Computational affordance detection for uncovering real-world product use deviations

Nicole Goridkov and Kosa Goucher-Lambert

University of California, Berkeley, Berkeley, CA, USA
goridkov@berkeley.edu

Abstract. Users frequently interact with products in ways that diverge from designer intent, yet this gap between intended and perceived affordances is rarely captured at scale. This paper introduces a data-driven framework leveraging large language models to extract and compare structured affordance representations from product documentation and online reviews. By embedding these representations in a shared semantic space, we quantify alignment between intended and perceived use. We demonstrate the approach in a case study related to sustainable design, analyzing two Kindle Paperwhite generations to identify how real-world user behaviors impact sustainability. The framework surfaced 2,756 perceived affordances, identifying critical mismatches such as high demand for physical page-turn buttons and unintended behaviors that drain battery life. These findings demonstrate that computationally comparing intended and perceived affordances at scale can provide designers with empirical, use-phase evidence to bridge the design intent - user perception gap.

Keywords: affordance theory, large language models, product use phase, sustainable design.

1 Introduction

Products are designed with specific interactions in mind, yet users routinely perceive and interact with features in ways that diverge from designer intent. Capturing these use deviations at scale is a challenge, as traditional user research methods like interviews and user studies are resource-intensive and can be difficult to generalize. Affordance theory offers a useful lens for this problem: since Gibson's foundational definition [1] and Norman's extension to perceived affordances in designed artifacts [2], the field has recognized a fundamental tension between what a product is designed to afford and what users actually perceive. Affordance ontologies have been developed to represent the interactions between various agents, yet the gap between perceived affordances and designer intent has largely been unexplored. While prior computational approaches have worked to identify affordances from user-generated text [3–5], they face limitations in handling the nuances of natural language at scale.

This research addresses this gap by developing a data-driven framework that automates the extraction of use-phase insights from massive volumes of online user

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feedback. We leverage the natural language capabilities of large language models (LLMs) and extensive product review datasets to computationally capture perceived affordances, or the action possibilities that users experience in practice [2]. Drawing inspiration from affordance ontologies developed by the design community [6], we propose a text-based affordance detector to systematically mine qualitative user feedback and reveal how products are understood or misinterpreted in practice. This affordance detector seeks to explore the following research question:

- **RQ:** *How do perceived affordances extracted from large-scale user feedback diverge from those expressed in product documentation?*

Our framework operationalizes both design intent and user perceptions in a shared affordance representation, enabling direct comparison between product documentation (our proxy for design intent) and user reviews. First, product documentation and user reviews are used as inputs to represent intended device interactions and user feedback, respectively. Second, a pre-trained large language model extracts structured affordance representations of intended and perceived functions/use cases from these inputs. Finally, semantic similarity is computed between user- and product-defined affordance descriptions to assess mismatch scores across multiple dimensions. Overall, the methodology performs a systematic comparison between the product functionality (as presented in product documentation) and the perceived use contexts (as reported by users).

To study this problem, we demonstrate a case study in the context of sustainable design, a domain where the mismatch between perception and intent is notably challenging. A product's use phase is a critical yet challenging stage to analyze in the field of Design for Sustainability (DfS). While designers frequently optimize physical features for efficiency or longevity, the actual environmental outcomes may depend on how users perceive and interact with those features [2, 7]. These perception-driven behaviors are difficult to anticipate and lack scalable, real-world data sources, leaving a persistent gap between design intent and sustainable use. In this case study, we apply our framework to a dataset of Kindle e-readers. We show how mismatch scoring can surface use contexts that are weakly reflected in product documentation, including both low-quality breakdowns and high-quality use cases that fall outside documented intent. Because the method scales across thousands of reviews, it offers an empirical view of use-phase behavior beyond the idealized life cycle analysis assumptions that designers are often forced to make.

Overall, this paper's primary contributions are 1) the development of an AI-enabled method for identifying product affordances, 2) a framework for identifying affordance mismatches as well as successes, and 3) evaluation of this method through a case study of Kindle e-readers. We argue that deeply understanding user behaviors and perceptions of various products can provide designers with useful context for designing products and systems that avoid counterintuitive behaviors that may undermine designed environmental savings. The methods proposed in this work serve as a technique for capturing these user behaviors to create better-informed designers.

2 Background

This work proposes a pipeline for automatically identifying affordances from both product documentation and user reviews using LLM-based processing and then scoring the difference between them to identify affordance mismatches and successes. It builds on prior research in affordance theory, methods for eliciting user needs from product reviews, and approaches to modeling the use phase in design for sustainability.

2.1 Affordances

James Gibson initially coined the term affordance in the field of psychology, defined as "*what [the environment] offers the animal, what [the environment] provides or furnishes, either for good or ill*" [1]. For example, a chair affords a user sit-ability while a knife affords an apple cut-ability. This concept was later expanded to the design field by Don Norman, who coined the phrase *perceived affordance*, referring to the action possibilities that a user perceives to be possible [2]. This definition marked an important distinction in considering what features the user themselves can perceive and interact with. This concept was then formalized into the practice of affordance-based design. For example, across a series of papers, Maier and Fadel proposed the idea that affordances are relational [8–10]. In affordance-based design, it is essential to consider the interactions between all agents involved when designing an artifact to properly account for user needs and desires. Mata and Fadel developed an affordance ontology to distinguish the key elements that comprise an affordance [6]:

- 1st object = primary entity, artifact providing affordance
- 2nd object = secondary entity, human or other
- Affordance description
- Polarity = direction of influence (positive/negative)
- Priority = importance compared to other affordances
- Quality = how well an affordance is achieved

Building on this perspective, Dark and Still proposed a cognitive lens of affordances, arguing that perceived affordances arise through automatized mental processes that are shaped by consistent user-artifact interactions over time [11]. From this lens, "intuitive" interactions are not purely perceptual but are learned through repeated exposure, highlighting the importance of design consistency in enabling effortless use.

Affordances have been described as "possible ways of interacting with products, or context-dependent relationships between users and artifacts" [7], and researchers have proposed methods for extracting these relationships from unstructured user feedback. Hou et al. proposed a framework that identifies various linguistic properties of an affordance within a product review and transforms them into a cohesive affordance containing many of the affordance elements outlined above [3, 4]. This approach allows for rapid identification of affordances from real user feedback but faces challenges in sifting through many of the nuances of natural language that appear in online reviews (e.g. sarcasm, passive voice). Still, researchers have identified user reviews as a rich data source for identifying user needs over time and categorizing large quantities of user needs [5]. This work builds upon this research, looking to explore how affordance extraction from reviews may be improved and used to measure how well product intent has been realized.

2.2 Using online reviews in design

Online user reviews serve as a publicly available, large-scale dataset of (primarily) real-world user feedback. These features help address many of the challenges of traditional methods for gathering user needs like interviews, focus groups, or user studies. Extracting user needs from product reviews has been done through techniques like network analysis [12] and rule-based natural language processing [5], which help categorize different kinds of users and their needs in a computational manner. Zhou et al. used product reviews to elicit latent user needs [13], showing promise in using NLP techniques to gain a better understanding of user opinions at scale.

Additionally, online reviews have been used to gather sustainable design insights and perceptions in many ways. Through crowdsourcing techniques, El Dehaibi et al. identified how product features were perceived by users and observed a difference in how users perceived sustainability features and true sustainability [14]. This gap between true and perceived sustainability was addressed in work by Saidani et al., who combined life cycle assessment (LCA) results with online reviews to identify where these mismatches occur [15]. User perceptions have also been interpreted to generate sustainable design insights that inform future iterations of new or similar products. Sustainability experts gathered and synthesized sustainability insights for a laptop, printer, and charging cord, though they were limited by resources and required highly experienced researchers [16]. As natural language processing technologies have improved, these tools have been incorporated to address some existing limitations. Saidani et al. proposed a machine learning pipeline for gathering, processing, and interpreting reviews for the generation of sustainable design leads [17]. Similar techniques were used to extract repairability insights from online reviews, using topic modelling to identify real user pain points and product failures [18]. Goridkov et al. used LLMs and aspect-based sentiment analysis to synthesize sustainability-oriented design insights from a variety of sustainability-certified consumer products [19]. This work showed the ability to identify sustainability insights that may be inherently very contextual and difficult to capture otherwise. Furthering the methods and motivation of this section, this work seeks to leverage many of the advantages of online reviews as a data source with the powerful natural language processing capabilities of LLMs.

2.3 Use phase in design for sustainability

Understanding user behavior and product interaction is crucial for accurately modeling environmental impact in an LCA and for designing products that foster sustainable habits. However, designers frequently face challenges in collecting this data, which poses challenges for accurate LCA modelling and sustainable design. Balicki et al. address this challenge through expert evaluation of multiple products, developing a framework to anticipate unsustainable misuse cases early in the design process [20]. Other approaches have looked at formalizing models that simulate different users' behaviors to have more detailed data available for the LCA process [21]. At a high-level, our work is motivated by calls in the design community to engage in research that enables *reboundless* design, or products that are intentionally designed to avoid rebound effects [22]. Rebound effects arise as negative consequences from changes in a system's behavior and can lead to a reduction in sustainability gains. The methods proposed in this work serve as a technique for capturing these user behaviors to identify the most prevalent behavioral patterns. By identifying common behaviors, this approach highlights high-impact areas for design focus, allowing designers to more effectively mitigate the counterintuitive actions that often undermine environmental performance.

3 Methods

This section describes the methods used to create the text-based affordance detector and then test it in a subsequent case study using Kindle e-readers as an example. Figure 1 provides a visual overview of the text-based affordance detector.

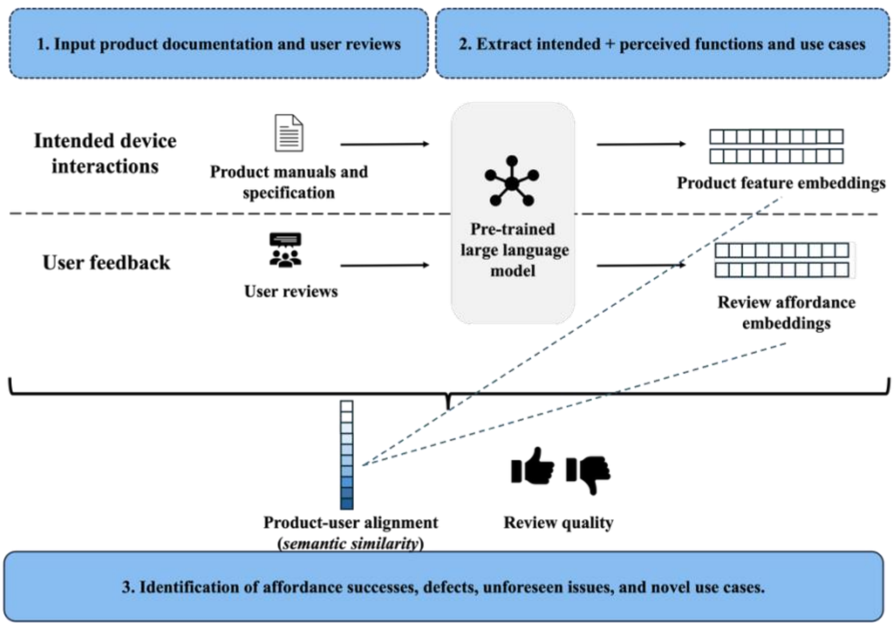


Fig. 1. Overview of text-based affordance detector to surface mismatches and alignment between design functions and user-perceived affordances, as described in Section 3.1.

3.1 Text-based affordance detector

The text-based affordance detector follows the three-stage pipeline illustrated in Figure 1. First, the pipeline takes product documentation and user reviews as inputs. Second, a pre-trained large language model extracts structured representations of intended and perceived functions and use cases from these inputs. Finally, semantic similarity is computed to assess mismatch scores across a variety of dimensions.

Input product documentation and reviews. We represent intended device interactions and user experience using two complementary data sources. Product documentation is used to capture intended functions and use cases from the design perspective. Then, online user reviews are used to capture perceived functions and enacted use cases at scale from the user perspective. User reviews provide direct evidence of how users interpret and operationalize product features in practice, while documentation reflects how those features are intended to be used. Together, these sources enable a structured comparison between design intent and real-world use.

Extract intended + perceived functions and use cases. This step intends to capture the action possibilities present in the input data sources. We use a pre-trained large language model to automatically extract structured use-related information from both the documentation and the reviews through prompt engineering. In this work, we adopt both Norman's and Maier & Fadel's definitions of affordance. First, we define affordances as *the action possibilities, both actual and perceived, that enable a user to achieve a high-level goal* [2]. Then, we decompose the elements of an affordance inspired by Mata and Fadel's affordance ontology [6]. For user reviews, each perceived affordance is represented as a tuple consisting of:

- **Affordance description:** verb + noun + adverb
- **Primary entity:** the product or feature of the product
- **Quality**: low/high
- **Polarity**: beneficial/harmful
- **Sentence of origin**: the exact sentence from the review that supports the affordance

Primary entity refers to the physical or digital feature of the product that enables the affordance. Quality of an affordance describes if an affordance is achieved. Low quality is indicated by the presence of negation words like not, hardly, etc. For example, the review "*It no longer has the button to push when turning pages, so to say you could read with one hand is a stretch because you have to let go with your thumb to swipe.*" has the affordance 'turn page with one hand', but this review indicates this action is *not* easy, so this sentence would be scored with low quality. Polarity describes the relationship of the affordance to the user. If the affordance would provide a positive effect for the user, it is scored as beneficial. If the affordance would come to bother, harm, or negatively affect the user, it is scored as harmful. To extract affordances using this ontology, we prompt the LLM as follows:

```
User Review Affordance Extraction

You are an expert in human-centered design and affordance
analysis.
Your task is to extract affordances from user review text.
An affordance must be grounded in an explicit user statement.
Product affordances are the action possibilities, both actual
and perceived, that enable a user to achieve a high-level
goal.
Each affordance must be represented as a tuple with the
following fields: [definition above]
```

For product documentation, we extract intended affordances using a reduced representation:

- **Affordance description:** verb + noun + adverb
- **Primary entity:** the product or feature of the product

Since this step is focused on 'objective' technical specifications, only affordance descriptions and the primary entity they are interacting with are extracted, as no opinions are encoded in these documents. Examples of affordance elements extracted from the data sources can be seen in Table 3. To extract affordances using this ontology, we prompt the LLM as follows:

```
Product Documentation Affordance Extraction

You are an expert in human-centered design and affordance
analysis.
Your task is to extract affordances from product information.
An affordance must be grounded in an explicit statement.
```

```
Product affordances are the action possibilities, both actual
and perceived, that enable a user to achieve a high-level
goal.
Each affordance must be represented as a tuple with the
following fields: [definition above].
```

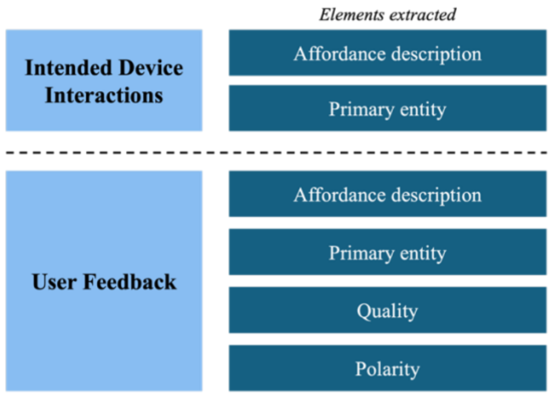


Fig. 2. Elements extracted for step 2 of the text detector, informed by [3, 6].

Identification of affordance successes, defects, unforeseen issues, and novel use cases. To evaluate the alignment between the intended device interactions and user feedback, we compute semantic similarity between affordance descriptions produced from both data sources. Using cosine similarity between vector embeddings of all affordance descriptions, we identify the closest product-defined affordance for each user-defined affordance. This alignment is then interpreted alongside a quality marker that captures users' reported experience with the affordance, allowing each instance to be situated within an alignment–quality matrix. We introduce this matrix as a tool for structuring use-phase feedback, enabling consistent categorization of affordances that differ in both their semantic alignment and reported quality. As shown in Figure 3, the matrix distinguishes four distinct outcomes: 1) successes, where intended and perceived affordances are well aligned and effectively supported in use; 2) defects, where intended affordances are present but exhibit low quality in execution; 3) potentially unforeseen issues, where perceived affordances show weak alignment with documented intent and low quality; and 4) novel use cases, where users present high-quality affordances not explicitly supported by design intent. This matrix supports designers by helping identify which interactions should be maintained, improved, or redesigned, and where opportunities exist for extending product functionality in future iterations. We can operationalize this by obtaining the total mismatch M_{total}:

$$M_{total} = (1 - S) * Q \tag{1}$$

where S represents the cosine similarity to the nearest product-defined affordance and $Q = [-1, 1]$ for quality values of [low, high].

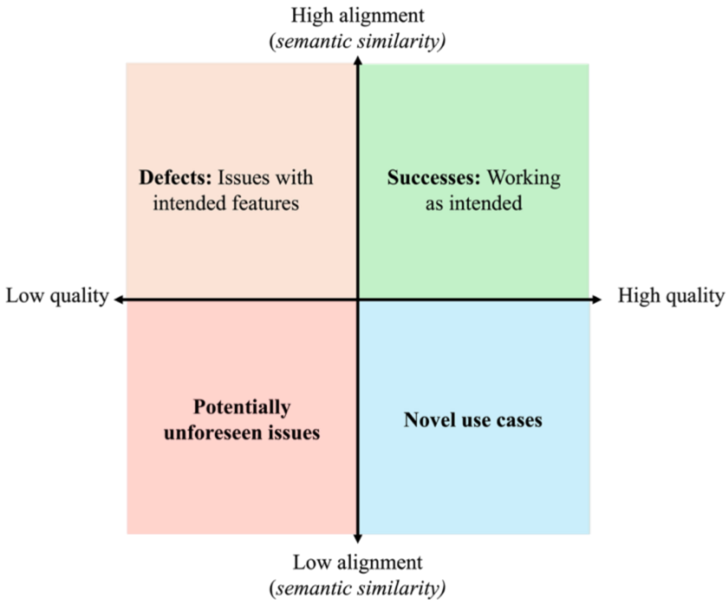


Fig. 3. Alignment–quality matrix used to prioritize design attention and categorize user feedback and perceived affordances.

3.2 Case Study

As a case study, we explored this AI-driven affordance detector using the Kindle e-reader. We analyzed the Kindle paperwhite across two generations to study how the addition of novel features may arise in the affordance detector. For a full set of the products used in this case study, see Table 1.

Table 1. Overview of Kindle e-reader products analyzed in this paper's case study

Product Line	Release Year
Kindle Paperwhite	2015 (8^{th} generation)
Kindle Paperwhite	2021 (11^{th} generation)

Product documentation and specifications. To understand how product information is shared with the users, we used publicly available product documentation. For this case study, we used Kindle e-reader user guides[1] as well as product specifications and information available on each product's respective Amazon webpage. This information was chosen given its status as product details that represent how the company is

[1] https://www.amazon.com/gp/help/customer/display.html?nodeId=G7N7RPHV2SW8CKBW

representing the product to the users. Future applications of this workflow could allow designers to augment the data with internal requirements and product requirement definitions, ensuring that product iterations align with specific organizational benchmarks.

Review dataset. Reviews were downloaded from a large-scale, publicly available Amazon review dataset [23]. Reviews were filtered to ensure they fulfilled the following criteria: 1) written in English, 2) indicated as a verified purchase, and 3) were at least 10 words long to ensure a minimum quality was met. Due to the scope of the initial dataset, reviews are only available for years prior to 2024. For each product, 500 reviews were randomly sampled.

Large language model. Open AI's GPT 4.1-mini model was used as a state-of-the-art model at the time of writing. We used this model for both the intended device interactions and user feedback steps of the affordance detector pipeline. The GPT 4.1-mini model was released in April 2025 and provides a balance of high-level reasoning and efficient processing for large-scale datasets[2]. The temperature parameter was set to zero to prioritize deterministic outputs since we were seeking analytical consistency. The model was used in its default configuration, without any task-specific fine-tuning.

Semantic similarity analysis. To calculate the mismatch scores, we generated vector embeddings of the affordance descriptions for both the product documentation and review datasets. We used OpenAI's `text-embedding-3-small` model which is well-suited for short, dense text and offers a balance of representational quality and computational efficiency[3]. We then computed cosine similarity using Python's `scikit-learn` package between the product documentation and review embeddings. This helped us identify the (semantically) closest affordance appearing in product documentation for each affordance mentioned in the review dataset. Mismatch scores were computed according to the equations described in Section 3.1. Prior work employed distributional word-level similarity (Word2Vec) for this task, which is sensitive to shared wording [3]. We approach this task with contextual LLM embeddings to better capture component- and function-level similarity.

4 Results

In this section, we summarize a case study in which the text-based affordance detector is applied to two models of the Kindle Paperwhite e-reader. First, we examine which product-driven affordances appear most prominently in user reviews, highlighting design areas that receive high amounts of user attention. Then, we illustrate the alignment–quality matrix through a focused quadrant example, surfacing novel use cases that users either experience in practice or express interest in for future product

2 https://openai.com/index/gpt-4-1/

3 https://openai.com/index/new-embedding-models-and-api-updates/?utm_source=chatgpt.com

iterations. Finally, we demonstrate how feature-based exploration of extracted affordances supports a component-level perspective for designers, using the Kindle's buttons as an illustrative example.

Table 2 shows the number of affordance descriptions surfaced from both product documentation and user reviews. Affordance descriptions could vary slightly even if similar. For example, the description "*read comfortably at night"* and "*read in low light*" both appear from the reviews, as they capture different pieces of feedback, yet refer to the same affordance of being able to read in a low visibility environment. As such, using general purpose language models allows for affordances of varying levels of abstraction to be extracted, enabling broad coverage of user behaviors, from granular interaction details to overarching use contexts. This range of abstraction explains why the set of user-perceived affordances surfaced from reviews can be orders of magnitude larger than the product functions extracted from documentation (as seen in Table 2). In the next section, we use semantic similarity to group these user-surfaced affordances with intended device interactions. Table 3 shows an example of the information extracted from both user reviews and product documentations.

Table 2. Summary of affordances extracted for case study per product.

Product	# affordances surfaced from product documentation	# affordances surfaced from reviews
Paperwhite 2015	87	1079
Paperwhite 2021	108	1482

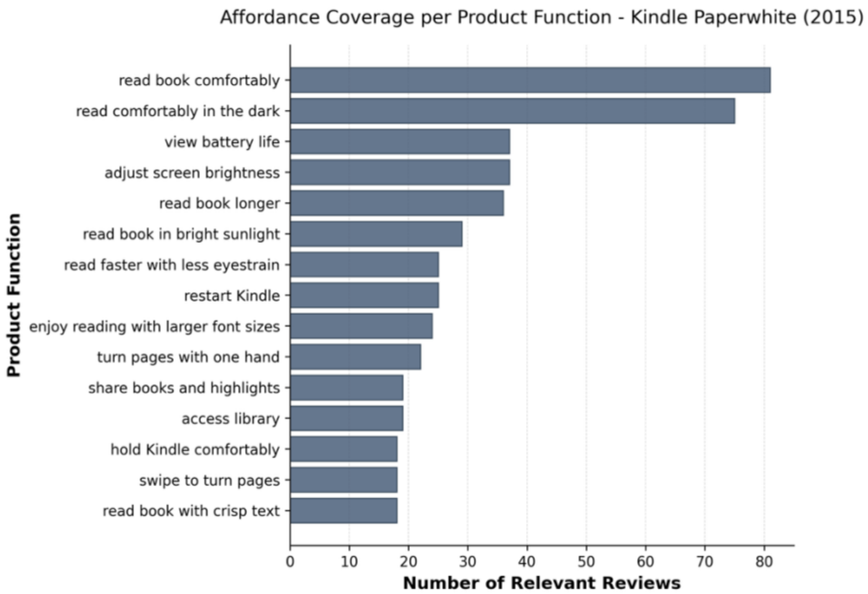
Table 3. Example elements extracted from product documentation and a review of the 2015 Kindle Paperwhite.

Data source	Affordance description	Primary entity (feature)	Quality	Sentence of origin
Intended device interactions	swipe to turn pages	touchscreen	--	*If you prefer, you can change pages by swiping the screen with your finger.*
	surf the web	browser	--	*Your Kindle includes an Web browser that enables you to surf the web and view most Amazon web pages.*
User	look up word definition	touchscreen	high	*So simple to still look up a definition of a work in the book I don't know, by holding a finger on the word.*

feedbac k	reduce eyestrain	display	high	*Since it's front lit the design lends itself to less eyestrain (which is a good thing for those who like to read in bed without disturbing their partners).*

4.1 Affordance coverage per product function

The text-based affordance detector identified descriptions from both the product perspective as well as the user perspective. In Figure 4, we present the product-driven affordances with the highest coverage, or density, of user-surfaced affordances present in reviews. For the Kindle Paperwhite 2021, the most common affordance ("*restart Kindle*") corresponded to any review that mentioned general Kindle affordances like "*use Kindle*" or "*read books"*. Notably, themes of being able-to-read in various contexts appear frequently, highlighting the different contexts this product affords use in, including reading "*in the dark*", "*in bright sunlight*", "*with less eye strain*", "*comfortably*".



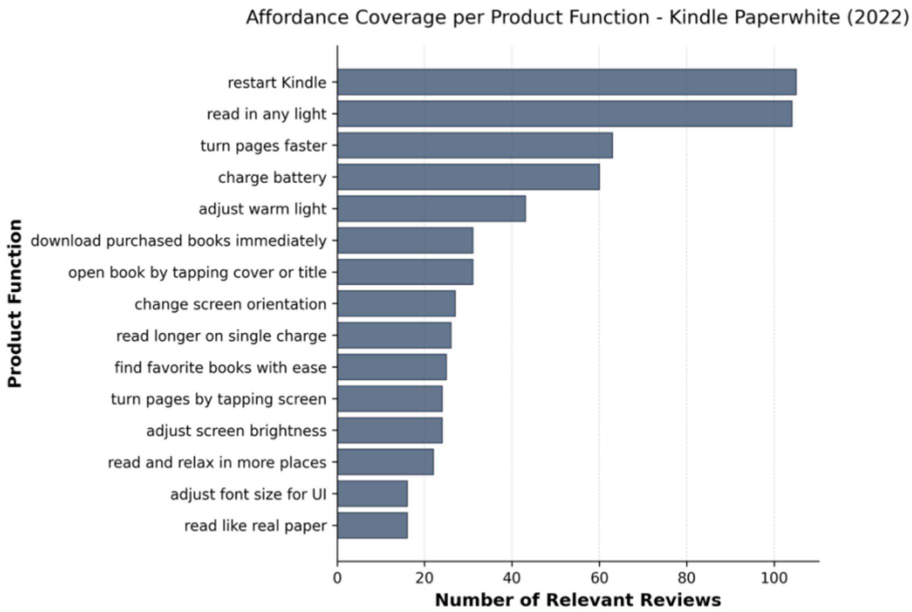


Fig. 4. The product-driven affordances with the most mentions in user-driven affordances.

When comparing the two models, the 2015 Paperwhite is characterized by affordances centered on reading comfort and environmental context, while the 2021 model reflects a wider spread of system- and interaction-level affordances. This may be attributed to initial generations of a product focusing intended interactions around core functionalities, while an established iteration of the product can broaden the functional scope of the device. For the 2021 model, commonly referenced affordances are often tied to incremental feature updates, like adjustable warm light, faster page turning, and USB-C charging, which extend or refine existing interactions rather than introducing entirely new ones. More substantial additions, like waterproofing, wireless charging, and Bluetooth integration, are referenced less frequently, suggesting that not all novel capabilities are equally prevalent in everyday use. Future research could examine these longitudinal trends more directly by relating the frequency of feature mentions to independent measures of their perceived or functional novelty. Overall, affordance coverage patterns reveal how successive product iterations shape intended device interactions, as well as how users describe and engage with the product in practice.

4.2 Novel use cases

Here, we explore findings from one quadrant in the alignment-quality matrix. To identify potential novel use cases of the product, we identify user-driven affordances that have low alignment but high quality. In Table 4, we see the top five novel use cases for both editions of the Paperwhite.

These use cases may represent existing ways the users interact with the product, or contexts in which they *desire* to interact with the product. Distinguishing existing features from desired but unimplemented ones should be explored in future work. For example, the 2015 edition of the paperwhite identifies novel use cases in being able to withstand extreme conditions as well as resist water, both of which are seen as desirable but not implemented in that version. Overall, these results suggest that novel use cases can surface a mix of current user practices and desired capabilities not yet supported by the product.

Table 4. Most novel use cases surfaced in user reviews for both editions of the Paperwhite.

Product	Affordance Description
Kindle Paperwhite 2015	*Endure physical abuse*
	Withstand extreme temperatures
	Resist water
	Withstand drops and crushing
	Be great for travel
Kindle Paperwhite 2021	*Help fight depression*
	Take pictures
	Use trade-in program
	Avoid distractions from notifications
	Have multiple holding positions

4.3 Feature-based exploration

This approach also enables us to explore the affordance space by product features, enabling designers to identify specific components which may already be identified as highly emissions related and explore user behaviors here. For example, in many consumer electronics products, the use phase and the electronics associated with them may be the source of highest emissions in a product. By exploring the visualization space using features, designers could identify affordances that are afforded by charging or the battery and focus on this subsection of the affordance graph. In Figure 5, we look at the embedding space using T-SNE of the product features associated with each affordance. We can identify features that are commonly being engaged with and zoom into these areas to explore the various affordances being described.

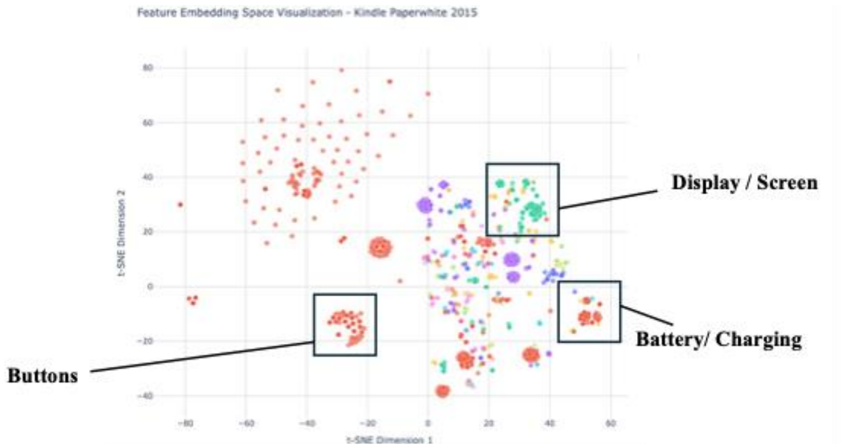


Fig. 5. T-SNE visualization of product features for the Kindle Paperwhite 2015. Grouping affordance descriptions by the feature they are engaging with allows for designers to observe feature-specific trends or navigate findings by components. Colors indicate different features.

To illustrate the utility of feature-based exploration, we can examine the cluster of affordances associated with the *buttons* feature of the 2015 Paperwhite. A summary of the affordance descriptions surfaced both from intended device interactions and user feedback are shown in Table 5. Here, we find product documentation delineates a variety of descriptions that the buttons may afford, including "*turning the Kindle on/off*" and "*restart[ing] Kindle*". However, users primarily focus on the lack of physical buttons to "*turn pages*" in the reviews. We also see that even though a user-surfaced affordance may align with the product documentation (i.e. "*turn on product accidentally"*), we observe a use context that is leading to undesirable behavior. Notably, not all affordance mismatches represent design failures and determining whether a given divergence is problematic or intentional ultimately requires contextual knowledge that the framework alone cannot provide. By organizing affordances around product features, designers can identify component-level use behaviors that diverge from intended device interactions.

Table 5. Feature-specific affordance overview related to buttons.

Data source	Affordance description	Example source text
Intended device interactions	turn Kindle on	*To turn your Kindle on, press the Power button located on the bottom edge.*
	turn Kindle off	*If you need to turn off your Kindle screen, press and hold the Power button for 7 seconds until the Power dialog box displays and then tap Screen Off.*

	put Kindle in sleep mode	*To put your Kindle in sleep mode, press and release the Power button.*
	wake up Kindle	*To wake up your Kindle, press and release the Power button.*
	restart Kindle	*If your Kindle does not power on or is unresponsive during use and you need to restart it, press and hold the Power button for 7 seconds until the Power dialog box displays and then tap Restart.*
User feedback	turn pages	*I just wish there were buttons to turn the page and an option to turn the touch screen off.*
	turn on product accidentally	*I find the battery low all the time because it has been turned on accidentally.*
	avoid hitting side buttons inadvertently	*I was always hitting the side buttons on the old Kindle inadvertently while reading.*

5 Discussion

In this section, we explore the case study findings' implications for affordance theory, and how this work bridges the intent-perception gap. We position these findings as a tool in sustainable design processes, which are particularly susceptible to challenges in understanding how users interact with designed artifacts in practice.

5.1 Bridging the intent-perception gap

While affordances provide a powerful lens for understanding the interactions and relationships between users and artifacts, the intent-perception gap between a designer and user has been difficult to capture and characterize at scale. By grounding affordance detection in thousands of reviews, this framework operationalizes that gap empirically. Still and Dark proposed that affordances are learned through repeated interactions, where users develop internalized mental models that may diverge from those anticipated by designers [11]. Approaching affordance detection through product reviews allowed us to measure the misalignment of these learned affordances at scale, capturing a diverse set of users and their learned expectations and constraints.

Kannengiesser and Gero's process framework offers a useful lens for interpreting these observed patterns, distinguishing reflexive affordances (habituated responses shaped by prior artifact experience) from reflective ones, where users generate entirely new action possibilities through exploration [24]. This distinction helps explain two findings in our case study: the persistence of button-related affordances in the 2015 Paperwhite reviews despite their absence from documentation, which reflects a reflexive mismatch driven by prior device versions, and the emergence of novel use cases like durability and emotional support, which reflect users constructing new functional meanings well outside documented intent. You and Chen further note that only a subset of possible affordances become salient depending on user goals and context [25], which helps explain why technically novel additions like Bluetooth and wireless charging appeared far less frequently in reviews than their novelty might suggest, as they had not yet become part of users' habituated interaction patterns. Together, these perspectives highlight that not all affordance mismatches are alike, and that understanding their nature is as important as detecting their presence. This framework supports designers in making those distinctions at scale, offering a structured lens for identifying when user behavior reflects entrenched schemas versus genuinely novel interaction patterns.

5.2 Using this framework as a tool for sustainable design

The field of sustainable design is particularly susceptible to misalignment challenges between a designer’s intent and the user’s perception. Many life cycle assessments assume ideal patterns of product use, yet real-world data can reveal whether these assumptions hold in practice. In this case study, user reviews provide direct insight into how people interact with their e-reader, exposing use contexts that are often invisible to traditional modeling approaches. These insights may support identifying usage variations, building representative user profiles, or estimating product lifespan, critical contributions of behavioral science toward improving LCA and ecodesign [26]. By identifying the specific components or use cases where product failures occur in real-world contexts, designers can move beyond theoretical durability to incorporating various design for sustainability strategies like design-for-repair with empirical grounding. We build on research using product reviews to identify repairability targets [18], enabling early-stage consideration of remanufacturing, repairability, and refurbishment to support product lifetime extension [27].

Broadly, we position this tool as a supporting element within the design for sustainability process. Once affordance patterns are identified, designers can integrate insights into existing frameworks to inform decisions based on observed use cases. For example, [28] proposes an eco-design framework centered on identifying potential usage drifts and corresponding design actions. Key steps include surfacing contexts prone to unintended behavior and modeling relationships between users, products, and contexts of use. The text-based affordance detector supports these steps by (1) identifying use cases enacted in practice and (2) linking these behaviors to specific product features.

6 Future Work and Limitations

This paper proposes an approach for surfacing user-perceived affordances from large-scale datasets and computationally comparing them with designer-intended functions. This case study was limited by the reviews available in existing research datasets and by the language models that were tested. In addition, our reliance on publicly available documentation as a proxy for design intent is a notable limitation, since internal product requirements and design rationale are rarely fully reflected in user-facing materials. Furthermore, we envision that the design intent pipeline can be augmented by using additional data sources as input, like ideation session notes, marketing directives, or product requirement documentation. Although we prompt the LLMs to ground extracted affordances in the data we provide, future work should formally validate these affordances using human interrater reliability. Finally, as mentioned in Section 4.2, examining how to distinguish between existing features and desired features within user feedback could provide an additional level of nuance that supports interpretation of the results in a design context.

We anticipate this method may be useful during early-stage design for established products as well as new products that have yet to be launched. If existing product reviews are not yet available, using synthetic review datasets that are generated from diverse personas may provide useful insights into potential use-cases that may arise [29, 30]. Future work could explore the efficacy of synthetic review data in generating relevant as well as novel affordances during the conceptual design phase. Further study into agentic workflows may enable more detailed identification of affordances and their component features.

7 Conclusion

This work proposes the text-based affordance detector, a data-driven pipeline for computationally identifying affordances from user feedback and translating these affordances into use-driven design insights. The text-based affordance detector is comprised of three steps. First, product documentation and user reviews are used to represent intended device interactions and user feedback, respectively. Then, an LLM is used to extract structured representations of intended and perceived functions and use cases from these inputs. Finally, semantic similarity is computed to assess mismatch scores across a variety of dimensions. This pipeline is presented in a case study of Kindle e-readers. Findings from this study demonstrate the feasibility of the text-based affordance detector and its potential to surface meaningful, use-phase insights from large-scale user feedback.

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