researchers have investigated both consumer behavior and product repair experiences. For instance, [16] integrated consumer repair decisions and the deterioration process of components to evaluate the lifecycle of consumer electronics (e.g., laptops). Additionally, [17] explored consumer repair motivation and barriers through workshops, resulting in a repair motivation and barriers model that includes technical, emotional, and value aspects of repair.

One strategy to support product repairability is the identification of product failure modes. For example, [18, 19] use Support Vector Machine (SVM) to forecast the failure modes of medical devices from repair and maintenance records. This would aid in determining appropriate repair strategies. While this approach also focuses on the identification of product failure modes, the approach presented in this work leverages customer feedback, which reflects the product experiences of a range of users.

2.2 Topic Modeling

Topic modeling is a machine learning technique for discovering semantic topics within a collection of documents. Topic modeling can be used for summarization, classification, and retrieval of documents based on their textual content. It has proven to be effective in extracting insights from text data and has been implemented to support the early stages of product design [20-23]. While several approaches exist for topic modeling, this research focuses on two methods: Nonnegative Matrix Factorization (NMF) and BERTopic. These methods are chosen for their efficacy in discovering semantic topics within short and unstructured text data, such as the Amazon product reviews used in this work [24].

2.2.1 Non-Negative Matrix Factorization (NMF)

Non-negative matrix factorization (NMF) is one method for topic modeling that has useful applications in text mining [25, 26]. NMF is a vector space method that makes use of non-negativity constraints to organize text data into meaningful categories [27]. In the NMF approach, a corpus of documents (here, product reviews) is represented as a word-by-document matrix that represents the frequency of words (rows) occurring in documents (columns). The matrix is factorized into 1) word-by-topic matrix, whose *ith* topic column is represented by a weighted distribution of words, and 2) topic-by-document matrix, whose *jth* document column is represented by weighted distribution of topics. This allows for representations of documents as linear combinations of topics and topics as linear combinations of words, where all coefficients must be non-negative [28].

2.2.2 BERTopic

The second topic modeling approach used in this research is BERTopic, a methodology developed by Maarten Grootendorst in 2020 [29]. In the BERTopic approach, the BERT transformer-based model is used to convert documents into vector representations called document embeddings. The dimensionality of the embeddings is reduced to form clusters of semantically similar documents where each cluster represents a topic. To extract the topic representation from each of these clusters, a class-based TF-IDF method is used [30]. BERTopic is novel in comparison to standard topic models (such as NMF) because it categorizes text without disregarding the "semantic relationships among words" [30]. Where NMF builds topics based on a collection of words, BERTopic also takes into consideration the context in which the words are used. In this research, both NMF and BERTopic are applied to text from repairability-related Amazon product reviews to learn more about the specific keyboard issues most often discussed.

2.3 Related Work

Previous work from Saidani et al. studied whether sustainable design insights could be obtained from Amazon product reviews using manual methods. The researchers also provided insight on machine learning approaches [31, 32]. Their manual method had three steps: 1) read customer reviews of Amazon Climate Pledge Friendly and standard products (e.g., cables, printers, laptops) and identify mentions of sustainability, 2) link sustainability mentions to specific product features and classify reviews by how directly they mention sustainability, and 3) interpret review content to obtain sustainable design leads. The results showed both general design insights and those specific to the cables, printers, and laptops examined. General design insights indicated that reviewers did discuss aspects of sustainable design and were most likely to mention sustainable aspects that directly benefited them (such as component durability). Furthermore, the researchers concluded that the reviews could be interpreted to obtain leads for product designers, and they recommended future work in automating such a process [31].

From their paper on machine learning approaches [32], Saidani et al. outlined a framework for automating the process of obtaining sustainable design insights from customer reviews. They described a three-step process: 1) make use of natural language processing (NLP) to construct a machine learning pipeline for automation, 2) evaluate and improve the models as needed, and 3) scale and deploy the design tool, ideally through an accessible web platform [32]. The work in the present paper falls under the first objective with a narrowed focus on design for repairability, which is a subset of sustainable design.

Additionally, previous work has combined life cycle assessment (LCA) results with information from sustainability-related online reviews to obtain insights for sustainable design. In their paper [33], Saidani et al. discuss the advantage of using user feedback to provide precise design insights to complement more generic LCA findings. While LCA provides numerous uses for quantifying environmental impact, leveraging online customer feedback could give designers sources of inspiration to address specific sustainability concerns [33].

Other NLP work using Amazon reviews includes efforts to understand latent customer needs, which are needs "implied in the semantics of use cases" [21]. By contrast, explicit needs (those mentioned directly) are much easier for text mining approaches to handle. In their work to unveil latent customer needs, Zhou et al. used sentiment analysis as a first step in differentiating types of customer use cases. They used sentiment analysis to evaluate whether users had positive or negative responses to specific product features [21]. Sentiment analysis can be applied similarly to sustainable design efforts because capturing more nuanced customer needs yields more comprehensive feedback. In the present research, sentiment analysis was used to separate product problems from praise.

Previous research has also applied topic modeling to failure mode identification of complex engineering systems, which is similar to using topic modeling to evaluate repairable design. In their work, Andrade et al. discussed applying latent Dirichlet allocation (LDA) topic modeling to NASA's Lessons Learned Information System. Their research goal was to determine if narratives surrounding engineering failures could be useful for failure mode prevention. Their approach extracted the cause, failure, and recommendation from each entry, resulting in a failure taxonomy for future reference [34]. Similar ideas could be applied to organizing the repairability design insights obtained from Amazon product reviews. The creation of a repair-need taxonomy for a variety of consumer electronics could give product designers access to specific repair-relevant information with little required effort. With the addition of device-specific insights such as those presented in this research, product designers would be well equipped to design devices that last, helping to reduce their environmental impact.

3. METHODOLOGY

To examine if customer feedback from Amazon reviews can help designers obtain repairability-related design insights, a two-part approach was used. This approach included 1) evaluating a comprehensive range of repairability-related issues across a category of devices and 2) comparing specific models within that category. Standalone computer keyboards were selected as a case study to examine the efficacy of this approach. This methodology is split into three steps: 1) obtain repairability-related Amazon reviews for keyboards, 2) perform topic modeling using NMF and BERTopic to discover general trends, and 3) compare failure modes for three specific keyboards. Each step is explained in detail in the following sections.

3.1 Extract Repairability-Related Text Data

This research used Amazon product reviews for 10 standalone computer keyboards found under the search term "office keyboard". The researchers selected keyboards with a large number of reviews in order to capture a diverse range of customer experiences. Since reviews typically contain a mix of opinions (e.g., likes and dislikes), they were parsed into sentences for the analysis presented in the subsequent sections. To capture repairability-related reviews, a filtering process was needed to distinguish repair-relevant review content from other customer comments. A repairability keyword list was developed for this purpose.

3.1.1 Method for Creating Repairability Keyword List

Developing the repairability keyword list involved an iterative process of brainstorming and refining. Initially, 300+ keywords were generated by reviewing iFixit articles and manually creating a list of words [6, 10]. Additional brainstorming to add to the list involved creating keywords for various categories related to repairability, such as tools, action verbs, and components related to repairing. Subsequently, the keyword list was refined by evaluating its performance in filtering repairability-related product reviews. This evaluation compared the automatically filtered results to manually sorted results. 2000 randomly selected review sentences were sorted manually by a primary coder based on whether they were related to repairability using the following criterion:

Reviews are considered repairability-related if they include content about a keyboard failure mode or attempted repair; this includes feedback about keyboard component malfunctions and physical damage but not feedback on undesirable design features.

For example, a repairability-related keyboard review is *"keyboard needs to be unplugged and plugged back into usb port daily in order to function"* because it describes a malfunction. On the other hand, an example of a non-repairability review is *"I am very surprised to find it has no feet in the back to provide a proper tilt for typing"* because the review is commenting on a perceived design flaw. Interrater reliability analysis was conducted by having a second coder independently sort 15% of the data with the provided criterion. The Cohen's Kappa was run to determine that there was a sufficient agreement between the two coders' decisions, κ=0.760. After achieving this Cohen's Kappa, the keyword list was refined iteratively by examining how slight changes affected what was flagged as repairability-related. Once 85% of the 2000 test sentences were correctly flagged, the keyword list was accepted. This resulted in a list of 42 repairability keywords. Examples from the list include "disconnect", "screw", "troubleshoot", and "unresponsive." The complete list of keywords is available upon request from the authors.

3.2 Topic Modeling with NMF and BERTopic

To prepare the filtered sentences for topic modeling, a few additional steps were needed. First, sentiment analysis was performed to categorize sentences as either being positive or negative. Only the negative sentences were used for topic

Table 1. Keyboards Selected for Comparison.

	Keyboard 1: Logitech K120 Wired Keyboard	**Keyboard 2: Arteck Wireless Keyboard**	**Keyboard 3: Amazon Basics Wired Keyboard**
Photo			
Manufacturer	Logitech	Arteck	Amazon Basics
Type	Wired	Wireless	Wired
Cost	~ $20	~ $40	~ $14
ASIN (Amazon Standard Identification Number)	B003ELVLKU	B07D34L57F	B07WJ5D3H4

modeling to maintain focus on keyboard failure modes. For NMF, the filtered sentences were preprocessed using NLP modules in Python. This included removing stopwords and tokenization. The words "work" and "keyboard" were added to the stopwords list to reduce noise in the data due to their frequent usage in the reviews. This preprocessing was not needed for BERTopic because it uses the transformer model BERT to effectively process the original text data.

Topic modeling was performed using both NMF and BERTopic on the collection of repairability-related sentences. Review sentences from all 10 keyboards were considered to examine failure mode trends across devices and provide sufficient text data for topic modeling.

3.3 Evaluation of Repairability-Related Issues for Specific Devices

After topic modeling was performed to analyze general trends, three keyboards were studied individually to determine 1) if the sentence filtering method could be used to learn about the repairability of individual devices and 2) if this method could be used to compare device repairability.

Three keyboards of a similar price range were selected from the original group of 10 keyboards. Table 1 gives further details on the three keyboards selected for comparison.

To compare these models, the keyword list was used to extract repairability-related sentences from the collection of reviews for each keyboard. These three keyboards had 217, 219, and 162 repairability-related sentences used for comparison, respectively. The extracted sentences were then manually read and synthesized to determine common failure modes for each device. Note that topic modeling was not conducted for comparison analysis due to the limited number of reviews available for each individual device. Results are presented in the following section.

4. RESULTS AND DISCUSSION

4.1 Topic Modeling Results for 10 Keyboards

For each of the 10 keyboards, 100 reviews were scraped for each star rating (i.e., 1~5-star ratings), resulting in 500 reviews for each product. This resulted in a total of 34,925 sentences.

Table 2. Failure Mode Representative Topics from NMF and BERTopic.

Failure Modes		**NMF**	**BERTopic**
Key	Keys sticking	<u>Topic:</u> **"key, stick, annoy, issue, already"** <u>*Example:*</u> *"the caps lock and shift on the left kept sticking"*	<u>Topic:</u> **"sticking, stick, keys, sticky, random"** <u>*Example:*</u> *"keys are sticking"*
	Letters wearing off the keys	<u>Topic:</u> **"letter, wear, key, easily, miss"** <u>*Example:*</u> *"eventually the white on the keys wears off, but only after a couple of years"*	<u>Topic:</u> **"wear, letters, wearing, keys, letter"** <u>*Example:*</u> *"letters are wearing off of the keys"*
Keyboard base/legs	Wobbly keyboard base	<u>Topic:</u> **"wobble, flat, desk, adjust, sit"** <u>*Example:*</u> *"the one I received is wobbly and does not sit evenly"*	<u>Topic:</u> **"wobbles, wobbly, desk, wobble"** <u>*Example:*</u> *"it doesn't lay flat and wobbles while I type"*
	Keyboard legs breaking	<u>Topic:</u> **"leg, break, flimsy, snap, plastic"** <u>*Example:*</u> *"even though they say it is built to last, one of the keyboards legs broke off within about a month of use"*	<u>Topic:</u> **"legs, feet, break, angle, kickstands"** <u>*Example:*</u> *"tilt legs break easily"*
Connection	Keyboard disconnecting	<u>Topic:</u> **"disconnect, random, frequent, wire, time"** <u>*Example:*</u> *"do not buy - these usb keyboards disconnect randomly after a few minutes"*	<u>Topic:</u> **"disconnects, connectivity, disconnect"** <u>*Example:*</u> *"now it is constantly disconnecting"*
	Bluetooth disconnecting	<u>Topic:</u> **"connect, device, bluetooth, disconnect, issue"** <u>*Example:*</u> *"I have to go to bluetooth on the mac to re-pair and reconnect, which takes a couple of minutes"*	<u>Topic:</u> **"bluetooth, disconnects, paired, device, pair"** <u>*Example:*</u> *"the bluetooth disconnects constantly and takes a while to reconnect"*
	Keyboard lagging	<u>Topic:</u> **"lag, long, frequent, input, click"** <u>*Example:*</u> *"there was also a lag in response time which made using the arrows and navigation buttons exasperating"*	<u>Topic:</u> **"unresponsive, lagging, issues"** <u>*Example:*</u> *"mostly no issues for first five or so months, but now totally unresponsive"*
	Need to unplug/re-plug	<u>Topic:</u> **"unplug, plug, usb, constant, need"** <u>*Example:*</u> *"you have to unplug/plug-in throughout the day"*	<u>Topic:</u> **"unplug, unplugged, plug, charging, charge,"** <u>*Example:*</u> *"at first, I could just unplug the usb and plug it back in, now that only works some of the time"*
	Missing letters/typing errors	<u>Topic:</u> **"type, letter, error, keystroke, miss"** <u>*Example:*</u> *"the keys are extremely unresponsive so a lot of words will be missing letters and you have to go back and fix it"*	<u>Topic:</u> **"missing, typing, type, letters, errors"** <u>*Example:*</u> *"I'm an experienced typist, but the sheer number of times I've had to stop to correct extra or missing letters is slowing my typing to a crawl"*

Using the keyword list, 1,886 repairability-related sentences were extracted.

The results for both the NMF and BERTopic approaches are given in this section, as well as a comparison between them. For the NMF approach, a coherence score methodology was used to determine the best number of topics based on the input data. This resulted in 75 topics. For BERTopic, 35 topics were identified, where the number of topics was selected automatically. For both NMF and BERTopic, many of the identified topics indicate keyboard failure modes and repair needs. Selected NMF and BERTopic results that represent failure modes are given in Table 2. Most topics are represented by five words determined by the topic modeling methods (a few topics only have three or four words depending on the topic modeling result).

As shown, both NMF and BERTopic identified relevant repairability information and failure modes from the Amazon product reviews. For instance, both approaches identified problems with keys sticking, Bluetooth disconnecting, keyboard legs breaking, and unstable keyboard bases. This continuity gives confidence to the notion that topic modeling of Amazon product reviews can identify failure modes and provide leads for designers. For example, feedback about keyboard legs snapping off might inspire designers to improve keyboard leg durability and provide or sell replacements.

In addition to meaningful topics such as those given in Table 2, results from both NMF and BERTopic include topic redundancy and noise in the data. For NMF, examples of topics that show noise in the data include *"year, use, break, wear, fix, sever, suppose, cable, decent, pretty," "problem, fix, doesn't, manufacture, search, appear, hope, care, amazon,"* and *"day, time, multiple, every, return, final, got, window."* Examples of duplicate topics from NMF include *"constant, disconnect, bluetooth, wifi, unfortunate, require"* and *"connect, device, bluetooth, disconnect, issue, another, wireless, lose."* Both topics are about the keyboard's Bluetooth disconnecting from the paired computer. While BERTopic generated fewer topics than NMF, there are still redundant topics and topics that do not represent failure modes. Examples of redundant topics include *"bar, space, spacebar, sticks, sticking"* and *"bar, space, spacebar, started, sticking."* Both of these topics are about the spacebar sticking. Examples of topics that show noise in the data are *"fix, troubleshooting, tried, fixed, problem," "key, expensive, board, need, used,"* and *"stars, star, fast, minus, purple."*

While repairability-related design insights can be obtained from both approaches, the approaches differed in performance. BERTopic resulted in more consolidated topics, with fewer duplicates and fewer topics without repair substance. On the other hand, NMF resulted in a greater number of incoherent topics, which matches previous performance with short text data [24].

The overall conclusion from this work is that repairability-related design insights can be derived from customer feedback. This methodology can be used by designers to improve the repairability, and thus sustainability, of their products. Additionally, there is room for future work to refine the application of topic modeling for this purpose.

4.2 Comparison Result for 3 Selected Keyboards

From manually evaluating different keyboards based on repairability-related sentences, keyboard-specific failure modes of three different devices were identified. Table 1 gives an overview of the three keyboards chosen for comparison. Results

Table 3. Keyboard Comparison Results.

Failure Modes	Keyboard 1: Logitech Wired Keyboard	Keyboard: Arteck Wireless Keyboard	Keyboard 3: Amazon Basics Wired Keyboard
Keys sticking	*"the keyboards are nice at first, then the keys get sticky and the letters rub off"*	*"after cleaning the keyboard there were a few that were sticking"*	*"after about a year of use, the spacebar started to stick"*
Letters wearing off the keys	*"the white paint they use to print the letters on the keys wear off on certain keys faster then others although the keyboards still work fine"*	X	X
Wobbly keyboard base	X	X	*"wobbles when I type and can't be adjusted"*
Keyboard legs breaking	*"tilt legs break easily"*	X	X
Keyboard disconnecting	X	X	*"disconnects even though wired in"*
Bluetooth disconnecting	X	*"constantly disconnects and need to charge the battery multiple times a day to even keep it functional"*	X
Keyboard lagging	X	X	X
Need to unplug/re-plug	X	X	X
Missing letters/typing errors	X	*"I thought at first it was just my typing but after using it for a few days and letting the battery get lower I noticed that if I let it get really low it was missing 1/2 the keys I pressed and I'd really have to push down on the buttons to get them to respond"*	X

for the failure mode comparison, including examples from customer reviews, are given in Table 3.

These results qualitatively show the repairability-related insights that can be obtained from customer feedback. While this evaluation does not present information on the magnitude of these issues, it is still useful to know the failure modes present for each device. Many of the same failure modes were present across devices and match the trends uncovered from topic modeling. For instance, all three keyboards had issues with sticky keys, and two of them had issues disconnecting from the paired computer. Unique issues were also picked up through this process, including letters wearing off keyboard #1 and keyboard #3 wobbling on the desk. These keyboard-specific findings indicate the potential for future work that uses customer feedback to compare the repairability of various electronic devices.

4.3 Applications

There are two main applications for repairability-related insights derived from customer feedback. First, as mentioned, this methodology could be used as a design tool. In early product design and development stages, product designers could employ this approach to learn about common repair concerns for devices already on the market. In doing this, they would learn aspects of their product where durability should be a priority, which components are repair-critical (to ensure easy-access and modularity), and which components to make available as replacement parts. Product designers could also use this approach to make improvements to their own existing products that have already received customer reviews.

The second potential application is for consumers. Repair-conscious consumers have the power to drive change by supporting the companies trying to change the disposable electronics paradigm. For consumers selecting a product with repairability in mind, a way to compare the repairability of different products based on customer feedback would be useful. While expert repairability scores (such as those from iFixit) reflect in-depth teardowns and design for repairability analysis, they do not necessarily predict the failure modes of a device based on real, long-term usage. Additionally, expert repairability scores are not available for all devices. For a consumer-facing platform, the methodology proposed here and future work automating a repairability comparison tool would likely need a user-friendly interface and web-accessibility.

5. LIMITATIONS AND FUTURE WORK

There are several limitations to this research and areas that warrant continued research and development. The first limitation is the performance of the keyword list for repairability-related sentence filtering. Additional methods for list refinement should be explored and tested with the goal of achieving a sorting accuracy above 85%. A second limitation is the quality of the topic modeling results. While still largely useful for deriving repairability-related design leads, the topics were sometimes unclear and unconsolidated. Improvements to the topic modeling approach would be useful for future development of this work as a design tool.

Other next steps in this research include applying it to other products of varying complexity and mechanical functionality (i.e., laptops or washing machines). It may also be useful to explore classifying failure modes as electrical or mechanical failures. Additionally, text data from online repair forums or expert reviews and performance tests could be used for topic modeling. This would allow comparison between the repairability design insights from these sources and the insights derived from customer feedback.

To ensure this process can be easily implemented, it would be useful to transform the device repairability comparison from a manual to an automatic process and make it more quantitative. There is also an opportunity to transform the topic modeling approach into a more user-accessible design tool and/or consumer reference.

Additionally, integrating qualitative repairability design leads with quantitative sustainable design metrics early in the product design process could magnify the environmental benefit. For instance, repairability design leads could be used with circular economy indicators to quantify the product circularity benefit from enhanced repairability [35]. Repairability design leads could also be coupled with other quantitative and qualitative sustainable design methods, such as the approach in [36] that focuses on improving end-of-use product value recovery.

6. CONCLUSION

This research presents a method for extracting repairability-related sentences, explores design insights derived from topic modeling, compares topic modeling approaches, and applies this thinking to compare three specific Amazon keyboards. The future directions for this work are exciting in their potential to improve design for repairability in consumer products. In turn, repairable products help keep e-waste out of landfills and reduce greenhouse gas emissions, both of which are necessary societal adjustments during the climate crisis.

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