Online review analysis : How to get useful information for innovating and improving products?

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Online review analysis: how to get useful information for innovating and improving products?

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RESUME

Avec le développement du commerce électronique, de nombreux secteurs d'activités cherchent à utiliser les données générées par les clients sur Internet. Dans les commentaires de client, les informations concernant les besoins des utilisateurs et leurs préférences sont identifiables, ce qui rend les commentaires en ligne précieux pour les concepteurs de produits industriels. Ces données, mise à jour à tout moment, contiennent en elles des informations utiles pour innover et améliorer le produit. Exploiter ces données pour identifier les besoins des utilisateurs se différencie grandement des méthodes traditionnelles telles que les groupes de discussion, les questionnaires et les entretiens.

L'objectif de cette étude est de développer une approche d'analyse automatique des commentaires en ligne permettant d'obtenir des informations utiles au concepteur pour guider l'amélioration et l'innovation des produits. Elle comprend deux étapes : la structuration des données et l'analyse des données.

L'objectif dans la phase de structuration des données est d'analyser et d'organiser les mots et les expressions liés aux besoins des utilisateurs à partir de phrases non structurées. Seules les données structurées sont ensuite analysables. Dans cette phase de recherche, un modèle ontologique est d'abord proposé pour formaliser les entités, les propriétés et les relations liées au mots et expressions décrivant les besoins des clients. Le modèle se compose de cinq concepts largement utilisés en conception : caractéristiques du produit, affordances du produit, conditions d'utilisation, perception et émotion. Ensuite, une méthode de traitement du langage naturel basée sur des règles linguistiques est proposée pour identifier automatiquement les mots et expressions liés à ces cinq concepts. Les expériences montrent que les performances de la méthode proposées sont comparables à celles d'études antérieures. Elle fournit aux concepteurs plus d'informations utiles sur les besoins des utilisateurs et leurs préférences pour la prise de décision pour le développement de nouveau produit.

Dans la phase d'analyse des données, l'auteur propose deux méthodes pour traiter les données structurées afin de détecter 1) les utilisations du produit relativement imprévues par les concepteurs, ce qui peut inspirer des innovations ; 2) l'évolution des préférences des utilisateurs avec le temps, ce qui inspire l'amélioration des produits. Pour ces objective, la première méthode emploie l'évaluation de similarité sémantique et des algorithmes de classification pour identifier les affordances des produits qui sont mentionnées moins fréquemment. La seconde méthode applique de manière innovante l'analyse conjointe traditionnelle pour classer quantitativement les affordances de produits dans le modèle Kano. Pour démontrer la praticabilité des méthodes, un cas d'application est traité : l'analyse des commentaires en ligne de liseuses Kindle Paperwhite téléchargés depuis le site amazon.com. L'analyse de ce cas débouche sur des conseils de développement de la prochaine génération de liseuse.

En comparant avec les méthodes traditionnelles d'identification des besoins des utilisateurs, cette étude fournit aux concepteurs des connaissances supplémentaires pour la prise de décision lors du développement de produits basé des données extraites depuis les commentaires des clients.

ABSTRACT

With the development of e-commerce, numerous business domains are looking for using at best the data generated by customers on the internet. Containing a large amount of information regarding user requirements and preference, online product review data are valuable for product designers. Comparing with the traditional user requirement identification methods like the focus group, questionnaire, and interview, these data have unprecedented characteristics: they are large in volume and they are renewing in real-time.

The purpose of this study is to develop a **design-oriented online review analysis approach** to get useful insights based on the unprecedented characteristics of the online review data into product improvement and innovation. The proposed approach consists of two stages: data structuration and data analytics.

The objective in the stage of data structuration is to mine and organize the words and expressions related to user requirements and preference from the unstructured review sentences. Only the structured data can be used for further analysis. In this research stage, an ontological model is firstly proposed to formalize the entities, properties and relationships of the words and expressions describing user requirements mentioned in the review sentences. The model consists of five concepts widely used through the process of design: product feature, product affordance, usage condition, user perception and user emotion. Then, a rule-based natural language processing method is proposed to identify automatically the words and expressions related to these five concepts. Experiments show that the performance of the proposed rule-based method is comparable to the previous studies. It provides designers with more information regarding user requirements to support decision-making.

In the stage of data analytics, the author proposes two methods to process the structured data to obtain 1) users' innovative usage of the product, which can inspire innovation path; 2) evolution of user preference on product affordances, which is useful for setting up product improvement strategies. The first method uses semantic similarity evaluation and classification algorithms to identify the product affordances that are mentioned less frequently. The second method innovatively applies traditional conjoint analysis to quantitatively categorize product affordances into the Kano model. Case studies with the online reviews of Kindle Paperwhite e-readers downloaded from amazon.com demonstrate the applicability of the two proposed methods in practice.

Comparing with traditional user requirement identification methods, this study provides designers additional knowledge for decision making during product development based on the unprecedented characteristics of online review data. Industry can directly benefit from the design-oriented online review analysis approach proposed in this research project. The research trail may also serve as a guide for further research in the domain of design-oriented online review analysis.

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GENERAL INTRODUCTION

I.   Context

The development of e-commerce has generated a massive amount of online reviews. According to the survey conducted by BrightLocal.com[1] in the year 2017,

- the number of reviews posted every minute by Yelp user is 26,380;

- 70% of consumers will leave a review for a business if they are asked to;

- 42% consumers of Amazon in the US have left a review;

- 90% of consumers read online reviews before visiting a business.

From these numbers, we observe that online reviews are becoming common in our daily life. With this large number of user-generated reviews, customers can make better purchase decision during their online shopping (Xu, Wang et al. 2017, Filieri, Hofacker et al. 2018, Huang, Li et al. 2018).

Entering the big data era, the review text has captured the interest of researchers and companies in multiple domains (Liu 2012, Ravi and Ravi 2015, Wamba, Akter et al. 2015, Jin, Ji et al. 2016). For example, online markets use online reviews to build recommendation systems to improve customers' shopping experience (McAuley and Leskovec 2013); hotels and movie industry read customers' complain in the online reviews to correspondingly improve their services (Zhuang, Jing et al. 2006, Duan, Gu et al. 2008, Koh, Hu et al. 2010, Xiang, Schwartz et al. 2015, Han, Mankad et al. 2016, Sparks, So et al. 2016, Xu and Li 2016, Geetha, Singha et al. 2017); the researchers in marketing management use online reviews to investigate how online feedbacks influence product sales, in order to set up new marketing strategies (Chevalier and Mayzlin 2006, Dellarocas, Zhang et al. 2007, Salehan and Kim 2016, Suryadi and Kim 2016, TheresBemila, Sarang et al. 2016).

Product designers are also one of the beneficiaries of the explosion of the review data. Research has found that the information concerning user needs is identifiable in online product reviews (Jin, Ji et al. 2016, Qi, Zhang et al. 2016, Min, Yun et al. 2018). Collecting and understanding user needs is critical to the success of new product development. Thus, analyzing these user-generated data bring insights into product innovation and improvement. We call this kind of research the "design-oriented online review analysis".

Traditionally, user needs are mainly collected by methods based on physical prototypes, for example, focus group, interview, questionnaire, field investigation (Morgan 1996, McDonagh-Philp and Bruseberg 2000, McKay, de Pennington et al. 2001). Comparing with the data provided by these methods, the characteristics of online review data are unprecedented.

First, online reviews are large in quantity, covering a wider range of consumers (Liu 2012, Ravi and Ravi 2015). With the help of the web crawling technique, one can easily download these data (Castillo 2005). While organizing focus groups or questionnaires requires a huge amount of resource. The coverage of consumers of traditional methods is limited.

Second, online reviews are anonymous and voluntary data. These data were reported to be less biased. In fact, in face to face situation, such as interviews, respondents have the tendency to answer the questions in a manner that will be viewed favorably by others (Zhan, Loh et al. 2009, Jensen, Averbeck et al. 2013).

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[1] https://www.brightlocal.com/

Third, online reviews are chronological data. It is easy to know when the review was published. By comparing the reviews posted in the past and the reviews posted recently, it is possible to monitor the trends in consumers (Min, Yun et al. 2018).

Finally, online reviews are unstructured data. People can talk about talk about all aspects of a product and their opinions in the review text. Some reviewers even post pictures to make their review more convincible.

These four characteristics can be summarized as volume, veracity, velocity and variety, which correspond to the "4Vs characteristics" of big data (Dijcks 2012, Lycett 2013, Ward and Barker 2013). With these unprecedented characteristics, online reviews bring new insights to product development.

Opportunities and challenges always coexist. Because of the unstructured nature, meaningful words and expressions must be firstly extracted and organized from the text data for further analysis (Liu 2012). This is called data structuration. Due to the large quantity, it is impossible to process data structuration with only human effort. With the development of natural language processing technique, several methods have been proposed to analyze the online review text automatically with the computer. However, these methods were only focused on the features of the product mentioned in the review text. It does not allow designers to understand user needs in a comprehensive manner, such as how customers use the product and in what context.

After the meaningful words and expressions are extracted, algorithms must be developed to analyze the structured data to draw insights into product development (Qi, Zhang et al. 2016, Zhang, Sekhari et al. 2016). This is called data analytics. Methods have been developed for analyzing the structured data to guide product design, for example, identifying lead users (Tuarob and Tucker 2014), setting up improvement strategies (Zhang, Sekhari et al. 2016), learning product position on the market (Xu, Liao et al. 2011, Jin, Liu et al. 2016). However, no data analytic method has been proposed to provide creative insights into product innovation or to investigate the trends in consumers based on the velocity characteristic of the online review data.

We try to tackle these issues through our research project (Ph.D.). The general objective of this research is to develop an approach that provides insights into product innovation and improvement based on the unprecedented characteristics of the online review data.

In our research trial, we choose a popular product as our research object: the e-reader. The reasons are that comparing with electrical appliances, such as a TV, refrigerator, or washing machine, the e-readers are a relatively emerging product on the market. The market of the e-reader is in the expansion[1]. User needs and requirements still need to be investigated and fulfilled. Comparing with more recently invented products, like wearable devices, a large number of online reviews is available for e-readers. It is thus a suitable research object for our research.

We simulate a realistic research context: Amazon, one of the world's leading retailer, requires suggestions on the development of their next generation Kindle Paperwhite e-reader based on the online review data of past generations. This simulation serves as a case study to evaluate the practicability of the approach proposed in this research.

II. Research process

Our research is processed according to the following four main stages:

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[1] https://www.statista.com/topics/1488/e-reader/

Stage one: Analysis of the state of the art and the definition of the research topics

> Previous studies have been conducted in design-oriented online review analysis. The audit of the state of the art aims to identify and determine the overall environment of our research project. This results in identifying a list of challenges and issues in the current practices.

> The results of the analysis of the state of the art allow to better determine the scope and focus of our research.

Stage two: The literature review

> As our research is based on interdisciplinary knowledge, a literature review in the domains of design science and the domain of natural language processing is required. This literature review allows to better understand the theoretical basis of our research in design engineering, as well as to follow the latest evolution of the natural language processing technique.

Stage three: Data structuration with the natural language processing algorithms

> This stage seeks a solution for the limitations in the current online review structuration methods. The words and expressions concerning user requirements and preferences are clearly defined. A new ontological model is proposed to organize meaningful words and expressions extracted from the review text. With the help of natural language processing algorithms, a new rule-based method is developed for automatizing the extraction of these words and expressions from the review text.

Stage four: Gaining insights into product improvement and innovation by analyzing the structured data

> Based on the structured data, this stage seeks solutions for the limitations of the current data analytics methods. Two new methods for data analytics are proposed. These methods can be used to support setting up managerial strategies during product development.

> Case studies based on the online reviews of Kindle Paperwhite e-readers are conducted to illustrate the practicability of the proposed data analytics methods. Practical managerial strategies for innovation and product improvement are identified for the design of the next generation e-reader.

Figure 1 illustrates the organization of the research stages all along the three years of the Ph.D. research.
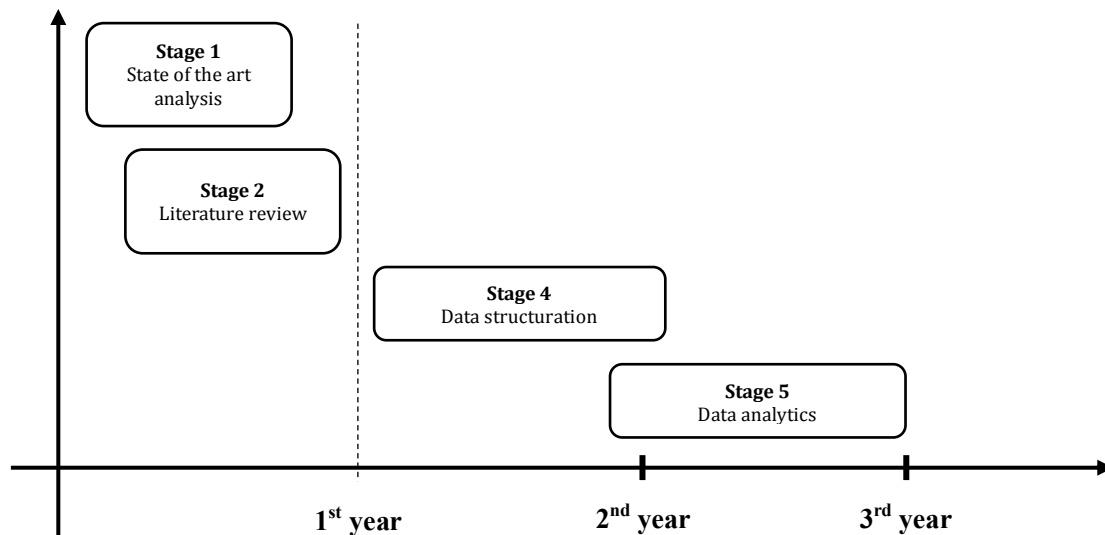
Figure 1. Stages of our research process

III. Overview of our contributions

Through our research project, we perform a survey on the previous studies of the design-oriented online review analysis. We are particularly focused on how they process the data structuration and the data analytics. The survey results in a list of limitations in these studies.

The current online review structuration methods mainly use feature-based opinion mining, which means that they are focused on the features of the product and the associated user opinions. Our data structuration method provides designers not only the information on the features of the product but also the information on other aspects concerned by the users, such as product affordances and usage contexts, enabling designers to learn a wider spectrum of user requirements and preference.

Meanwhile, to the best of our knowledge, we are the first to seek to extract product affordances and usage context from the review text in a highly automatized manner. The performance of our proposed method is comparable to the current feature-based opinion mining methods.

For data analytics, our methods are proposed based on the unprecedented characteristics of the online review data. Therefore, they can provide the insights that cannot be given by the traditional user requirement identification methods. More specifically, we profit from the large volume of the review data to identify the novel affordances that customers discovered in their practical use of the product. These novel affordances inspire product innovation. In addition, we profit from the velocity of the review data to study the changes in user preference on product affordances in recent years. The findings indicate how to improve the product to follow the trends in consumers.

The results of our case study on Kindle Paperwhite e-readers are promising. Designers can set up managerial strategies based on the results. The proposed approach is implemented in one of the most frequently used computer language in natural language processing, i.e. Python. Therefore, it can be applied directly in industry.

IV. Reading guidelines

This dissertation is composed of four parts and each part is composed of two or more chapters. The structure of the document is illustrated in Figure 2. Part I analyzes the state of the art of

online review analysis, develops the research questions based on the limitations in the previous research and presents the framework of this research [(Chapter 1, 2 and 3)].

Part II reviews the literature in the domain of design science and the domain of natural language processing [(Chapter 4 and 5)].

Part III develops our new ontological model to structure the words and expressions concerning user requirements from the online review data and presents our new rule-based natural language processing method to automatically structure the online review text according to the proposed ontological model [(Chapter 6 and 7)].

Part IV develops our new methods to gain insights for product innovation and to monitor the dynamic changes of user preference, in the objective of setting up strategies for product innovation and improvement [(Chapter 8 and 9)].

DOCUMENT STRUCTURE

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Chapter 1 –
Research context: analyzing the state of the art in online review analysis

Chapter 2 –
Research questions

Chapter 3 –
Research framework

Part II –
Literature review

Chapter 4 –
Literature review of design models and design methods

Chapter 5 –
Literature review of natural language processing

Part III –
A new ontological model and method for automatic online review structuration

Chapter 7 –
A new online review structuration model

Chapter 8 –
A rule-based method for automatically structure the online review data

Part IV –
New data analytics methods to gain insights for product design

Chapter 9 –
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Chapter 10 –
A method to follow the dynamic change of user preference for product improvement

General conclusion

Figure 2. Document structure

PART I
Research context, research questions, and research framework

Chapter 1. The need to bring online review analysis into product design

I. The explosion of online reviews

With the development of e-commerce, the number of online reviews published on the Internet is under expansion. According to the survey conducted by BrightLocal.com[1] in 2017, 90% of the consumers read online reviews before visiting a business, 84% of people trust online reviews as much as personal recommendations. Positive reviews make 73% of the consumers trust a business more. 49% of the consumers need at least a four-star rating before they choose to use a business. Over 80% of the consumers indicate that the online reviews can increase confidence in making purchase decisions, make it easier to imagine what the product will be like, help reduce risk and uncertainty and make online shopping efficient. Over three-quarters of the readers say that online reviews reduce the likelihood of regret, make online shopping more enjoyable, and make them feel more excited about the purchase.

Definition 1 – Online reviews (Wikipedia)
An online review is the review of a product or a service made on the web, by a customer who has purchased and used or had experience with the product or the service. Online reviews are a form of customer feedback on electronic commerce and online shopping sites.

These numbers show that online reviews are becoming increasingly common in our daily life. They have been influencing the way that people shop online. However, online shoppers are not the only readers of the review text. With the arrival of the big data era, these data have also captured the interest of researchers and companies in multiple domains. Being a kind of word-of-mouth, they are more and more important in online and offline commerce (Sundaram, Mitra et al. 1998, King, Racherla et al. 2014, Filieri, Hofacker et al. 2018, Hussain, Guangju et al. 2018).

Definition 2 – Word-of-mouth (Wikipedia)
Word-of-mouth or mouth-of-word is the passing of information from person to person by oral communication, which could be as simple as telling someone the time of day. Storytelling is a common form of word-of-mouth communication where one person tells others a story about a real event or something made up.

II. The role of online reviews in engineering design

Engineering design is one of the domains that can profit from the expansion of online review data.

Definition 3 – Engineering design (Papalambros 2015)
Engineering design is a process of devising a system, component, or process to meet desired needs. It is a decision-making process (often iterative), in which the basic science and mathematics and engineering sciences are applied to convert resources optimally to meet a stated objective. Among the fundamental elements of the design process are the establishment of objectives and criteria, synthesis, analysis, construction, testing, and evaluation.

The practice of engineering design includes understanding the complexity of the products, understanding the people who design them and those who use them, the process of designing, together with the organization around the process.

A. The importance of collecting user needs in engineering design

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[1] https://www.brightlocal.com/

For product designers, Steve Jobs once said, "You've got to start with the customer experience and work backward to the technology. You cannot start with the technology and try to figure out where you are going to sell it[1]." It can be concluded that understanding customer needs before developing solutions is mission-critical to create a product that truly speaks to customers' problem. Therefore, collecting user needs is generally the first step in the process of product development (Eppinger and Ulrich 2015) (Table 1).

Definition 4 – User requirement/user need (Wikipedia)
In product development and process optimization, a requirement is a singular documented physical or functional need that a particular, product or process aims to satisfy. It is commonly used in a formal sense in engineering design, including for example in systems engineering, software engineering, or enterprise engineering. It is a broad concept that could speak to any necessary (or sometimes desired) function, attribute, capability, characteristic, or quality of a system for it to have value and utility to a customer, organization, internal user, or other stakeholders. Requirements can come with different levels of specificity; for example, a requirement specification refers to an explicit, highly objective/clear requirement(s) to be satisfied by a material, design, product, or service.

Table 1. Generic design process (Eppinger and Ulrich 2015)

Phase	Marketing	Design
Phase 0: Planning	- Articulate market opportunity - Define market segments	- Consider the product platform and architecture - Assess new technologies
Phase 1: Concept Development	- Collect customer needs - Identify lead users - Identify competitive products	- Investigate the feasibility of product concepts - Develop industrial design concepts - Build and test experimental prototypes
Phase 2: System-Level Design	- Develop a plan for product options and extended product family - Set a target sales price point(s)	- Generate alternative product architectures - Define major subsystems and interfaces - Refine industrial design
Phase 3: Detail Design	- Develop marketing plan	- Define part geometry - Choose materials - Assign tolerances - Complete industrial design control documentation
Phase 4: Testing and Refinement	- Develop promotion and launch materials - Facilitate field testing	- Reliability testing - Life testing - Performance testing - Obtain regulatory approvals - Implement design changes
Phase 5: Production Ramp-up	- Place early production with key customers	- Evaluate early product output

Customer needs are the measures of customers' value. They are actionable and controllable through product design, predictive of success and independent of a solution or technology (Jiao and Chen 2006). Having a full set of customer needs impacts all aspects of innovation, the way markets are segmented and sized, the way product and pricing strategies are formulated, and the way ideas are constructed, tested and positioned (McKay, de Pennington et al. 2001). With

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[1] https://en.wikiquote.org/wiki/Steve_Jobs

a complete set of desired outcomes at hand, a company is able to evaluate a proposed solution to determine just how much better the requirements are fulfilled (Eppinger and Ulrich 2015).

B.   The traditional methods for identifying user needs

Since the collection of user requirements is so important, methods must be developed to extract these desired outcomes (Table 2). Customers do not naturally share their needs towards a product (Eppinger and Ulrich 2015). In market-driven product design, customer requirements are usually obtained from consumer surveys (Gretzel, Yoo et al. 2007, Yoo and Gretzel 2008). Trained interviewers can extract desired outcomes from customers in nearly any form of personal interviews, group interviews (Morgan 1996, McDonagh-Philp and Bruseberg 2000), using ethnographic or anthropological research.

Table 2. Traditional user needs identification methods

Qualitative/Quantitative	Method	Description
Qualitative methods		
	Usability-lab studies (Interview) (Vermeeren, Law et al. 2010)	Researcher and participants enter the lab, which is equipped with a specific usage condition. The participants are asked to finish several tasks, to observe the feasibility of the product or services
	Ethnographic field studies (Interview) (Vermeeren, Law et al. 2010)	Researchers and participants meet in daily life, to observe the usage in a natural way
	Participatory design (Tuarob and Tucker 2014)	Equipped the participants with heuristic elements. The participants are asked to express their ideal products or services with these elements.
	Focus group (McDonagh-Philp and Bruseberg 2000)	Participants are asked to take part in a discussion, responses are collected through discussions
	Dairy analysis, customer journey map (Nenonen, Rasila et al. 2008)	Participants are asked to keep dairy for the use of certain products or services.
Quantitative methods	Eye tracking and other captures (Jacob and Karn 2003)	Researchers observe the movement of participants' eyes, heartbeat, etc. to observe their interests
	Questionnaires (Eppinger and Ulrich 2015)	Participants are asked to answer the questions. The questionnaires can be distributed hand by hand, through websites and emails

However, one of the drawbacks of these interview-based methods is that they require a large amount of human effort. With the limit of time and resources, only a fraction of consumers has the potential to participate in these studies. Meanwhile, in the face to face conditions, survey participants have the tendency to answer the questions in a manner that will be viewed favorably by others, especially for the questions concerning ecological behaviors (Fisher 1993, Milfont 2009). The results can thus be biased.

C.   Identifying user needs from online reviews

Much research has pointed out that a large amount of information concerning user requirements and preference can be extracted from online reviews (Bakar, Kasirun et al. 2016, Jin, Liu et al. 2016, Maalej, Nayebi et al. 2016, Qi, Zhang et al. 2016, Min, Yun et al. 2018). This kind of information can be used to help decision making during product development, especially for those designers who must continually renovate their products in today's competitive market. In this dissertation, we call this kind of research the design-oriented online review analysis.

Comparing with the traditional user need identification methods listed in Table 2, collecting online reviews are much easier (van der Vegte 2016), as the online review data are open to everyone, and the web crawling technique allows to fetch the data automatically (Sanu and Meyerzon 2000).

III. Online review data and their characteristics

To better understand how online reviews can be used for product design, in this section, the motivations for posting online reviews are summarized. Besides, we observe the web pages of several major online markets to learn the detailed contents in the review data. In addition, based on the definition of the big data, the four characteristics of the online review data, which are unprecedented in the data provided by the traditional user requirement identification methods, are specified. To discover new insights from the online review data, we must rely on these four unprecedented characteristics.

A.   Motivations for posting online reviews

Four reasons for posting online reviews are summarized based on the research conducted by Gretzel, Yoo et al. (2007), Yoo and Gretzel (2008), Hussain, Guangju et al. (2018). First, many people simply enjoy sharing their experiences and expertise with others, and the share of information is often considered as one of the joys of the online shopping (Litvin, Goldsmith et al. 2008). The hedonic perspective understands consumers as pleasure seekers engaged in activities for enjoyment, amusement, and fun. Therefore, enjoyment is an important motivation for online review contributions (Wang and Fesenmaier 2004). Meanwhile, successful consumption experiences make consumers want to share their positive feelings with other people. Online review sites are a possible venue for consumers to express their positive emotions by writing reviews. Comparing with traditional word-of-mouth, the level of social interaction is low in online review sites. This motivation is rather described as inner feelings of self-enhancement through contributions.

Second, different from traditional word-to-mouth communication, online reviews are relatively anonymous, available to multiple individuals for an indefinite period of time and also accessible to companies interested in learning about consumer feedbacks (Hennig-Thurau, Gwinner et al. 2004). It thus provides an immense opportunity for consumers to express their dissatisfaction against companies. In addition, emotions such as sadness, anger, and frustration felt after disappointing consumption experiences motivate consumers to seek ways to lessen the frustration and reduce anxiety (Sundaram, Mitra et al. 1998). These desires often drive consumers to articulate their negative personal experiences (Alicke, Braun et al. 1992), and online review sites can serve as a place to ease negative feelings associated with unsatisfying consumption experiences.

Third, people often share their experiences with others to help or warn them. This motivation is closely related to the concept of altruism: disinterested and selfless concern for the well-being of others (Hennig-Thurau, Gwinner et al. 2004), and altruism has been suggested as an important motivation for consumers to generate traditional word-of-mouth (Sundaram, Mitra et al. 1998).

Finally, consumers share their experiences to support the service provider. When consumers have a satisfying experience with a product, it results in a desire to reciprocate the favor (Sundaram, Mitra et al. 1998). Thus, consumers often engage in word-of-mouth communication to return something to the company for their good experience (Hennig-Thurau, Gwinner et al. 2004). This motivation can be understood based on equity theory (Oliver and Swan 1989), according to which, consumers seek an equitable and fair exchange. When consumers receive a higher output/input ratio than the company, the consumers try to find a

way for the output/input ratio to be equalized. Writing positive reviews about the company that provided good products or services can be one way to equalize the ratio (Hennig-Thurau, Gwinner et al. 2004).

It can be concluded that consumers have a strong motivation for posting online reviews when they have satisfying or dissatisfying experiences with the product. When the reviewers are dissatisfied, they write online reviews to tell their story to warn others, and they express their negative feelings. When the reviews are satisfied, they write online reviews to tell their story to recommend the product to others, express their positive feelings, and give suggestions to help the company. Based on this theoretical analysis, online reviews contain users' experiences when they use the product, users' positive/negative feelings, and users' suggestions.

B. Content in the online reviews data

Review text is the main content in online review data, in which reviewers write their experience, suggestions, requirements, preference, etc. (Popescu and Etzioni 2007, Zhan, Loh et al. 2009, Ngo-Ye and Sinha 2014, Han, Mankad et al. 2016). However, review text is not the only content in the review data. Other contents in the review data may also provide useful information. The contents vary with online markets (Table 3).

Table 3. The structure of online review in the main online markets

	Amazon	BestBuy	Aliexpress	Walmart	eBay
Sort by	Top rated Most recent	Best reviews Most helpful Most recent Highest rating	By default By latest	Most relevant Most helpful Most recent Highest rating	
Star rating	5 grades	5 grades	5 grades	5 grades	5 grades
Title	x	x		x	x
Reviewer ID	x	x	x	x	x
Country			x		
Date	x	x	x	x	x
Configuration	x		x		New/used
Verified Purchase	x			x	x
Review text	x	x	x	x	x
Pictures	x		x	x	
Comments	x	x			
Thumb up (Utility)	x	x	x	x	x
Thumb down		x		x	x
Recommendation		x			
Logistics			x		

Generally, online markets provide a template to guide people to write online reviews. Besides the review text, a review consists of a star rating, a reviewer ID and a posting date. The star rating shows the reviewer's general satisfaction level towards the quality of the product. Usually, it has a scale from 1-star to 5-star, where 1-star means that the reviewer is extremely unsatisfied with the product, 5-star means that the reviewer is extremely satisfied with the product. The reviewer ID is the identity of the reviewer in the online market, through which the reviews that the reviewer give to other products can be easily tracked. The review text on the online market is unstructured in general. Several online markets allow reviewers to give a title to summarize the main idea in their review text. Recently, online markets also allow reviewers to upload pictures and videos to make their review more convincible.

As one of the motivations for posting online reviews is to gain self-enjoyment by interacting with others, to make a better experience in review writing, some online markets have added a thumb up function to the review page, showing how many readers think the review is helpful. Readers can even discuss with the reviewer if they have questions.

The online reviews are displayed in different divisions in the HTML document (Figure 3). Most online markets sort online reviews in the order of helpfulness or relevance. Online markets have their own algorithms to quantify the helpfulness and relevance. Sorting the online reviews chronologically is also available on most websites.

The contents summarized in Table 3 provide additional information for online review analysis. For example, in the study of Zhang, Sekhari et al. (2016), the star rating was regarded as an indicator of the reviewer's overall satisfaction level of the review text. In the studies of Korfiatis, García-Bariocanal et al. (2012), Lee and Choeh (2014), the thumb up was regarded as an indicator of the credibility of the review text.
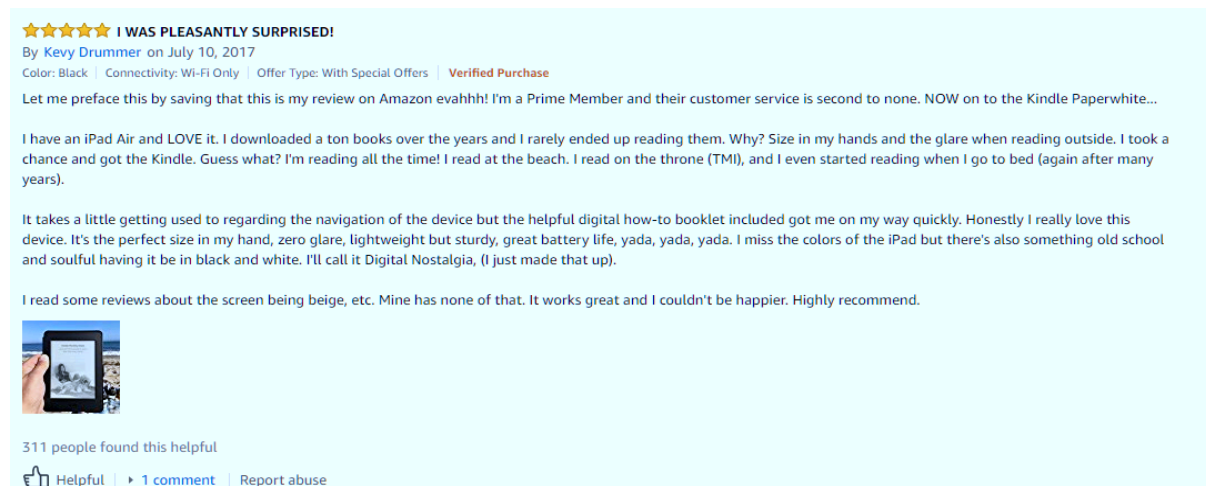
Figure 3. A sample of online review (Kindle Paperwhite 3 on Amazon.com)[1]

C. The characteristics of online reviews

Comparing with the data collected by the traditional user requirement identification methods, we summarize four characteristics of the online review data. First, without a doubt, the number of online reviews is large. In our research trial, we downloaded the online reviews of Kindle Paperwhite 2 and Kindle Paperwhite 3 from amazon.com. As shown in Table 4, nearly 100,000 online reviews have been collected. Whereas interviewing such a large number of people is nearly impossible due to the limit of time and resource.

Table 4. The descriptive statistics of the online review dataset collected from amazon.com

Product name	Kindle Paperwhite 2	Kindle Paperwhite 3
Release date	Sep 2013	June 2015
Average star-rating	4.5	4.5
Number of reviews (5 stars)	33455	40776
Number of reviews (4 stars)	6874	7929
Number of reviews (3 stars)	2291	3398
Number of reviews (2 stars)	1375	1699
Number of reviews (1 star)	1833	2832
Total number of reviews	45829	56634

Second, online reviews are unstructured data. In fact, reviewers can talk about everything related to a product in the review text (Kang and Zhou 2017). They can even insert pictures

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[1] https://www.amazon.com/Amazon-Kindle-Paperwhite-6-Inch-4GB-eReader/product-reviews/B00OQVZDJM/ref=cm_cr_dp_d_show_all_top?ie=UTF8&reviewerType=all_reviews

and videos to support what they have written in the text, making their reviews more convincing (Figure 3).

Third, online reviews are chronological data, which means each review has the information about the date when it was posted. Meanwhile, online review data update at all times. According to the survey conducted by BirghtLocal.com in 2017[1], the number of reviews posted every minute by Yelp user is 26,380. The continually updating characteristic makes the online review data a viable information source to monitor trends in online commerce (Tucker and Kim 2011, Min, Yun et al. 2018).

Finally, the quality of the online review data is uncertain. Some researchers insist that the online review data are more reliable, as the anonymous and voluntary natures make people tell their genuine feelings (Zhan, Loh et al. 2009, Jensen, Averbeck et al. 2013). However, various investigations have pointed out the problem of fake reviews (Mukherjee, Liu et al. 2012, Lin, Zhu et al. 2014). The results of the survey conducted by BrightLocal.com[1] shows that 79% of the consumers have seen one fake review in the year 2016. 84% of the consumers worry that they cannot spot fake reviews. These fake reviews may degrade the credibility of the results of online review analysis. Various spam filtering methods have been proposed to eliminate fake reviews before further analysis (Ngo-Ye, Sinha et al. 2017, Singh, Irani et al. 2017, Wu 2017, Zhou and Guo 2017).

These four characteristics correspond to the 4Vs characteristics of the big data: volume, variety, velocity and veracity (Dijcks 2012) (Figure 4). To summarize, the volume is the main characteristic that makes the data "big". To be considered as big data, there should be enough information worth analyzing. The velocity refers to how quickly new data become available. It requires that the data be processed in real-time. The variety concerns the type and the nature of the data. The big data can be structured or unstructured. They are in multiple forms: text, images, audio, and video. The veracity emphasizes the uncertainty of the quality of data. The credibility of data needs to be discussed before processing further analysis.

> **Definition 5 – Big data (Wikipedia)**
> *Big data is a term used to refer to the study and applications of data sets that are so big and complex that traditional data-processing application software is inadequate to deal with them.*
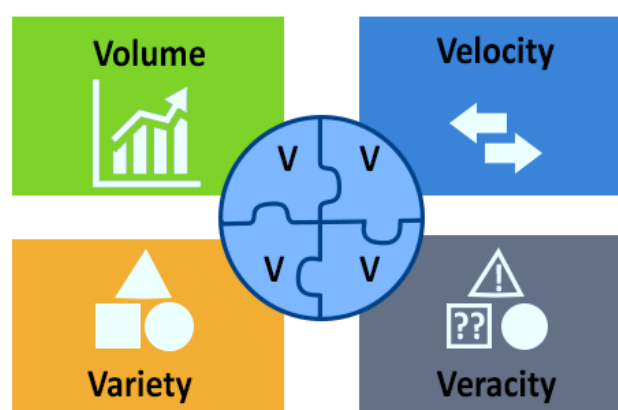
Figure 4. The 4Vs of big data (IBM)

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[1] https://www.brightlocal.com/

Based on our analysis in this section, to bring new insights into product design from online reviews that cannot be provided by the traditional user requirement identification methods, our research project must rely on these four unprecedented characteristics.

IV. Online review analysis – the state of the art

Multiple research has been conducted to exploit the value of the online review data. In this section, the state of the art of online review analysis is summarized.

A. The general process of online review analysis

Online review analysis is generally processed within two stages: data structuration and data analytics (Jin, Ji et al. 2016, Zhang, Sekhari et al. 2016, Kang and Zhou 2017). The objective in the stage of data structuration is to mine and organize the words and expressions (hereinafter referred to as words) related to user needs from the unstructured review sentences. Only structured data can be fed to a computer for further analysis. This stage consists of two critical steps. First, the raw online review text is automatically downloaded from the Internet using the web crawling technique. Second, meaningful words and expressions are identified automatically with the help of the natural language processing technique.

The objective in the stage of data analytics is to draw practical insights from the structured data to help decision making. This stage consists of three critical steps. First, exploratory data analysis is processed to discover meaningful patterns in the structured data. Descriptive statistics features, such as average, median, variance, co-occurrence, and graphics, such as boxplot, histogram, odds ratio, dendrogram, may be generated to help understand the patterns (Tuarob and Tucker 2014, Qi, Zhang et al. 2016). Second, the explorative analysis is implemented into an algorithm. Mathematical formulas or models, such as filtering, sorting, clustering, are applied. Third, the structured data are fed to the implemented algorithms to gain practical insights. The results of data analytics are communicated to the user of the data with tables, diagrams, or other visualization techniques.

This above-mentioned two-stage process corresponds to the general process of data analysis summarized in the research of O'Neil and Schutt (2013) (Figure 5).
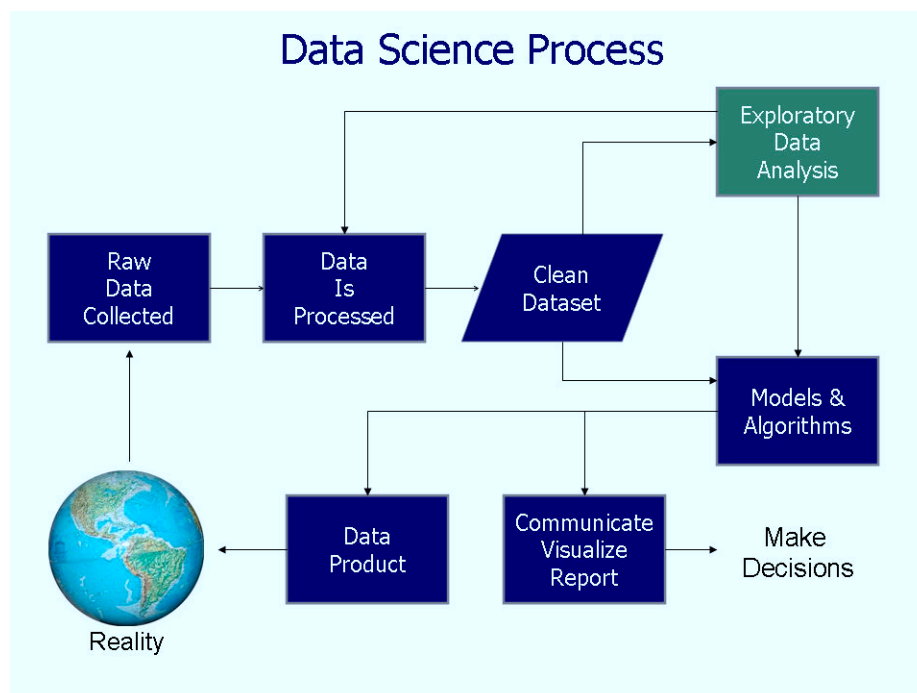
Figure 5. The general process of data science (O'Neil and Schutt 2013)

Online review analysis: how to get useful information for product improvement and innovation

B.   The method for data structuration

As the number of online reviews is growing large, it is impossible for designers to read them one by one. Therefore, researchers, especially the researchers in the domain of computer science, have proposed various methods to automatically identify and structure meaningful words and expressions from online reviews using the natural language processing technique, in order to summarize the main idea of the review text. Feature-based opinion mining is widely used in online review structuration.

Definition 6 – Opinion mining (Wikipedia)

Opinion mining (also known as sentiment analysis) refers to the use of natural language processing, text analysis, and computational linguistics to systematically identify, extract, quantify, and study affective states and subjective information.

Sentiment analysis is widely applied to the voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine.

Generally speaking, opinion aims to determine the attitude of a speaker, writer, or other subjects with respect to some topic or the overall contextual polarity or emotional reaction to a document, interaction, or event. The attitude may be a judgment or evaluation (see appraisal theory), affective state (that is to say, the emotional state of the author or speaker), or the intended emotional communication (that is to say, the emotional effect intended by the author or interlocutor).

Hu and Liu (2004) first proposed a feature-based opinion mining method to analyze the polarity of the reviewer's subjective opinions towards a set of product features. Product feature words and subjective opinion words were targeted based on the following assumptions: the product feature words are the nouns and noun phrases that appear frequently in the review text; the opinion words are the adjectives associated with the product feature words. The polarity of the opinion words was determined with the help of existing sentiment lexicon SentiWordNet[1]. Finally, for each product feature, the number of positive opinion words and the number of negative opinion words are counted. More positive opinion words mean that reviewers are satisfied with the product feature. More negative opinion words mean that the reviewers are unsatisfied with the product feature.

Definition 7 – Product feature (Liu 2012)
A product feature is defined as a component or an attribute of the product. For example, the size of the camera, the resolution of the screen.

Definition 9 – Opinion (Liu 2012)
An opinion is a subjective feeling of the reviewer.

Based on the method proposed by Hu and Liu (2004), Zhuang, Jing et al. (2006) and Cataldi, Ballatore et al. (2013) extended the usage of the feature-based opinion mining on movie reviews and hotel reviews. In their studies, the dictionaries that concern movie features and hotel features were manually created by the authors before processing opinion mining. The automatized identification methods verify if the words in the review text can be found in these dictionaries. They reported that the feature-based opinion mining works well on movie reviews and hotel reviews.

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[1] http://sentiwordnet.isti.cnr.it/

Following these pioneering studies, researchers found that using solely the two assumptions in the research of Hu and Liu (2004), some non-feature nouns or noun phrases and non-opinionated words are extracted (Table 5) (Hu and Liu 2006, Zhang, Liu et al. 2010, Liu 2012, Jin, Ji et al. 2014, Lee, Yang et al. 2016, Kang and Zhou 2017). These words are considered as "noise" in the identification results. Many studies in computer science were later conducted to improve the accuracy in identifying product feature words and opinion words. They can be collapsed into two groups: the rule-based method and the supervised machine learning method (Table 6).

Table 5. The non-feature nouns or noun phrases (Lee, Yang et al. 2016)

Types	Examples
Proper nouns (time, place, name)	September, Beijing, Tom
Brand names	Canon, Samsung, Apple
Verbal nouns	Feeling, something
Personal nouns	Friend, father

1) The rule-based method

The rule-based method identifies meaningful words using several manually constructed IF … THEN … statements based on domain knowledge. The hypothesis part, i.e. IF …, mainly concerns the regular patterns of statistical features, such as the frequency of occurrence and the probability of co-occurrence, and linguistic features, such as part-of-speech, grammatical dependency and lemma. Indeed, the method proposed by Hu and Liu (2004) is a rule-based method.

Definition 8 – Linguistic feature
Linguistic features are language form, language meaning, language structure, etc. of a text corpus. For example, phonetic features refer to the pronunciation of the word, morphological features refer to the different form of the word, syntactical features refer to the syntactic structure of the sentence, sentiment polarity features refer to the sentiment score of the word or sentence, etc.

Popescu and Etzioni (2007) proposed to use the text corpus on the internet to improve the accuracy in identifying product feature words. They firstly constructed a small list of product feature words manually. Then, the Point-wise Mutual Information (PMI) score between each word in the review text and each word in the product feature word list is calculated through an internet search engine. PMI is a measure of association, which is widely used in information theory. Finally, the words with higher PMI score were added to the list of product feature word. In the study of Quan and Ren (2014), the authors used both term frequency-inverse document frequency (TD-IDF) and PMI to evaluate the score. They reported that their method outperformed other product feature word identification method.

In the study of Lee, Yang et al. (2016), the authors assumed that genuine product feature words were usually modified by multiple adjectives, while genuine opinion words modified multiple product feature words. Therefore, they used the PageRank algorithm (Brin and Page 2012) to measure the co-occurrence of pairs of words in the review text. High co-occurrence means that the word pair is a candidate pair of product feature word and opinion word. In the study of Lee, Yang et al. (2016), the authors used a Latent Dirichlet Allocation (LDA) algorithm to quantify the co-occurrence of word pairs. They then used a perceptual map to visualize their opinion mining results.

In the method of Zhang, Liu et al. (2010), the authors used a series of grammatical dependency rules to identify product feature words and opinion words. For example, in the dependency pattern "NP + Prep + NP", where "NP" signifies noun/noun phrase and "Prep" signifies

prepositions, a part-whole relation between product features can be identified, where the first NP describes the "part" feature and the second NP describes the "whole" feature. Consequently, in the phrase "resolution of screen", "resolution" and "screen" are both product feature words, and "resolution" is part of "screen". Following this idea, Kang and Zhou (2017) added more dependency patterns to improve the performance in product feature word identification.

Ding, Liu et al. (2008) proposed a method to improve the accuracy in opinion orientation determination. They found that apart from opinion words, idioms like "cost (somebody) an arm and a leg" can also provide information on reviewers' opinions. Therefore, a sentiment lexicon containing 1,000 idioms was manually constructed. Moreover, they found that it was brutal to determine the polarity of each adjective only relying on existing sentiment lexicons. For example, from the sentence "the battery life is very long", it is unclear whether "long" means a positive or negative opinion on the product feature "battery life". Therefore, they added three rules based on the contextual information in other reviews of the same product to determine the polarity of opinion word.

Wang and Lee (2011) applied an approach based on Hownet, i.e., a large Chinese lexical database, to extract opinion phrases from Chinese blog posts concerning digital camera. They employed window-based opinion extraction method, which considered the same polarity for words utilized along with other opinion words in the same window. Cruz, Troyano et al. (2013) used several domain-specific resources to extract opinion words, including feature-taxonomy, feature cues, and dependency patterns. Meanwhile, they used a dictionary-based approach like PMI-, SentiWordNet-based classifier to determine the polarity of opinion words. In the method proposed by Zhang, Sekhari et al. (2016), the authors firstly used dependency patterns to jointly identify product feature words and opinion words. Then, dictionary-based method and fuzzy measurement algorithm were employed to determine the polarity of the opinion words.

2) Supervised machine learning

Due to the ambiguity of the natural language, the manually constructed identification rules cannot be exhaustive. The supervised machine learning technique is introduced in data structuration. This kind of methods requires a mass of high quality manually annotated data to train the probabilistic human language models. The trained model can then be used to identify meaningful words directly.

Pang and Lee (2008) were the first to apply supervised machine learning in feature-based opinion mining. They used NB (Naïve Bayes), ME (Maximum Entropy) and SVM (Support Vector Machine) to identify and classify sentiment from online movie reviews. Dang, Zhang et al. (2010) reported that SVM had higher performance in sentiment classification. Saleh, Martín-Valdivia et al. (2011) used SVM for identifying both sentiment strength and product feature words. Zhang, Ye et al. (2011) classified sentiments using NB and SVM for restaurant reviews written in Cantonese.

Wang, Sun et al. (2014) compared the performance of three popular ensemble methods, i.e., bagging, boosting, and random subspace based on five base learners: NB, ME, DT (Decision Tree), KNN (K-Nearest Neighbor), and SVM for sentiment classification. They experimented with ten different datasets and reported that among the base learners, SVM outperformed other supervised machine learning methods. In addition, ensemble methods have better accuracy over base learners at the cost of computational time. Moraes, Valiati et al. (2013) also compared SVM and NB with ANN-based (Artifical Neural Network) approach for sentiment classification. They found that ANN-based learner performed better than other learners, even SVM.

Chen, Qi et al. (2012) compared the CRF-based (Conditional Random Fields) opinion mining method to three methods: 1) model-based methods such as L-HMM (Lexicalized Hidden Markov Model); 2) statistical methods like association rule-based techniques; 3) rule-based method on the basis of several opinion mining units: basic product entities, opinions, intensifiers, phrases, infrequent entities, and opinion sentences. They observed that the CRF-based learning method was more suitable for mining aspects, opinions and sentiment intensifiers in comparison to L-HMMs based methods, statistical methods and the rule-based method.

Garcia-Moya, Anaya-Sanchez et al. (2013) introduced a language modeling framework for feature-based summarization of reviews. The framework combined a probabilistic model of opinion words and a stochastic mapping between words. It estimated a unigram language model of product features. EM (Expectation–Maximization) was utilized to minimize the cross-entropy, which was based on the background language model of English. To retrieve the product features, the iterative strategy was followed, which started with an initial list of features and expanded using a bottom-up strategy. A kernel-based density estimation approach was utilized to learn the model of opinion words, which started with a list of seed words from SenticNet.

Xu, Liao et al. (2011) proposed a method to identify the comparative information in online reviews. The identification consists of four steps. First, online review data were collected from online markets, customer review sites, blogs, social network sites, and emails. Second, some basic pre-processing steps were carried out on the review data to extract linguistic features, including tokenization, sentence splitting, word stemming, syntactic tree parsing, dependency parsing and so forth. Advanced pre-processing steps were proposed based on observations on the manual comparative relation identification process. For example, capitalization information, which probably indicates product names; prefixes and suffixes, such as "-er" or "-est", which probably signify comparisons. In the third step, the product names and the sentiment words were identified using the dictionary-based method. Finally, the comparative relation was extracted using a two-level CRF with unfixed interdependencies.

Jin, Ji et al. (2015) proposed a probabilistic language analysis approach to translate automatically keywords of online reviews into engineering characteristics. The engineering characteristics were manually defined by designers before analysis. In their method, the co-occurrence information between keywords and nearby words was analyzed. Based on the unigram language model and the bigram language model, an integrated impact learning algorithm is advised to estimate the impacts of keywords and nearby words respectively.

However, the supervised machine learning method carries the disadvantages of being domain-dependent (Zhang, Sekhari et al. 2016, Kang and Zhou 2017). New training data are needed when the supervised machine learning methods are applied to the reviews of new product categories. Preparing the corpora is a challenge because creating a large-scaled annotated corpus can be very expensive (Kang and Zhou 2017).

Table 6. Distribution of articles based on techniques for identifying product feature words and opinion words

The technique used in meaningful words identification	References
Rule-based method	Hu and Liu (2004), Popescu and Etzioni (2007), Quan and Ren (2014), Lee, Yang et al. (2016), Lee, Yang et al. (2016), Miao, Li et al. (2009), Mostafa (2013), Li, Guan et al. (2012), Xu and Li (2016), Htay and Lynn (2013), Kumar and Raghuveer (2012), Zhang, Liu et al. (2010), Kang and Zhou (2017), Ding, Liu et al. (2008), Penalver-Martinez, Garcia-Sanchez et al. (2014), Liu, Nie et

	al. (2012), Zhu, Wang et al. (2011), Cruz, Troyano et al. (2013), Eirinaki, Pisal et al. (2012)
Supervised machine learning	Li, Han et al. (2010), Xu, Cheng et al. (2013), Chen, Qi et al. (2012), Garcia-Moya, Anaya-Sanchez et al. (2013), Jin, Ho et al. (2009), Jin, Ji et al. (2016), Xu, Liao et al. (2011), Moghaddam and Ester (2013), Kim, Zhang et al. (2013)

C. The method for data analytics

Based on the data structured by feature-based opinion mining, various data analytics methods were proposed to support decision making. Based on their objective, the current data analytics studies can be collapsed into two groups: helpfulness measurement and product development.

1) Helpfulness measurement

Based on a survey conducted on 1,480 participants, Gretzel, Yoo et al. (2007) summarized the types of information that are important when consumers evaluate a review. The majority of respondents rated the following three types of information as being extremely or very important when evaluating a review: detailed description (71%), type of website on which the review is posted (65%), and the date the review was posted (59%). Other criteria concerns purchase data, photo, purpose of consumption, other readers' ratings of the usefulness of the review, reviewers' demographic information, the spelling grammar mistakes, the length of review, the tone and clarity of the writing, providing facts, a balance of pros and cons and consistency with other reviews. Most respondents perceived the reviewer's credibility based on online shopping experience (75%), engages in similar products on the market (66%), writes in a polite and friendly manner (60%) and similarity in terms of demographic information (59%).

Ghose and Ipeirotis (2007) proposed several features that influence the helpfulness of review, including subjectivity levels, informativeness, readability and spelling errors. They used RF (Random Forest) algorithm to predict review helpfulness. Liu, Jin et al. (2013) found four features that can be used to determine the helpfulness of online reviews in the viewpoint of product designers: linguistic feature, product feature, information quality feature, and information theory feature. Based on these four features, they used a regression method to predict the helpfulness of online reviews.

Racherla and Friske (2012) proposed that review and reviewer's characteristics indicated review helpfulness. Reviewer's characteristics included the reviewer's identity, expertise, and reputation. Review characteristics included review elaborateness and review valence. They used ordinary least squares regression to predict the helpfulness of reviews. Mudambi and Schuff (2010) also applied a regression model to measure the helpfulness of online reviews based on product experience or search, number of votes to a review, number of people found a review to be helpful, number of stars and word count. Their study was further extended by Huang, Chen et al. (2015), in which the regression equations were slightly modified, as they found that considering reviewer's information, product metadata and subjectivity can improve the performance in helpfulness measurement.

Min and Park (2012) suggested that a review written by an experienced customer was more important than a professional reviewer. They considered the duration of product use, the number of products used from the same brand, and temporal detailed description of product use in online review helpfulness measurement.

Chen and Tseng (2011) proposed that the information quality of an online review should be evaluated from nine dimensions, including believability, objectivity, reputation, relevance, timeliness, completeness, appropriate amount of information, ease of understanding and concise representation. They use manually labeled data to train an SVM model to predict online review helpfulness.

2) Product development

Tuarob and Tucker (2013) found that 1) the number of positive and negative sentences in social media can indicate product longevity; 2) there is a positive correlation between product longevity and product sales. Therefore, they proposed a method using positive and negative sentences to predict product market adoption. Suryadi and Kim (2016) found that the influence of the frequency of occurrence of product feature words on the sales rank was different. The frequency of occurrence of product feature words could thus be used as an indicator to predict sales rank.

Min, Yun et al. (2018) studied the changes in the number of positive reviews and negative reviews of mobile applications over time. They explain the dynamic change patterns using the Kano model. Tuarob and Tucker (2014) assumed that lead users discussed more latent features than others. Latent features are product features that seldom appeared in product specification documents. Therefore, the frequency of occurrence of latent features in the review text indicated whether the reviewer can be regarded as a lead user.

Xu, Liao et al. (2011), Zhang and Zhu (2013), Ji and Jin (2015) were focused on the comparative sentences in online reviews. In their studies, the syntactical structure "A is better than B" indicated that the positioning of the product A is higher than the product B. Consequently, these sentences can be used to analyze products' market positioning.

Bing, Wong et al. (2016) proposed a probabilistic method for mapping the product features and the product attributes. It helped the designers build the design structure matrix automatically from online reviews analysis. The matrix was filled with numbers representing opinion orientation of each product attribute. Thus, the weak component of the product could be found easily from the matrix. Jin, Liu et al. (2016) conducted a study to explore the value of online review data from the perspective of product designers. In their method, a Kalman filter method was employed to forecast the trends of customer requirements. The trends were defined based on polarity scores.

Liu (2012), Raghupathi, Yannou et al. (2015), Ravi and Ravi (2015), Zhang, Sekhari et al. (2016) assumed in their study that negative sentiment indicated that the product feature should be improved, while positive sentiment indicated that the product features should be maintained. Based on this assumption, they proposed methods to quantify the overall sentiment strength of each product feature and rank the product features by the sentiment strength.

D. Discussion

In this section, we summarize the state of the art in the domain of online review analysis. More specifically, we review the methods proposed in the previous studies for data structuration and data analytics. Based on our analysis, we found that domain knowledge plays an important role in both the two stages.

In the stage of data structuration, the rule-based method requires manually constructed heuristic rules based on the domain knowledge to target the meaningful words in the review text. The exhaustivity of the rules determines the performance of the data structuration method. While in the stage of data analytics, the practical meaning of the statistics of the structured data must be developed based on the domain knowledge to gain insights in reality.

V. The challenges in design-oriented online review analysis

Although various methods have been proposed, the online review analysis is still a non-trivial task. In this section, we summarize the main challenges in the design-oriented online review analysis.

A. The challenges in web crawling

Before analysis, the data must be downloaded. Although many open sourced packages of web crawling can be used directly to download the data automatically from the websites, tuning the configurations of the packages is still complicated (Sanu and Meyerzon 2000, Castillo 2005, Olston and Najork 2010). In fact, the crawling cannot be fully automated as it is highly dependent on the structure of the website and the data one would like to download. The web is a dynamic space with inconsistencies in data formats and structures. There are no norms to be followed while building a web crawler. For example, if one configures a crawler, but the web site structure changes, then he/she needs to modify the configuration of the crawler.

Another challenge concerns the rise of the anti-scraping tools. Many websites are not easily accessible by the web crawler, as protections against the crawling have been widely deployed. Services and tools such as ScrapeShield[1], ScrapeSentry[2] that are capable of differentiating bots from humans make an attempt to restrict web crawlers. In fact, during our research, we have been blocked by the website amazon.com several times, each time lasts a couple of hours, as our connection requests are too frequent in a short time. Also, when we try to download online reviews from ebay.com, the website demands a verifying code, i.e., the CAPTCHA (Computer Automated Public Turing test to tell Computers and Humans Apart), to filter out the connections created by the unwelcomed web crawlers. These techniques have raised the difficulty to get the online review data.

B. The challenges in natural language processing

Due to the large quantity of the online review data, it would be extremely time and resource consuming to process analysis with only human effort. Consequently, natural language processing technique must be applied in online review analysis. It allows the computer to automatically construct linguistic features of text data (Liu 2012).

> **Definition 9 – Natural language processing (Wikipedia)**
> *Natural language processing (NLP) is an area of computer science and artificial intelligence concerned with the interactions between the computer and the human (natural) languages, in particular how to program the computer to process and analyze a large amount of natural language data.*

However, natural language processing is difficult for the following reasons. First, modeling the natural language in a computer-friendly way is a very complex thing (Gangopadhyay 2001). Languages are used by billions of people and they are used in different manners. There are multiple ways to describe the same thing. For example, "Please open the window" and "I feel hot here" both come down to one possible meaning that the speaker wants to open the window. It's hard to find a general rule for all the natural languages. To tackle this issue, today's natural language processing methods are statistic-based (Bird and Loper 2004). However, the statistical models are just scratching the literal meaning, modeling in-depth semantics has yet to be achieved (Liu 2010). Machines do not actually understand "language" per se. They merely recognize patterns and try to respond in such a way that people think that they are smart.

For example, when one tells a chatbot to "send a text message to Jignesh", the bot just recognizes the pattern by seeing the word "send" and "text message". If one writes something gibberish in between, it won't mind. In addition, consider the following sentences in the same sentence structure: "Mary and Sue are sisters" and "Mary and Sue are mothers". From the first

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[1] https://blog.cloudflare.com/tag/scrapeshield/
[2] https://www.crunchbase.com/organization/scrapesentry

sentence, we understand that Mary and Sue are sisters to each other, but the second sentence means that Mary and Sue are mothers but not to each other. A computer has to divine this, which is possible only if it has the world knowledge. Because of this, computers have a hard time figuring out the intent of the user and get stuck.

Moreover, in the natural language, people use idioms and sarcasm, which are sometimes not very clear even to the human if people don't know them (Bird and Loper 2004). Then, how would a computer differentiate from an idiom and a literal usage of a phrase or understand sarcasm? Therefore, it is difficult to process the natural language with 100% accuracy.

Second, languages are naturally ambiguous (Wilson, Wiebe et al. 2005). The meanings of words vary by context. Consider a word like "jaguar" or "mercury". There are a huge number of possible meanings to those (Wikipedia) [1]. Another good example would be "I love Blackberry". In this case, Blackberry could mean both phone or a fruit. Such ambiguities are hard for computers to interpret. To interpret correctly, contextual information is essential. Computers sometimes do not have enough contextual information and hence face trouble comprehending. Therefore, there is no way to define a word in a fully unambiguous way.

The ambiguity not only occurs at the word level. A typical challenge in natural language processing is the segmentation issue (Matusov, Mauser et al. 2006). For example, "Adi was found by the mountain". In this, was Adi found near a mountain (place) or was Adi found by Mountain (person)? Another example concerns the expression "The old city bus stop". Here we understand that it is a bus stop in old city we are talking about, but a computer might segment it differently. It might form the city-bus as one word, which is valid but has a different meaning i.e. a city-bus stop which is old.

Third, every language has its own uniqueness. For example, English is formed by words, sentences, paragraphs and so on. But in Thai, the concept of the sentence does not exist (Aroonmanakun 2007). That's why the Google Translator or any other machine translators struggle to perfectly convert a piece of text from one language to another.

Finally, languages are changing every day, especially in the online environment (Ritter, Clark et al. 2011, Meng, Wei et al. 2012, Tuarob and Tucker 2014, Tuarob and Tucker 2015). Words can have different meanings depending on their context, and they can acquire new meanings over time (e.g. apple [a fruit], Apple [a company]). They can even change their part of speech (e.g. Google --> to google, unfriend, retweet, bromance). Machines have a hard time adapting to any new constructs that humans come up with. Sometimes, even the human gets confused with the newly invented terms because they are just beginning to enter the common use but have not yet been accepted into the mainstream language.

For example, suppose a teenager is looking at the twitter feed and come across a word he/she has never seen before, he/she might not understand it's meaning instantly. But this does not mean he/she cannot adapt. After looking at the word in several different tweets, the teenager might be able to understand why and in which context that the word is to be used. This is merely impossible with machines. Machines can only handle the data that they have seen before. If something new comes up, they get confused and are unable to respond. Therefore, a natural language model can't be used permanently.

C. The challenges in data analytics

The first challenge when deploying a data analysis is the business case (Lycett 2013). Until one has meaningful output from a data analytics platform, it is hard to say where they may bring

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[1] https://en.wikipedia.org/wiki/Jaguar_(disambiguation)

potential benefits or not. To draw meaningful insights into product design, what should be extracted from the online review? Previous studies suggested that user requirements should be extracted. However, what is the definition of user requirement? Can the product feature words and opinion words cover all aspects of user requirement? We can't do the analysis if we don't understand our data in the first place. That means, we should have a good understanding of the type of the data, sources of data sets and what should be derived from the data as a result.

The second challenge concerns how to translate the data pattern to the meaning in practice. As is discussed in Chapter I, Section IV.D, the data are just raw information. Descriptive statistics, such as average, median, and graphical techniques, such as boxplot, histogram, odds ratio, dendrogram, may be generated to help understand the patterns. The mathematical formulas or models, such as filtering, sorting, clustering, are applied to identify the relationship between the variables, such as correlation and causation. However, what is the practical meaning of these descriptive statistics? For example, if we found in the structured data that a product feature is hardly mentioned by the reviewer, what does it mean? Instinctively, it means that the existence of the product feature or the quality of the product feature is not important. To go a step further, it suggests that this product feature might be removed to reduce the cost. To identify this kind of patterns, a comprehensive understanding of domain knowledge is needed.

The third challenge is the application of the proprietary knowledge to the outputs of the data analytics platform (Dijcks 2012). In fact, every major company has vast stores of information in increasingly complex databases. However, despite having more data than ever before, most data analytics still fail to provide actionable insights. For example, a data analytics may observe a component on which the reviewers have a strong negative feeling. But does this mean that the component should be changed/improved/removed? The results given by the data analytics are difficult to evaluate in practice (Ravi and Ravi 2015). In previous studies, product sales were used as an indicator of the quality of the product (Zhu and Zhang 2010, Tucker and Kim 2011, Suryadi and Kim 2016, Zhang, Sekhari et al. 2016), which means that following the correct suggestions given by the online review analysis, the sales should be increased. However, we argue that the sales of the product do not only rely on the quality of design, but also on the marketing strategy, the pricing, etc. So, the suggestions given by data analytics methods are merely indicative, instead of decisive. In order to make effective decisions, designers need more than the output of the data analytics platform.

The fourth challenge concerns the authenticity of the review data (Mukherjee, Liu et al. 2012, Lin, Zhu et al. 2014). As the data comes from different sources, there are at most chances for junk in them as well. We have to ensure that we are processing and analyzing the data of high authenticity.

Chapter 2. Definition of the research questions

I. Limitations in the previous research

Based on the analysis of the state of the art in Chapter 1, we identified the following limitations in previous studies of the design-oriented online review analysis.

A. The lack of a theoretical basis in the feature-based opinion mining

One major difference between the online review data and the data provided by traditional user requirement identification methods may be the shift from the structured transactional data to the unstructured user-generated content (Ravi and Ravi 2015). The words that are meaningful for product design must be identified and structured before providing further insights into decision making.

The feature-based opinion mining dominated online review structuration (Liu 2012, Ravi and Ravi 2015). Reviewers' sentiment orientations towards the feature of the product were summarized from each review sentence. For example, the sentence "the screen is bad" would be summarized as a negative sentiment to the screen. Various methods have been proposed to make use of the extracted product features and sentiment orientations to gain insights into product design. To remind, Liu, Jin et al. (2013) filtered helpful reviews in perspective of design based on the frequency of product features mentioned in the review and the strength of the sentiment. Tuarob and Tucker (2014) identified lead users from social media data based on the frequency of unexpected product features mentioned by the reviewers. Tuarob and Tucker (2015) used social media data to quantify product favorability based on the sentiment strength and orientations. Jin, Liu et al. (2016) analyzed the strength and weakness of the product based on the comparative opinion on product features. Zhang, Sekhari et al. (2016) proposed several improvement strategies based on the strength of negative sentiment for each product features. Qi, Zhang et al. (2016) sorted the product features based on their influence on the sentiment polarity and strength.

However, on the one hand, product features alone did not cover all aspects of user needs that have been mentioned in the online reviews (Zhan, Loh et al. 2009). Reviewers describe not only their judgment on the product feature but also their experiences of using the product, how they use the product, in what condition they use the product, etc. For example, in a 5-star review of Kindle Paperwhite 3, the reviewer said, "I can read books without hurting my eyes at night". Although no product feature has been mentioned, this sentence suggests that the designer should prevent the e-readers from hurting user's eyes in the dark environment.

To tackle this issue, Lee (2007) proposed a needs-based analysis method. The intuition of this method is that a review embeds a need-attribute pair. Using association rule mining, a matrix of reviews relating customer needs to product attributes could be built. The matrix could help designers capturing the rapid change of customer needs and thus modified the product attributes to meet the change. De Weck, Ross et al. (2012) proposed a method to visualize the relationship among product abilities. The occurrence of two product abilities indicates that they have a dependent relationship. Chou and Shu (2014) studied the possibility to identify novel affordances from online reviews using a couple of cue phrases, in order to provide innovative ideas for product development. However, the authors in these studies did not provide a method to identify the words related to these concepts (user needs, product abilities, novel affordances) from online reviews in a highly automatized manner.

On the other hand, in previous feature-based opinion mining, user preference was generally confused with user perception. Preference means whether the customer likes or dislikes the product, while perception is defined as the way in which the product is regarded, understood or interpreted (Schütte 2005). In the previous studies, the authors implicitly assumed that the perceptual word associated with product feature indicated whether customers like or dislike the

product feature. They use sentiment lexicon to determine the polarity of the sentiment expressed through the perceptual words (Liu 2010, Raghupathi, Yannou et al. 2015, Ravi and Ravi 2015, Zhang, Sekhari et al. 2016). However, we find that this assumption is a gross approximate. For example, the word *low* in "low battery capacity" is translated as a negative perception in many sentiment lexicons, such as Vader[1], SentiWordNet[2], DAL[3]. Nevertheless, it does not necessarily mean that the customer dislikes the battery. A customer who is used to carry a power bank can tolerate the low battery capacity.

This limitation was summarized as the problem of cross-domain sentiment analysis in the research of Ravi and Ravi (2015), i.e., the opinion expressed for one domain will be reverted for the other domains. For instance, the polarity of the sentence "The screen is curved" may be positive for a TV but negative for a mobile.

To summarize, the lack of a theoretical basis in the feature-based opinion mining entails a detailed discussion on the definition of user needs, user requirements and preference. What are user requirements and preference? How they are described in online reviews? Answers to these questions must be developed at the beginning of our research project.

B. How to monitor the change in user preference from online reviews?

Being one of the four unprecedented characteristics of online review data, the velocity requires to process the incoming data with high frequency (Wamba, Akter et al. 2015). It enables designers to capture the trends in consumers at all times, especially the change of user preference. Traditional methods, like focus groups and interviews, failed to reconstruct the information about user requirements and preferences in a past period. That is why the computation of the dated review data looks so promising.

Tuarob and Tucker (2013) tried to predict the market adoption of a product by analyzing the correlation degree between product longevity and product sales using online social media data in a series of time spans. The product longevity was defined based on the number of positive sentences and negative sentences in social media data. Suryadi and Kim (2016) found that the influence of the frequency of occurrence of product features on the sales rank is different. The online reviews could thus be used to highlight the product features that influence the sales rank more importantly. Zhang, Sekhari et al. (2016) analyzed the correlation between the sentiment strength of each product feature and the volume of sales of the product. Based on the correlation, they proposed a method to target the product features that should be improved. Min, Yun et al. (2018) studied the dynamic change of the number of positive reviews and negative reviews towards mobile applications over time. They used the Kano model to explain the dynamic change patterns.

The previous studies were mainly focused on what trends could be concluded by analyzing the correlation between the frequency of the occurrence of product features and the sales of the product. However, they did not provide the reasons behind these trends, i.e. how user preference changes over time. This information is critical for setting up product improvement strategies.

C. What insights can be provided for product innovation?

Today's online review analysis methods provide different insights into product development, such as lead user identification (Tuarob and Tucker 2014), product improvement strategy

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[1] https://github.com/cjhutto/vaderSentiment
[2] http://sentiwordnet.isti.cnr.it/
[3] https://www.god-helmet.com/wp/whissel-dictionary-of-affect/index.htm

construction (Zhang, Sekhari et al. 2016), consumption trends identification (Tucker and Kim 2011, Qi, Zhang et al. 2016, Suryadi and Kim 2016), etc. These methods, based on the structured data given by the feature-based opinion mining, were mainly focused on the product features on which people have expressed their opinions. Nevertheless, as people can only make a judgment on the product features that exist, these methods only gave insights on how to improve the existing product features.

However, product design is an activity that requires innovation. New functions, new usages, and new components must be developed and integrated into the product to adapt user requirements. As consumers use the product in multiple ways, they can discover new usages of the product. They can even modify the product to meet their specific needs (Shu, Srivastava et al. 2015). Previous studies have shown that people talk about the stories on their innovative usages of the product (Chou and Shu 2014). That makes online reviews a valuable source to inspire the ideas for product innovation. However, how to extract this inspiring information is less studied.

II. Industrial and academic needs

A. Industrial needs

In the background of the big data, the brands that offer personalized products typically enjoy a 50 percent higher loyalty. Unfortunately, the traditional manufacturing methods are designed for mass production, not for customization. To be successful in today's market, learning customers' voice has become increasingly important for the development of new products (Liu, Jin et al. 2013, Tuarob and Tucker 2013, Jin, Liu et al. 2016). With the development of e-commerce, it is possible to collect the needs of the customer rapidly to adapt the production line to meet the trends on the market. That is especially important for those designers who must continually renovate their products in the competitive market (Franke and Piller 2003).

The forward-thinking companies and designers can make higher-quality products more efficiently and react more quickly to shift consumer demands, build customer-loyalty and thus gain market share. However, companies face formidable challenges, as introducing a new technology forces the companies more exposed to the market competition. Therefore, this research project is conducted to answer the question commonly faced by today's industrial companies: how to introduce online review analysis into design activity in the context of the big data.

B. Academic needs

Since the 21st century, there has been a large amount of research conducted in the domain of design-oriented online review analysis. In these years, this topic has attracted increasing interests from researchers, as testified by the many specialized events and workshops, as well as by the growing percentage of online review analysis papers in design engineering conferences and issues. However, the previous studies were mainly conducted by researchers in computer science. They are more focused on how to perform natural language processing in online review analysis, and how to improve the accuracy of natural language processing. For design engineering, there is still a gap between the flat data and the reality. Therefore, a roadmap in the design-oriented online review analysis needs to be constructed to bridge this gap. Our scientific goal has been to go through this gap with a systemic approach in order to process the design-oriented online review analysis.

III. Research questions

Based on the limitations summarized in Chapter 2, Section I, we develop the following research questions (Table 7). These research questions have a dependent relationship. For example, the

output of the research question 1 would be the input of the research question 2. To summarize, the research questions 1 and 2 are in the stage of data structuration. The first one is in the scope of ontology construction. The second one is in the scope of computer science. The research questions 3 and 4 are in the stage of data analytics.

Table 7. Formalization of research questions

Challenge and limitation	Research question
Limitation in the definition of user requirement	Research question 1 and 2
Limitation in profiting from the velocity of data	Research question 3
Limitation in providing insights for product innovation	Research question 4

<u>Research question 1</u>: What is the ontology of user concerns in the online review?

Before processing data analytics, the text data must be structured. However, how to structure the text data is still in discussion, as there lacks a definition of user requirement. Only considering the product feature and the user opinion does not cover all the user concerns that have been expressed in the online reviews.

The solution to this research question is an ontological model that organizes the concepts that describe user concerns and specifies the relations between those concepts.

<u>Research question 2</u>: How to automatically structure the online reviews according to the proposed ontology?

This issue is situated in the domain of computer science. Multiple data structuration methods are proposed for the readers to understand the main idea in online reviews easily. These methods mainly identified product feature words and opinion words using the natural language processing technique. However, based on the first research question, in our research project, we are not only focused on these two concepts. Therefore, methods the using natural language processing technique must be developed to automatically structure online review data according to the ontology that we propose.

To clarify the scope of our study, note that the natural language processing algorithms are not perfect, mistakes cannot be totally avoided (See Chapter 1, Section V.B). Our research aims to use the structured data to provide insights into product design. Therefore, we do not delve into the improvement of the accuracy of the natural language processing algorithms. Rather, we provide data structuration method to structure user concerns from the online reviews, where the accuracy is comparable to today's data structuration method. In this way, manually correcting the mistakes in the structuration results is feasible in limited time.

<u>Research question 3</u>: How to analyze the structured data to capture the change of user preference for product design?

In the background of the big data, to be successful in today's market, learning customers' voice has become increasingly important for new product development. As one of the unprecedented characteristics of the online review data, the velocity requires to process the incoming data with high frequency (Wamba, Akter et al. 2015). Based on this characteristic, it is possible to capture the evolution by comparing the current review data and the review data in the past. However, how to process data analytics to gain insights for product improvement based on the velocity still needs to be studied.

<u>Research question 4</u>: How to analyze the structured data to find innovation leads?

Today's online review analysis methods provide different insights for improvement of existing product features. However, people not only talk about their judgment on existing product

features, but they also describe their innovative usages of the product. This information is critical in generating ideas for product innovation.

Chapter 3. Research framework and research process

I. Research framework and research scope

In the previous chapters, we have pointed out the importance of the online review analysis in design activity. We also have analyzed the state of the art of the online review analysis, the challenges and the limitations of the previous studies and we have specified the research questions. In this chapter, we develop our research framework based on the research questions. Meanwhile, we summarized our research process.

To remind, the four research questions are:

1. What is the ontology of user concerns in the online review?

2. How to automatically structure the online reviews according to the proposed ontology?

3. How to analyze the structured data to find innovation leads?

4. How to analyze the structured data to capture the change of user preference for product design?

As our research project is closely related to the online review data and the industry, we simulate a real practical industrial context: Amazon requires strategies for developing its next-generation Kindle e-reader. Therefore, we download the online reviews of several versions of Kindle e-readers from amazon.com. The review data of the Kindle e-readers will be used all along the following part of our research trial.

As is discussed in Chapter I, Section IV.D, the domain knowledge is important in our study. Therefore, our research methodologies are the literature review and the observation of the online reviews. Note that although we only use the e-reader as our research object, we pay attention to the generality of our solution to the online reviews of other product categories.
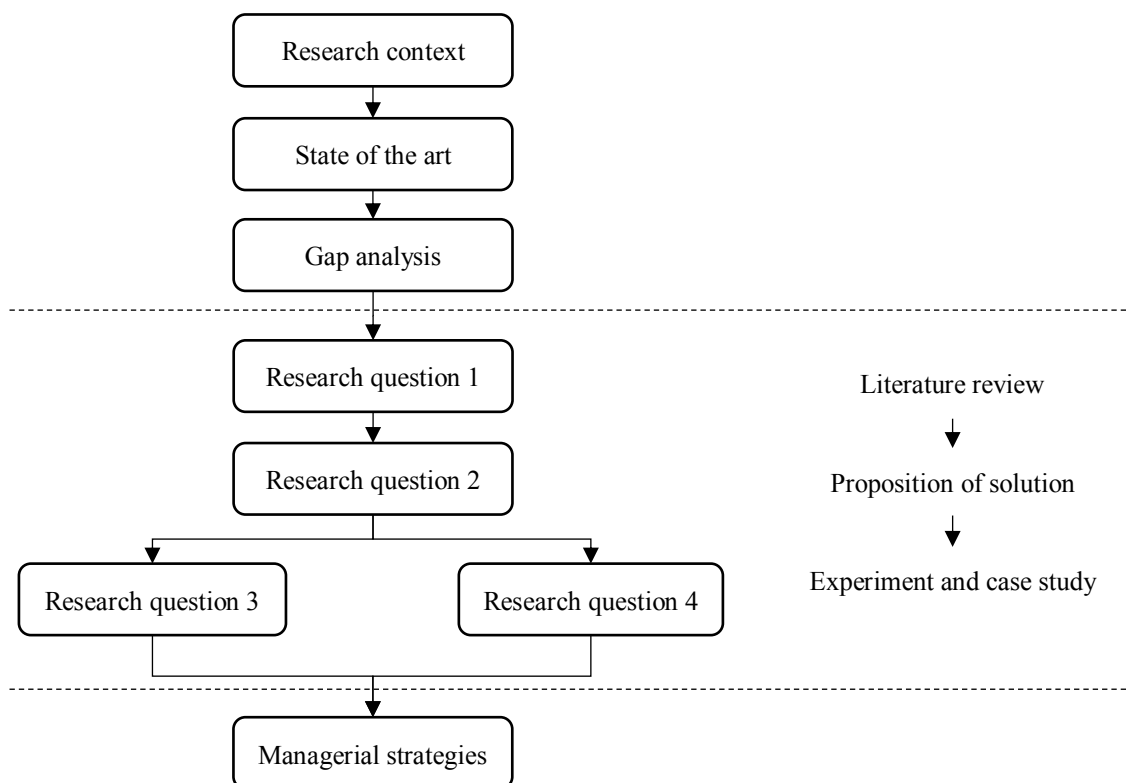
Figure 6. Research framework

Figure 6 shows the research framework and the organization of the four research questions. Clearly, how to automatically structure the online review text depends on the solution to the

first research question. And how to process data analytics (research question 3 and research question 4) is based on the structured data. Each research question is studied in mainly three steps: 1) the literature review, 2) the proposition of solution, 3) the experiment/case study. Finally, based on the findings in the case study, we give managerial strategies for the design of the next generation Kindle e-reader.

The literature review in design engineering helps to answer the first research question. During the literature review, we are focused on the following questions:

- how the user requirements and preference can be used to guide product design,

- what are the concepts and terms that define user concerns, and

- how are these concepts described in the natural language.

We manually label the words concerning the user needs in a set of online reviews, in order to investigate whether and how these concepts are mentioned in the reviews. Also, the manual analysis helps better define the concepts and terms in user concerns and the relations between these concepts. Based on this manual analysis, an ontological model is constructed as a solution to the first research question.

The second research question is the basic portion of our research project. The literature review in natural language processing helps to follow the latest development of this domain, ensuring the performance of our solution. We are focused on the following questions:

- what is the accuracy of the natural language processing algorithms,

- what are the inputs and outputs of the natural language processing algorithms, and

- are there open-sourced natural language processing packages?

Several high-performance open-sourced natural language processing packages are installed and configured. The manually labeled words are regarded as ground truth or gold labels, i.e., the human-defined labels for each corpus that we try to match in the automatization. The online reviews are fed to the natural language processing algorithms to get the linguistic features of each word in the review text.

As the supervised machine learning methods were reported to be domain dependent (Zhang, Sekhari et al. 2016, Kang and Zhou 2017), we are focused on the rule-based method. We observe the linguistic patterns and statistical patterns of the manually labeled corpus. Based on the observation and the literature review in design engineering, we propose several identification rules. We then iteratively add rules to improve the performance of the data structuration until the performance is comparable to the current research in the feature-based opinion mining. Due to the ambiguity of the natural language (Chapter I, Section V.B), it is impossible to process the text data with 100% accuracy using today's natural language processing algorithms. Therefore, we require that the performance to be comparable to the current research in feature-based opinion mining, so that the mistakes in the automatized data structuration results can be corrected manually in limited time.

For the third and fourth research question, as is discussed, the key is to identify the practical meaning of the structured data. Therefore, we observe the structured data to learn their patterns. The patterns should be reasonable in practice. Then, we implement mathematical algorithms to gain practical insights based on the discovered patterns. Note that our research is focused on data analytics, we provide suggestions from the online review data for product design. These suggestions are indicative, not decisive. Before taking real actions, designers need more than the output of the data analytics, which entails a future research project in the scope of design engineering.

To summarize, the scopes of our research are the ontology construction, the text mining based on natural language processing and the data analytics.

II. Overview of the research process

This section summarizes the whole process of the research project. Figure 7 shows the synoptic of the research project.

To answer the first research question, we identified from the literature review that consumers mainly show their concern on the product feature, the product affordance, the emotions, the perception, and the usage condition (see Chapter 4. Section I for the detailed definition of these concepts). Design models and design methods were developed based on these concepts.

We find that the product affordance can be used as a concept complementary to the concept of product feature to summarize user concerns expressed in the online review. Product affordances are defined as the potential behaviors between the product and the customer. For example, the chair affords "sit-ability", the ball affords "throw-ability". Using affordance as the basis for online review analysis, designers are able to learn how consumers use the product, in what condition they use the product, etc., and thus understand why they are satisfied or unsatisfied with the product.

While in feature-based opinion mining, designers only know that the customer has a bad impression on the product feature, such as "bad screen". However, why the screen is "bad", how to improve the "bad" screen is still confusing.

To answer the second research question, we observe how the product affordance is described in the natural language. Heuristic rules based on the linguistic feature of the words in the review text are constructed based on a trial of manual structuration of the online review corpora. The heuristic rules are implemented in Python with the open-sourced natural language processing algorithms, which enables to automatically structure the online reviews according to the proposed ontological model. An experiment is conducted to evaluate the performance of the heuristic rules by comparing the ground truth and the automatic structuration results. Here, the ground truth is the manual structuration results. The comparison shows that the performance of our proposed data structuration method is comparable to the previous feature-based opinion mining research.

Now we have a program to automatically structure the online reviews. This program is the basis for the solution of the last two research questions. For the third research question, we find that novel affordances can inspire product innovation. Novel affordances are defined as the usages of the product that is unintended by the designer during the development of the product. Based on the pattern: novel affordances are talked by fewer people, we propose a method to cluster similar affordances in the structured data. Then, the affordances are ranked based on their frequency of occurrence in all the review text. The affordances having a lower frequency of occurrence are considered as more novel. A case study is processed to evaluate the practicability of the proposed method to identify novel affordances. The strategies of product innovation can thus be concluded from these novel affordances.

The fourth question concerns the velocity of the online review data, from which it is possible to learn the information on the change in user preference. We first use the conjoint analysis to study the perceptions and the preference separately. In fact, it is common to see in the online reviews, people express different perceptions to the same affordance, and people having the same perceptions give different star ratings to the product. For example, for the affordance "*ability to read book*", some customers perceived that they can use the product to read books, while others reported that they cannot read books on Kindle because the screen hurt their eyes,

the battery does not last long enough, or some other reasons. We particularly pay attention to this kind of affordances, i.e., the affordances on which people have opposite perceptions. We apply the conjoint analysis to quantify the weight of each perception to the star rating. As the star ratings are ordered discrete values, ordered logit model is used in the conjoint analysis.

Then, the Kano model is introduced to explain the results of the conjoint analysis. The affordances can thus be categorized in the five attribute categories proposed in the Kano model. Next, by analyzing the online reviews posted in different time spans, designers can conclude the changes of the categorization of the affordance in the Kano model. Finally, a case study is processed to evaluate the practicability of the proposed method. A set of strategies is set up for designing the next generation e-reader.
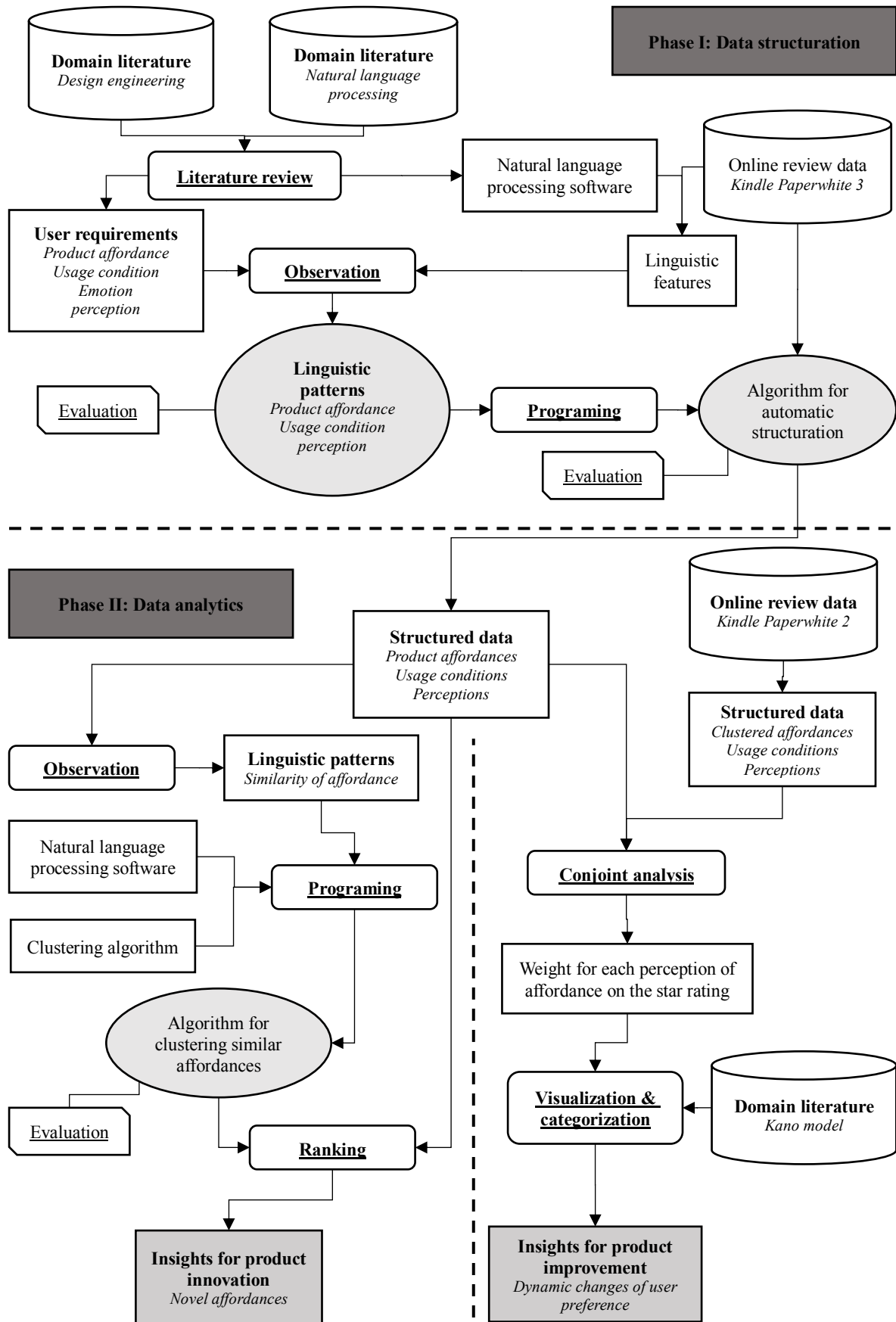
Figure 7. Synoptic of the research project

Part II
Literature review

Chapter 4. Design models and design methods

I. Introduction

A. Generic process of product design

The generic process of design consists of six phases: concept development, system-level design, detail design, testing and refinement and finally and production ramp-up (Eppinger and Ulrich 2015) (Table 1). In the phase of concept development, the needs of the target market are identified. Designers analyze the needs and extract the information they care in the statement of user needs. Based on different kinds of information, design models and design methods are developed to translate user needs into product structure and specifications (Cross 1993, Laurel 2003). Alternative product concepts are generated and evaluated, and a single concept is selected for further development. A concept is a description of the form, function, and features of a product and is usually accompanied by a set of specifications, an analysis of competitive products, and an economic justification of the project.

The phase of the system-level design includes the definition of the product architecture and the division of the product into subsystems and components. The final assembly scheme for the production system is usually defined during this phase. The output of this phase is usually a geometric layout of the product, a functional specification of each of the product's subsystems, and a preliminary process flow diagram for the final assembly process.

The phase on detail design includes the complete specification of the geometry, materials, and tolerances of all the unique parts in the product and the identification of all the standard parts to be purchased from suppliers. A process plan is established, and tooling is designed for each part to be fabricated within the production system. The output of this phase is the control documentation for the product.

The testing and refinement phase involves the construction and evaluation of multiple pre-production versions of the product. Early prototypes are usually built with product-intent parts. Early prototypes are tested to determine whether or not the product will work as designed and whether or not the product satisfies the key customer needs.

In the production ramp-up phase, later prototypes are usually built with parts supplied by the intended production process but may not be assembled using the intended final assembly process. Later prototypes are extensively evaluated internally and are also typically tested by customers in their own use environment. The goal of the beta prototypes is usually to answer questions about performance and reliability in order to identify necessary changes for the final product.

As can be seen, the customer needs are measures of customer value, actionable and controllable through product design, predictive of success and independent of a solution or technology (Jiao and Chen 2006). Having a full set of customer needs impacts all aspects of innovation, the way markets are segmented and sized, the way product and pricing strategies are formulated, and the way ideas are constructed, tested and positioned (McKay, de Pennington et al. 2001). With a complete set of desired outcomes in hand, a company is able to evaluate a proposed solution to determine just how much better the requirements are fulfilled (Eppinger and Ulrich 2015).

B. User requirement identification

Customers do not naturally share their needs towards a product (Eppinger and Ulrich 2015). Consequently, a method must be developed to extract these desired outcomes from them. In market-driven product design, customer requirements are usually obtained from consumer surveys (Gretzel, Yoo et al. 2007, Yoo and Gretzel 2008). Trained interviewers can extract desired outcomes from customers in nearly any customer setting including personal interviews, group interviews (Morgan 1996, McDonagh-Philp and Bruseberg 2000), and using

ethnographic or anthropological research. Other kinds of user requirement identification method are shown in Table 2.

C. The definition of user requirements

As can been seen in the definition (see Chapter 1, Section III.B), the concept of user requirement is broad (Almefelt, Andersson et al. 2003, Jiao and Chen 2006). In the research of Rosenman and Gero (1998), the authors clarified the concept of structure, behavior, and function that are used in design (Figure 8). Based on their discussion, the function should be the result of behavior, whereas the behavior should be described by state transition. Therefore, they categorize user requirements into structural requirements, behavioral requirements and functional requirements.
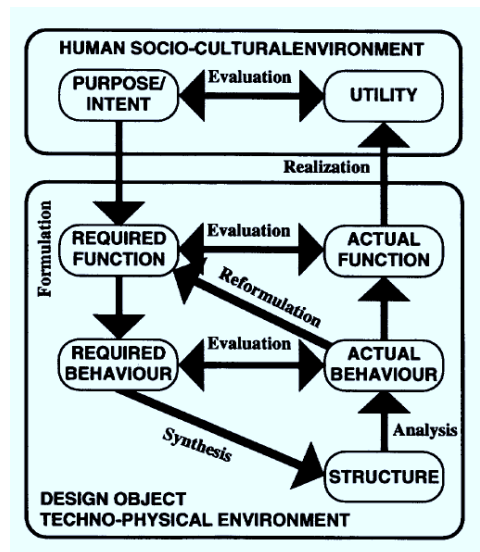
Figure 8. Design process (Rosenman and Gero 1998)

However, there are also non-functional requirements. For example, users may require that the product be reliable, maintainable, recyclable, etc. The broadness of the scope of the requirements makes it difficult to clarify what characteristics a user requirement statement should possess, what information it should contain, its purpose, and how it should be structured (Gupta and Prakash 2001, McKay, de Pennington et al. 2001).

As is mentioned in the generic design process, after user needs are collected, designers analyze the needs and extract the information they care in the statement of user needs. Based on different kinds of information, design models and design methods are developed to translate user needs into product structure and specifications. Therefore, we process a comprehensive literature review on the design models and design methods. This literature review helps us to better understand what kinds of information in user requirement statements that designers care, and how they should be structured. We are able to find the design models and methods based on four concepts: affordance, perception, usage context and emotion.

II. Affordance-based design

A. The concept of affordance: development and definition

The concept of affordance was first put forward by Gibson (1978). It has been later introduced into engineering design by (2004) and Maier and Fadel (2003). They define affordance as a relationship between two subsystems in which potential behaviors can occur that would not be possible with either subsystem in isolation (Maier and Fadel 2009). Based on this definition,

the affordance-based design is proposed. Maier and Fadel (2006) pointed out that the design is a process of favoring beneficial affordances and preventing harmful affordances.

1) Gibson's affordance

The concept of affordance was first put forward by Gibson (1978). The term "affordance" comes from its verb form "afford". As a perceptual psychologist, he invented this concept to explain how animals perceive the environment around them. It is defined as what the environment offers to the animal, what it provides or furnishes, whether it is beneficial or harmful to the animal. Take the ground as an example: a terrestrial surface, which is nearly horizontal (instead of slant), nearly flat (instead of convex or concave), sufficiently extended (relative to the size of the animal) and rigid (relative to the weight of the animal), can afford support-ability to animals. In this example, "nearly horizontal", "nearly flat", "sufficiently extended" and "rigid" are the physical properties of the ground. Gibson proposes that in the ecological approach to visual perception, when animals perceive an object, they observe the object's affordance, not its physical properties. He pointed out that perceiving affordances of an object was easier that perceiving the many physical properties an object may have. For example, what people perceive directly from the ground is its affordance "afford support", rather than the four physical properties mentioned above. The inference from physical properties to affordance properties is processed in the subconscious. That is why in Gibson's view, affordance is both subjective and objective or, in other words, both psychological and physical. It is objective because the property that "the ground can support human" exists naturally. It is subjective because, on the one hand, without the presence of a human, affordance is meaningless. On the other hand, for different people, what an object affords them are not always the same. For instance, research shows that the response of today's young people and senior people towards screens is different. For today's children, screens are something touch-able, while not for grandparents. That is because what human perceive as product's affordance is based on their cognition.

2) Norman's affordance

In the above-mentioned example, children think that screens are touch-able by visual perception. However, do all the screens really give the response to human touch? More generally, does visual perception of product allow people to make a correct inference to the real affordance? These questions are discussed in Norman's work (Norman 2004). Based on his discussion, the concept of affordance is introduced in the design of icons in human-computer interface.

From the products that people use every day, Norman found that the affordances perceived visually by people are not always the real affordances of the product. For example, for a glass door with handles at two sides, people notice by visual that it is push-able and pull-able. Only after pushing or pulling the door does he knows that the door should be slid to open. Therefore, Gaver (1991) proposed a framework to clarify the relation between perceptual information and the real affordances of the product (Figure 9). In Norman's work, he further defines "signifier" as something from which people can perceive the affordance of an object (Norman 2008). It can be the shape of the product, the presence of a certain component, or a label with simple phrases, such as "wet floor". In this way, the perceived affordances and the physical properties of the object are correlated. Once designers found that the perceived affordance is not in accordance with the real affordances, i.e. false affordance and hidden affordance in Figure 9, modifying the corresponding signifiers can remove the discordance (Norman 2015). For the glass door that we discussed, the signifier which leads to the perceived affordance "pulling or pushing" is the knob. Therefore, changing the shape of the knob, or adding a label with word "slide" or an arrow are possible ways to show the real affordance of the glass door.
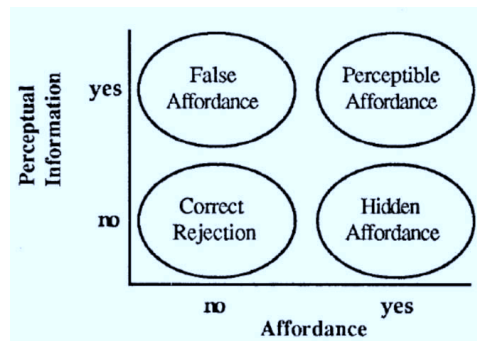
Figure 9. The relation between perceived affordance and real affordance (Gaver 1991)

Comparing with Gibson's definition (Gibson 1978), Norman (2004) distinguishes the affordance perceived by people and the real affordance of the product. He suggests that in the design of icons in human-computer interface, perceived affordance should be in accordance with real affordance.

3) Maier and Fadel's affordance

The function model had been widely used in product design ever since design science began. Lawrence D. Miles proposed the method of functional analysis as part of his method for value analysis in 1947. In much work, the function has been described as transforming material, energy or signal, or as an abstraction of behavior, or as a transformation of input into output (Maier and Fadel 2001).

However, Maier and Fadel (2003) found that the function model is unsuited to the design of products other than mechanical systems of a transforming character, as such products cannot be represented in an input/output model. For example, the design of a chair for sitting on does not involve any transformation of energy, material or information. Also, a function-based approach is unsuited to products where humans are involved as active users, because functions model the work of a product, not its interaction with people. While affordance can tackle these issues.

Definition 10 – Affordance (Maier and Fadel 2009)
A relationship between two subsystems in which potential behaviors can occur that would not be possible with either subsystem alone

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Another advantage of the affordance-based design is that it can be used to better explain the evolution of product design (Sean and Maier Jonathan 2007). For instance, the vacuum cleaner is initially invented to clean carpet by suction. The function of the vacuum cleaner remains more or less unchanged, i.e., clean by suction. The information flow, material flow, and energy flow that go through the system of vacuum cleaner also remain the same. However, its physical parameters, like appearance, trigger's position, motor's position, etc. change a lot. Of course, we can say that the cleaner is changed for "better clean". But how to define "better" is beyond the ability of function-based reasoning.

In affordance-based design, the evolution of vacuum cleaner can be summarized as changes of hold-ability, move-ability, power consuming ability, etc. Therefore, Maier and Fadel (2009) insisted that the concept of affordance is a more general concept which should be the theoretical basis for design. They define affordance as a relationship between two subsystems in which potential behaviors can occur that would not be possible with either subsystem in isolation (Maier and Fadel 2009). Comparing with Gibson's definition and Norman's definition, their definition concerns the real affordance of the product.

B. Difference between affordance-based design and function-based design

The function-based design is widely used in industry. A functional model is a graphical representation of the transformation of energy, material or information flows as they pass through a system. Such a model would be built in the early design phase. It ensures that each modular part of a device has only one responsibility and performs that responsibility with the minimum of side effects on other parts.

In the research of Rosenman and Gero (1998), the authors pointed out the terminology in function-based design was unclear. Therefore, they discussed the difference between the terms *function*, *behavior*, *purpose* and *structure*, which had been widely used in the function-based design and proposed a function-behavior-structure ontology to structure the knowledge in function-based design.

Definition 11 – Ontology (Gruber 1995)

An ontology is an explicit specification of a conceptualization. It provides a formal representation of knowledge, which enables reasoning. It is better than taxonomy or relational database management system since it captures the semantic association between concepts and relationships as well.

In their proposition, a function is the result of behavior, whereas the behavior is described by a state transition. The purpose only exists when related to human values of utility. For example, the function of a clock is always "telling the time", while the purpose may be "knowing the time". The process of design begins at the purpose level and ends at the structure level (Figure 8).

In the research of Eckert (2013), the author observed different approaches people use in industry and how the functions were conceptualized in these approaches. An experiment was conducted where twenty individual designers were asked to generate a functional model of a product. The author found that the function was a problematic concept for practicing design. The designers had to describe what was not form about a product and thus do not have easy and intuitive ways of doing so. Rather than being able to adopt and apply a coherent and explicit definition of the function, designers fall back on their everyday language understanding of function. In a study of Vermaas, Eckert et al. (2013), the authors pointed out that first, there was no clear and overarching understanding of what function was, and why these apparently disparate research attempts should be called a research area with common goals and outcomes. Second, while there were multiple views of function, all of which seemed useful in various contexts, no overall justification existed as to why these views were not just pragmatic attempts at solving the problems at hand but were theoretically inevitable in designing. Therefore, the authors reviewed the existing definition of function and proposed a common definition of function based on the attributes in common: function is always about intent (what a device should do) and function is always about change (between current but undesired scenario and desired scenario). Their definition of function was "an intended change or its enablement, between two scenarios – before and after the introduction of the design". They specified that for an intended change or its enablement to be a function, it must be intended by designers.

Since its proposition, describing the difference between function and affordance has prompted much discussion (Brown and Blessing 2005, Gero and Kannengiesser 2012, Kannengiesser and Gero 2012, Brown and Maier 2015). These studies pointed out that the terminologies used in these two concepts are similar. Both can be described as behaviors between the product and other systems. That is why the difference between function and affordance is confusing.

Brown and Blessing (2005) tried to differentiate these two concepts by establishing the model of objects (i.e. products) and user actions in the world, with its associated terminology and concepts (e.g. operation, function, behavior, etc.). Table 8 shows the terms and examples of the

model. Given a device D in a world W, the rest of the world (non-D) is the environment E. At a particular time, there must exist some relationships R between D and E. Some relationships are referred to as structural as many of them are stable physical relationships. Other relationships may occur due to operations (i.e., actions) carried out by the human. Over a period of time, a set of relationships R can form a mode of deployment M. More specifically, the mode of deployment M describes how one has to hold the device or place it when one needs it to function. However, to have an intended effect, the device needs to behave. Behaviors B can be values of state variables or relationships between them. They are often described with verbs, e.g. the voltage increases, the beam bends. Some behaviors are desirable, by designers, or by users. In the case that the behavior is desired by some agent, then we say that the device provides a function F in the environment. In other words, function F is associated with user or designer's goal of usage. In the case that the behavior desired by the user corresponds to the behavior intended by the designer, the device is providing an intended function. In the case that the behavior is desired by the user but is not what was intended by the designer, the device provides an affordance.

Table 8. Example of objects and user actions model (Brown and Blessing 2005)

Term		Example
Device (D)		Pen
Structural element		Tip, ink container
World (W)		A pen, a sheet of paper, a human and other things
Environment (E)		A sheet of paper, a human and other things
Relationships (R)	Structural relationship	The pen is *on* the paper
	Operation (O)	The top of the pen *is contacted with* the paper.
Mode of deployment (M)		Human is *gripping* pen; the pen is *tip down*; the tip is *in contact with* paper; the tip *exerts pressure* on the paper.
Behavior (B)		Ink *flows* from the tip; ink *coats* the paper; the tip is *moving*.
Function (F)	Desired function	The pen *writes* on the paper
	Intended function	The pen as a *hole puncher*
Goal (G)		To have another human *know* the information that you want to tell them
Intention (I)		*Get* paper, *get* pen, *write* message, *transfer* paper to other humans.
Plan (P)		*Grip* pen, *orient* pen, *put* pen tip to paper, *apply* pressure, move pen
Condition (C)		The pen must be of *small enough diameter* to be grip-able, *rigid enough* to resist the pressure applied, *light enough* to lift and move, and *have* ink available at the tip.

Therefore, a key ingredient of the definition of the function is "desire". Consider an agent using the device to achieve a goal, G. The goal must be transformed into specific statements of what is to be done, i.e., intentions I. The intention is still not specific enough to control actual actions. Therefore, an intention can be decomposed into a plan. The plan is a set of executable operations, probably a sequence, which corresponds to all or part of the intention. It should make progress towards achieving the goal. The operations have conditions, C. these conditions may be pre-conditions, or may occur during the operation. In either case, the conditions must be true for the operation to complete.

Based on the model of function developed above, the authors pointed out that in fact, "user behaviors" are the operations O that form part of the plan P, either to achieve the user's goal, G, or reduce the complexity of the intention, I. Hence the affordances, A, of a device are the set of all potential human behaviors B, O, P, or I, that the device might allow. While the plan and the intention imply the existence of a goal, operations might not. Therefore, unlike

functions, affordances may or may not be associated with a goal. More specifically, affordances may or may not support a goal. They are only dependent on conditions C. These conditions are provided by the device in question, or by the environment.

For product design, suppose that the function is given as the main requirement. With the function known, designing requires searching for a known device with the given function or generating a new device, perhaps by using function decomposition (i.e. development of the intentions and plans). However, this cannot be done with affordance. In fact, the closer to a description of the device one gets, the easier it should be to discover the affordance. This is because precise conditions are needed to determine what behaviors are allowed by the device.

Therefore, Brown and Maier (2015) pointed out that affordance reasoning in the design process is complementary to function reasoning. The later one assumed that the behavior intended by the designer was the actual behavior of the device, which was considered to be the behavior desired by the user. As a consequence, the focus of reasoning was narrowed down to the functions the device should have, rather than could have. While many liability cases were based on the serious negative effects of incorrect, unforeseen use of devices, while at the same time, the device in its environment did allow the behavior. The affordance approach required a broader, more environment-centric view that could help identify potential failures or negative effects which other methods had difficulty identifying. Based on the discussion above, the authors concluded that affordances were an important consideration while designing, it is not always easy to reason out what they are. However, once a design or a conceptual design was developed, affordances clearly had a role to play in investigating, undesirable possible actions, perhaps leading to designs that were safer and easier to use (Brown and Maier 2015).

In the research of Pucillo and Cascini (2014), the authors proposed a framework of user experience, needs, and affordances based on the framework of Hassenzahl's model of user experience (Hassenzahl 2007). Hassenzahl (2007) defined interactions as a goal-directive action mediated by an interactive product. At the lowest level, motor-goals (e.g. pressing the keys of a cellphone) performed in order to accomplish a do-goal in the middle level (e.g. sending a text message). At the highest level, be-goals motivated an action. Sending a text message was not a meaningful action in itself: the be-goals (e.g. feeling closer to a distant person), arising from basic human psychological needs, gave meanings to the action. Be-goals fulfilled user's need, which generated pleasure. Fulfillment of do-goals generated satisfaction.

Based on this model, Pucillo and Cascini (2014) categorized affordances into three groups: experience affordance, use/effect affordance, and manipulation affordance, which allowed a user to achieve respectively be-goals, do-goals, and motor goals. There was a hierarchy relation among these three groups. Experience affordance entailed use/effect affordance, use/effect affordance entailed manipulation affordance. The difference between use affordance and effect affordance is that use affordance entailed a goal or a desire, while effect affordance is the effect caused by the behavior, no matter whether it corresponds users' goal or not. They pointed out that the distinction between use/effect affordance and manipulation affordance totally depended on user's desire. For example, manipulation itself might be the user's goal. Someone may "press the button" because he/she just wants to do it. In this case, "press button" is no longer a manipulation affordance, it is a use affordance.
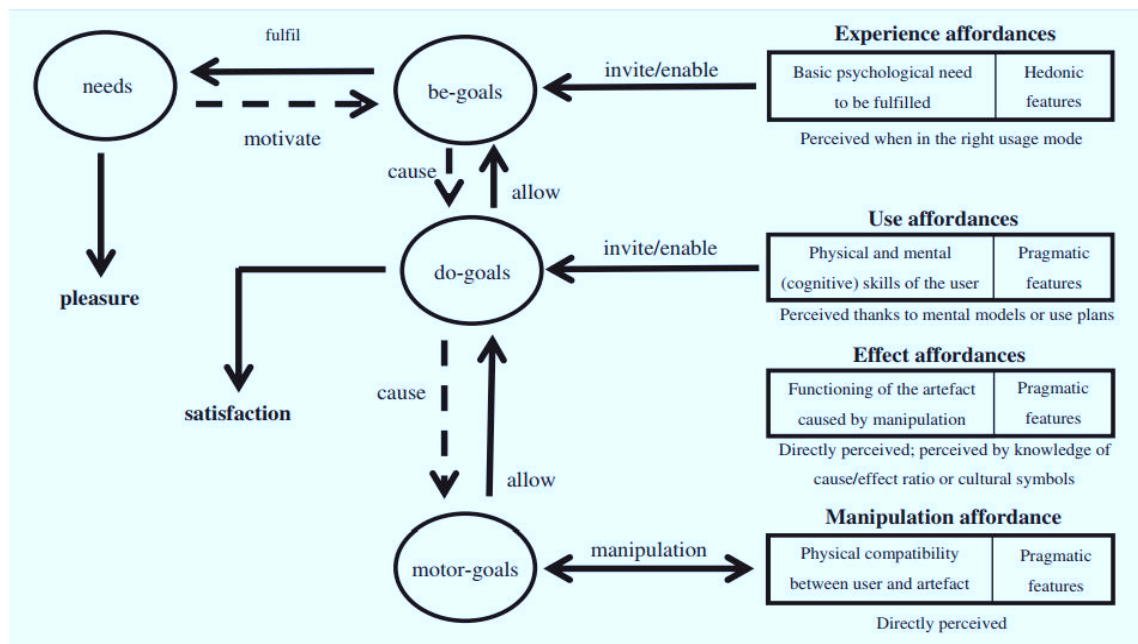
Figure 10. A framework of user experience in interaction based on affordances (Pucillo and Cascini 2014)

In the research of Ciavola (2014), the author holds the same opinion. Functions and affordances are both ways to convey behaviors. Functions were intended behaviors, described either in terms of what a device itself did or in terms of the external effects that the device had on its environment. Function modeling provided tools for representing "what the device and its components do or what the purpose of the device and its components are". While affordance modeling provided tools for representing "what it is possible to do in a particular situation". The shift from function to affordance entailed a move from the intention to the possibility.

In the research of Wu, Ciavola et al. (2013), the authors compared the function-based design and affordance-based design from multiple dimensions, including philosophical assumption, theory breadth, theory maturity, design scope, user experience, the role of innovative design, etc. Their conclusion was similar to that of Brown and Blessing (2005). The concepts of function and affordance did not conflict. The function-based design was a specific tool for developing operational structures of complicated technical systems, while affordance-based design provided a comprehensive toolset for capturing user needs, assessing design quality, and optimizing design parameters across the design process.

In our research, we strongly agree with this point of view. In fact, users do not always use the product as designed. There are misuse and innovative usages. Therefore, functions can be regarded as a subset of affordances. Functions emphasize the behaviors in the view of designers and expectations, while affordances emphasize the behaviors in the view of users and multiple realities.

To summarize, although still debated, the consensus is that affordances do not include the notion of teleology (Kannengiesser and Gero 2012). More specifically, functions refer to what a product is designed to do, while affordances refer to what users do with the product. Affordance emphasizes the potentiality of the behaviors between two systems (Mata, Fadel et al. 2015), such as maintainability, upgrade-ability, sit-ability, even the potential behaviors that are not initially intended by product designer. Affordance modeling is more appropriate to guide innovation in the redesign of "mature" products (Sean and Maier Jonathan 2007, Maier, Sandel et al. 2009), especially when novel affordances are discovered and become important.

C. Affordance description form

Investigation affordance description form helps us understand how the affordances are described in natural language and thus define how to structure the affordances mentioned in online reviews.

Three affordance description forms were summarized by Hu and Fadel (2012) (Table 9). In these description forms, the indispensable element was the verb, which defined the potential behavior between the product and another system (e.g. end user, postman). Alternative elements were the object of the verb, which further defines the receiver of the behavior, and the suffix -ability, which shows that affordance is indeed a kind of potentiality.

Table 9. Existing affordance description forms, summarized by (Hu and Fadel 2012)

Form	Alternative form	Example
Verb + -ability		Grab-ability, waist-ability
Verb + noun + -ability	Noun + verb + -ability	Lift handle-ability, rotate gear-ability
Transitive verb + noun	Intransitive verb	Collect water, lubricate part

Based on these description forms, Mata, Fadel et al. (2015) proposed the affordance-based design ontology (Figure 11). In the ontology, the affordance class contained two objects and four properties. The first object was denoted as "primary entity". It defined the artifact which provides the affordance. The second object was denoted as "secondary entity". It indicated the second entity involved in the potential action, which was either a human, an artifact, or an environmental material. These two objects were fundamental elements of an affordance. The four properties were "affordance description", "polarity", "priority" and "quality". Affordance description defined how affordances are represented in words. Polarity referred to the direction of influence of the affordance. It had two orientations: positive and negative. For example, the cut finger-ability of a knife was negative because it could hurt the user. Priority informed how important the affordance was compared with the other affordances of the product. It was usually defined by designers in the design process based on the target users. Quality defined how well an affordance was achieved. For example, a chair and a briefcase both have the affordance of sit-ability. It was expected that the sitting-ability of a chair had a higher quality than that of the briefcase. The ontology suggested quantifying the quality level with integers, ranging from 0 to 3.
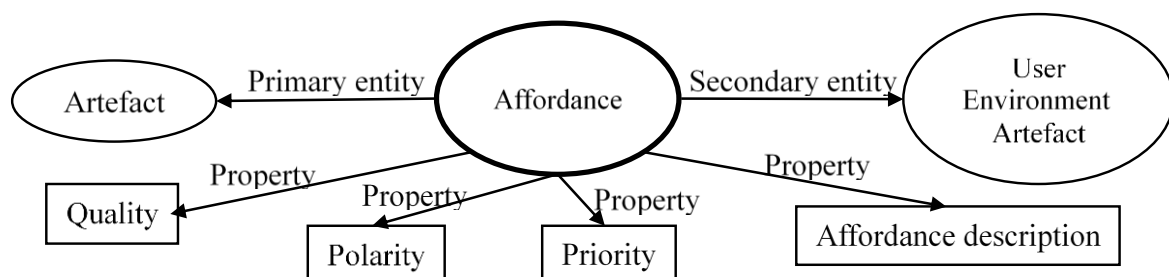
Figure 11. Affordance-based design ontology proposed by Mata, Fadel et al. (2015)

D. Identifying affordances

Various methods have been proposed to identify affordances, such as pre-determination, direct experimentation, interview, online survey (Galvao and Sato 2005, Maier and Fadel 2005, Maier, Sandel et al. 2009, Cormier, Olewnik et al. 2014, Hsiao and Yang 2016). Pre-determination used generic affordance structure to identify the generic affordances that should be provided by all products. Maier and Fadel (2003) provided a generic affordance template having eight categories of affordance (Figure 12). Cormier, Olewnik et al. (2014) completed the template by grouping the affordances into 21 categories (Table 10). However, the disadvantages of the

pre-determination method were that pre-determination was only focused on the general affordances that the products should have. It did not allow to identify affordances existed on a particular product.
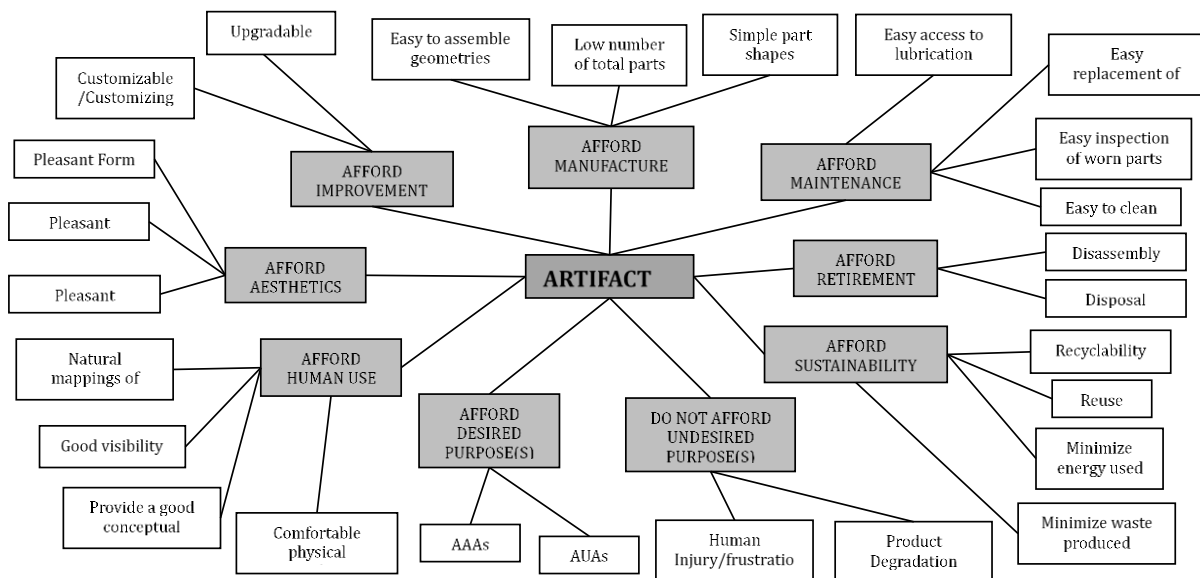
Figure 12. Generic affordance structure template (Maier and Fadel 2003)

Table 10. Affordance structure (Cormier, Olewnik et al. 2014)

Affordances	Definition	Example
Augmentation	Improve an object's existing capabilities during interaction with the principal artifact	Binoculars afford the user improved vision at long distances
Production	Allow an object to create an object or resource	An air compressor affords the user the ability to produce compressed air
Provisioning	Allow an object to provide or supply something to another object	An air compressor provisions air tools with compressed air
Transformation	Allow an object to change or significantly alter the state of another object or resource	An oven affords the user to transform raw batter into cooked brownies
Conditioning	Allow an object to put another object into its proper state	Honing steel affords the user the ability to condition the cutting edge of a knife
Shaping	Allow an object to give definite form to an object (itself or a different object)	A spokeshave affords the user the ability to shape wooden parts (via material removal)
Incorporation	Allow an object to combine two or more objects or resources into a single mixture or entity	A stand mixer affords users the ability to incorporate ingredients (as does a whisk)
Join	Allow an object to connect two or more individual units, components, or elements	A welding machine affords the user the ability to join metal components
Separation	Allow an object to divide an assemblage into individual units, components, or elements	Different size sieves afford landscapers the ability to separate out certain particle sizes
Capture	Allow an object to gain control or exert influence over another object by force or stratagem; allow an object to represent or record information in the lasting form	The Havahart trap affords the user the ability to capture an animal; a camera affords the user the ability to capture an image or series of images

Storage	Allow an object to accumulate or put away an object, set of objects, or resources for future use	Most power drills afford users the ability to store a driver bit on the drill when not in use
Aestheticization	Make an object pleasing to the senses (relative to the user)	A laptop skin affords users the ability to aestheticize their computer's appearance
Communication	To make information (condition, status, intent) or data known to an object	A turn signal on a car affords the user the ability to communicate their intent to turn
Organization	Allow the user to arrange objects systematically	Queuing rails allow an event organizer to organize participants
Transportation	Afford an object the ability to transport one or more objects	A backpack is used to transport objects; a bicycle is used to transport the user
Protection	Preserve an object, environmental entity, or resource from injury, damage, theft, contamination, embarrassment, discovery, etc.	A helmet affords the user protection from impact injury; the Google attachment checker affords the user protection from embarrassment
Entertainment	Allow an object the ability to hold the attention of a user pleasantly or agreeably	A portable media device affords the user entertainment (via consumption of media)
Control	Allow an object to exercise restraint or direction over another object's operation, movement, behavior, etc.	A dog leash affords the owner the ability to control a dog's movement; many circular saws afford the user the ability to control cut depth
Cleaning	Allow an object to remove foreign or extraneous matter from an object or environmental entity	A pressure washer affords users the ability to clean sidewalks
Positioning	Allow an object the ability to physically place the object in a specific location; this could be the principal artifact, another artifact, or a user	A tripod base affords the user the ability to position a camera at a certain location in space
Orientation	Allow an object the ability to physically place the object relative to a frame of reference	A pillow affords the user the ability to orient their head relative to their spine

Direct experimentation required that an artifact already exist to be experimented upon, such as artifacts that already exist in the environment. While designers were in the process of determining what a new artifact would be, physical prototypes were the chief tool available for direct experimentation. Obviously, the higher the fidelity of the prototype, the more in-depth and accurate an analysis of the affordances could be. Prototypes ranged from virtual prototypes on paper or computer screen to crude physical prototypes (say of wood or paper) to rapid prototypes (say of plastic or metal) to full-scale mockups.

When a physical prototype could not be built, whether by nature of the artifact being designed, or due to time, cost, or other constraints, the designer was still responsible for identifying and refining the affordances of the artifact under design. Particularly during the very early stages of design, before a concept architecture has been found, or during the ideation process itself, the designer's greatest tools were his or her own mind and experience. It was called indirect experimentation. Based on a lifetime of knowledge and experience, designers could similarly recognize the affordances of concepts before they were prototyped. This could occur very naturally during ideation before ideas were even sketched when concepts and geometries were fluidly manipulated in the mind.

Using modern technology, designers could go one step beyond relying solely on human experience (Maier Jonathan and Fadel 2007). Expert knowledge about the affordances of

existing artifacts could be captured in a database and integrated into a computer-assisted design environment. Geometries could then be pattern matched against the database to identify automatically the affordances, both positive and negative, of new geometries. The development and implementation of such a system was the subject of on-going research and did not yet exist to aid designers in identifying affordances.

The most serious limitation of such a system was the inability to recognize affordances not documented in the database. Such as a system could, therefore, assist a human designer in identifying common affordances (such as sharp edges that afford to cut) but the designer would still be responsible for identifying new affordances, using either direct or indirect experimentation.

In the research of Chou (2015), the authors conducted an explorative study on how to identify novel affordances from online reviews based on several cue phrases, such as "as opposed to". However, they did not provide a method to extract novel affordance in a fully automatic manner.

III. Usage context-based design

Usage context was also called usage condition or usage environment. It comprised all the factors characterizing an application and the environment in which a product is used (Green, Tan et al. 2005). Knowing usage conditions was important in design evaluation, usage scenario simulation, and user pain identification because usage context influenced customer behavior through product performance, choice, and customer preference (Bekhradi, Yannou et al. 2015, Yannou, Cluzel et al. 2016). Based on this observation, Yannou, Hen & He developed usage context-based design (Yannou, Wang et al. 2009, He, Hoyle et al. 2010, He, Chen et al. 2012, Yannou, Yvars et al. 2013).

Various usage situation models have been proposed. Belk (1975) described a model that split user situations into five groups: task definition, physical surroundings, social surroundings, temporal perspective and user's antecedent states (Figure 13). Green, Tan et al. (2005) narrowed down the scope of usage context to two major components: application context and environment context. He, Chen et al. (2012) emphasized that usage context covers all aspects related to the use of a product but excludes customer profile and product attributes.
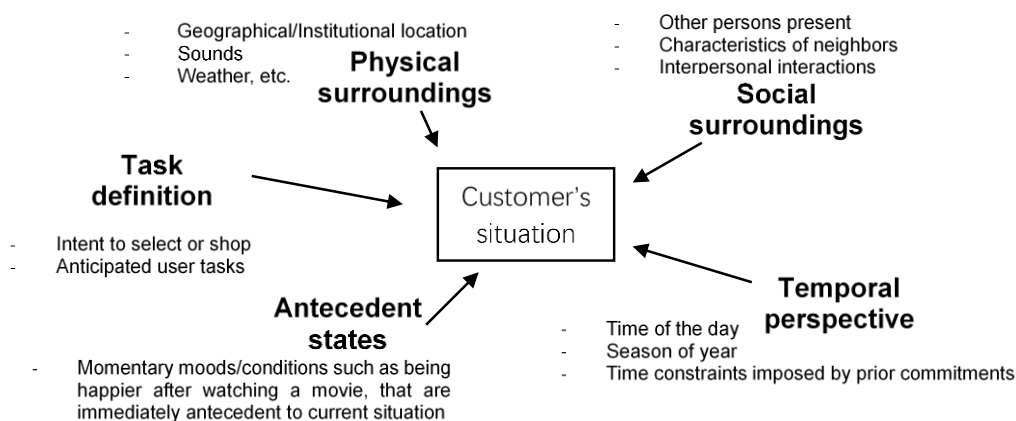
Figure 13. Situation variables categorization (Belk 1975)

IV. User perceptions and product semantics

Definition 12 – Perception (Wikipedia)
Perception is the organization, identification, and interpretation of sensory information in order to represent and understand the environment.

In the field of industrial design, the perception of a product usually interpreted as product semantics (Krippendorff and Butter 1984, Lin, Lin et al. 1996). It came from the esteem and aesthetic functions, such as brand image, personal aesthetics, current trends, etc. (Petiot and Yannou 2004). Researchers in this field intended to understand how human being interpreted the appearance, the use and the context of a product and thus guided design. Therefore, product semantics research is defined as the study of symbolic qualities of man-made forms in the context of their use and the application of this knowledge to industrial design (Krippendorff and Butter 1984). For example, a person may describe a glass with words like "modern", "traditional", "fragile", "strong", etc.

Petiot and Yannou (2004) proposed a semantic differential method to measure the consumer perceptions of the product. In their study, first, the semantic attributes were defined freely by the subjects. A list of semantic criteria was created. Second, a multidimensional scaling method was used to build the perception space. As some of the semantic criteria were similar, the semantic differential method was then used to reduce the dimension of perceptual space. In the third step, the products were weighted under each semantic attribute using the pairwise comparison, which allowed placing the products in the semantic space more precise than in the second step. Finally, after the semantic need was defined, the specifications of the ideal product were achieved by pairwise comparisons. Once the potential product products were proposed, they could be evaluated using the semantic space by pairwise comparisons relatively to the existing products.

Concerning describing perception in natural language, Petiot and Yannou (2004) and Hsu, Chuang et al. (2000) collected 24 pairs of adjectives to describe users' perception on the telephone and 17 pairs of adjectives on the table glass. It was found that perceptions were described with adjectives usually paired with antonyms (Figure 14).
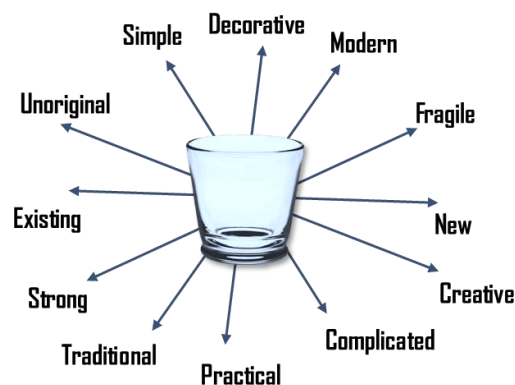
Figure 14. The antonymous perceptual words

V. Emotional design

The emotional design was first proposed by Norman (2004). Emotions represented "our subjective feelings and thoughts" (Liu and Zhang 2012) which "arise in response to appraisals one makes for something of relevance to one's well-being" (Bagozzi, Gopinath et al. 1999). They were shaped by culture and language (Elfenbein and Ambady 2002).

Norman (2004) insisted that design should bring positive emotions. He tried to understand how emotions had a crucial role in the human ability to understand the world, and how they learned new things. In his book "emotional design", based on the ABC (Affect-Behavior-Cognition) model of attitudes proposed in the field of psychology, he proposed three dimensions in emotional design: visceral, behavioral and reflective, insisting that the design of most objects was perceived on all three dimensions. Norman (2004) claimed that a designer should address

the human cognitive ability to elicit appropriate emotions so as to obtain a positive experience. A positive experience might include positive emotions (e.g., pleasure, trust) or negative ones (e.g., fear, anxiety), depending on the context (for example, a horror-themed computer game).

The Kansei engineering was also focused on designing feelings into products (Schütte 2005). The "Kansei" was a word in Japanese. It was the sensitivity of a sensory organ where sensation or perception took place in answer to stimuli from the external world. It incorporated not only the emotion but also the meaning of sensitivity, sense, sensibility, feeling, aesthetics, affection and intuition (Nagamachi 2002). In the field of psychology, Kansei was closely related to appraisal theory, where the emotion was explained as the result of people's interpretations and explanations of their circumstances, which means perception.

These design models aimed at the development or improvement of products and services by translating the customer's psychological feelings and needs into the domain of product design. They were focused on the users' physiological needs on their emotion. They parametrically linked customer's emotional responses to the properties and characteristics of a product or service.

Theories of the psychological domain led to the creation of lexicons capable of analyzing emotions in texts. Many of the emotional dictionaries[1] were easily available to marketers (Bradley and Lang 1999, Strapparava and Valitutti 2004, Scherer 2005, Mohammad and Turney 2013). For example, the ANEW (Affective Norms for English Words) consisted of 1,034 words which were rated in terms of pleasure, arousal, and dominance (Bradley and Lang 1999). The NRC (National Research Council Canada) Word–Emotion Association Lexicon contained more than 8,200 words, with each word being subcategorized into the eight dimensions of Plutchik (1994). The GALC (Geneva Affect Label Coder) consisted of 267 seed stem words, which had been categorized into 36 emotion dimensions (Scherer 2005). In contrast to the NRC Word– Emotion Association Lexicon, the categorization was not performed by thousands of amateurish participants but was rather conducted by one psychologist. The WordNet Affect Lexicon was created by enriching 1,903 emotional seed terms with their synonyms, which were derived from the WordNet dictionary, thus assuming equivalence of emotional loading among synonyms (Strapparava and Valitutti 2004)

However, not a set of emotions that all researchers agreed (Liu 2012). For example, Plutchik (1994) proposed eight primary emotions, grouped by positive-negative opposites: joy versus sadness; anger versus fear; trust versus disgust; and surprise versus anticipation (Figure 15). These feelings might be visibly expressed by the first layer (e.g., joy, trust) and lost their intensity vertically when considering the outer layers (e.g., serenity, acceptance). Mixing the first layer of emotion dimensions would lead to a combined emotion dimension, i.e., when someone felt joy and trust (which had been triggered by the inherent feelings of ecstasy and admiration), this could be called "love". However, Ekman did not agree with Plutchik (1994), in terms of trust, anticipation and stated joy, fear, surprise, sadness, disgust, and anger as being the most basic emotions (Ekman 1992).
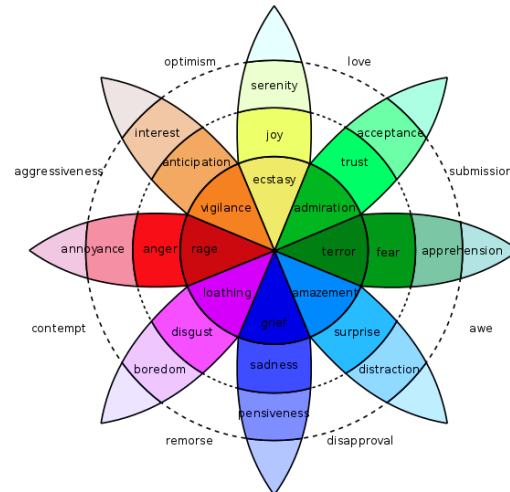
Figure 15. Wheel of emotions (Plutchik 1994)

VI. Discussion

From the literature review, it can be seen that each design model clearly takes a different angle in translating user requirements to guide engineering design. Therefore, focusing solely on product feature does not enable designers to perform a comprehensive analysis of user requirements and the weaknesses and strengths of their product.

We find that compared with the product feature, product affordance is more suitable to summarized user requirements expressed in online reviews. Product affordances are defined as potential behaviors between product and customer. For example, chairs afford "sit-ability", balls afford "throw-ability". Using affordance as the basis for online review analysis, designers are able to learn how consumers use the product, in what condition they use the product, etc., and thus understand why they are satisfied or unsatisfied with product features.

While in feature-based opinion mining, designers only know that customers have bad impressions on the product feature, such as "bad screen". However, why the screen is "bad", how to improve the "bad" screen is still confusing.

Chapter 5. Natural language processing algorithms

I. Introduction

The natural language processing is widely used in online review analysis as it allows the computer to identify automatic meaningful words from online reviews.

Definition 13 – Natural language processing (Wikipedia)

Natural language processing (NLP) is an area of computer science and artificial intelligence concerned with the interactions between computers and human (natural) languages, in particular how to program computers to process and analyze large amounts of natural language data.

As basic tools in our research, natural language processing algorithms provide us language features of text data. The language features can be used as the basis for data structuration and data analytics. Therefore, in this section, we summarized the current natural language processing algorithms to see what linguistic features these algorithms can extract.

As multiple open-source natural language processing packages are available for some algorithms, we compare their performance using a sample of 10 reviews downloaded from amazon.com. The errors of these packages are manually annotated. Finally, we choose the package having the highest performance to continue our search.

II. Sentence segmentation

Sentence segmentation was essential to decide where sentences begin and end. Natural language processing algorithms often required their input to be divided into sentences. The input of sentence segmentation algorithms was a text string. The output of sentence segmentation algorithms was a list of segmented sentences.

Typical strategies in sentence segmentation were (Matusov, Mauser et al. 2006):

- If it's a period, it ends a sentence.
- If the preceding token is in the hand-compiled list of abbreviations, then it doesn't end a sentence.
- If the next token is capitalized, then it ends a sentence.

Various open-sourced sentence segmentation algorithms are available, such as Natural Language ToolKit [1] (NLTK), Spacy [2], Segtok [3]. Table 11 shows our analysis of their performance.

Table 11. Performance of open-sourced sentence segmentation algorithms

Algorithm	Accuracy
NLTK	93%
Spacy	**96%**
Segtok	91%

III. Part-of-speech (POS) tagging and parsing

A POS tag is a tag that indicates the part of speech for a word, such as noun, adjective, verb (Schmid and Laws 2008). POS tags have been used for a variety of natural language processing tasks and were extremely useful since they provided a linguistic signal on how a word was being used within the scope of a phrase, sentence, or document. For example, the word "run"

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[1] http://www.nltk.org/
[2] https://spacy.io/
[3] https://github.com/fnl/segtok

could be used as a verb "I run 5 miles every day" or as a noun "I went for a run". Sometimes the POS was useful in cases where it distinguished the word sense. In other cases, it was still useful in explaining the syntactic role of a word and semantic information could often be inferred from this due to domain knowledge of how this syntactic role was commonly used semantically.

The input of POS tagging algorithms is sentence string. The output of POS tagging algorithms is a list of part of speech tag for each word. There are various inventories of part of speech tags. The most widely used inventory for English is universal dependencies[1]. It includes 38 kinds of part of speech tags.

Parsing, also called as syntax analysis or syntactic analysis, is the process of determining the syntactic structure of text by analyzing its constituent words based on an underlying grammar of the language, such as subject, predicate, object (Collins 2003).

The input of parsing algorithms is sentence string. The output of parsing algorithms is a dependency tree. Figure 16 shows an example of the dependency tree. In the example, the word "jumps" is the headword of the expression "The quick brown fox" and the word "over". The expression "The quick brown fox" is the subject (nsubj) of the word "jumps". The word "over" is the preposition (prep) of the word "jumps". There are also various inventories of dependency tags. The most widely used inventory for English is also universal dependencies. It includes 42 kinds of dependency tags.
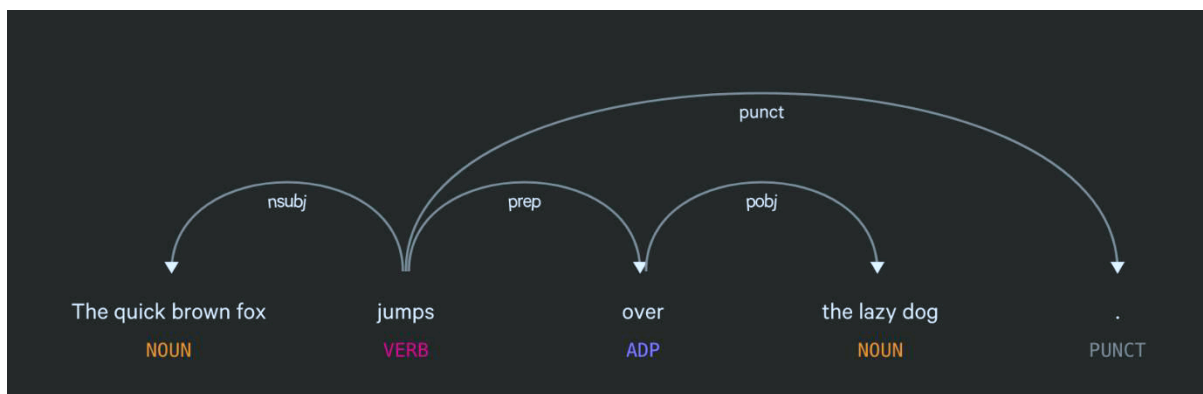
Figure 16. Example of the dependency tree

Typically, POS-tagging and parsing algorithms involved supervised machine learning. Probabilistic language models like Hidden Malkov Model (HMM), Conditional Random Field (CRF) were trained with the manually tagged corpus.

The open-sourced natural language processing packages Stanford CoreNLP[2] and Spacy contain POS tagging and parsing algorithm. The probabilistic language model in these algorithms was pre-trained with the large manually tagged corpus. Table 12 shows our analysis of their performance.

Table 12. Performance of POS tagging and parsing algorithms

Algorithm	The accuracy of POS tagging	The accuracy of parsing
Stanford CoreNLP	89%	85%
Spacy	**92%**	**88%**

IV. Lemmatization

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Lemmatization is the process of converting the words of a sentence to its dictionary form (Plisson, Lavrac et al. 2004). For example, given the words "amusement", "amusing", and "amused", the lemma for each and all would be "amuse". The input of lemmatization algorithms is a list of words and their part of speech tag. The output of lemmatization algorithms is a list of lemmatized words.

The open-sourced lemmatization algorithms implemented in NLTK and Spacy are both based on WordNet (Fellbaum 1998). It is a large English lexical database that contains the lemma of each word.

V. Coreference resolution

Coreference resolution is the task of finding all expressions that refer to the same entity in a text (Elango 2005). It is an important step for a lot of higher level natural language processing tasks that involve natural language understanding such as document summarization, question answering, and information extraction. Figure 17 shows an example of coreference resolution. The input of coreference resolution algorithms is a text string. The output of coreference resolution algorithms is resolved text string.

Coreference resolution algorithm involves supervised machine learning. Neuralcoref[1] is an open-source algorithm for coreference resolution. It uses neural network language model, and the model was pre-trained with a large amount of manually resolved data.
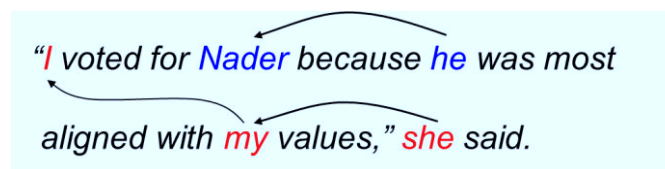
Figure 17. Example of coreference resolution

VI. WordNet

WordNet[2] is a large lexical database of English (Fellbaum 1998). Nouns, verbs, adjectives, and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. Synsets are interlinked by means of conceptual-semantic and lexical relations.

WordNet superficially resembled a thesaurus, in that it grouped words together based on their meanings. However, there were some important distinctions. First, WordNet interlinked not just word forms—strings of letters—but specific senses of words. As a result, words that were found in close proximity to one another in the network were semantically disambiguated. Second, WordNet labeled the semantic relations among words, whereas the groupings of words in a thesaurus did not follow any explicit pattern other than meaning similarity.

WordNet was widely used in natural language processing. As a dictionary, it provided the semantic feature of words, such as the meaning, the lemma, the derived forms. Meanwhile, relations among words can be found in WordNet, including synonymy, hyperonymy, hyponymy, meronymy, troponymy, etc. These relations can be used to evaluate the similarity among words (Wu and Palmer 1994, Resnik 1995, Jiang and Conrath 1997, Leacock and Chodorow 1998, Leacock, Miller et al. 1998, Lin 1998).

VII.   Word2vec

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[1] https://github.com/huggingface/neuralcoref
[2] https://wordnet.princeton.edu/

Word2Vec is an implementation of word embedding techniques (Mikolov, Chen et al. 2013). It estimates word representations in vector space. Word embedding tries to represent relationships that may exist between the individual words (those contained in processing texts) by giving them each a vector with same predefined dimension. In this vector space words that share common contexts may be located closer.

Word2vec takes a large corpus of text as inputs and produces a large dimension vector space, in which each word in the corpus is represented as a vector. It uses two-layer neural networks that are trained to reconstruct the linguistic context of words. Therefore, the vectors produced by word2vec is the distributional representation of the word in the linguistic context. The semantic similarity between two words can then be quantified by the Cosine of the two vectors (Figure 18).
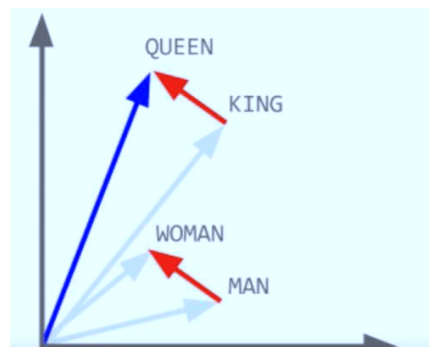
Figure 18. Representation of semantic similarity between two pairs of words embedded by Word2vec. The two pairs of words are (queen, king) and (woman, man)

Part III Online review text structuration

Chapter 6 Data structuration model

I. Introduction

Online reviews must be structured before further analysis. However, as pointed out in Chapter 2, Section I, there lacks a discussion on how to structure user requirements from online reviews. In fact, in the online reviews, the reviewers express their like and dislike not only on the feature of the product. In addition, they concern how the product performs in certain environments, whether it can help them achieve their goals, what their first impression of the product is. Answers to these questions are important for designers to better understand why the user like or dislike their product. The feature-based opinion mining provides limited information.

Apart from the product feature, four concepts that are widely used in design models and design methods: affordance, emotion, perception and usage context (Chapter 4). Therefore, to make better use of the online review data, in this chapter, we propose an ontological model to structure these five concepts and organize the words concerning these concepts identified from the online review. The linguistic pattern for describing these concepts is observed. The pattern can serve as identification rules in automatic data structuration.

To do so, we firstly refer to the literature review of the affordance-based design to construct an affordance description form. Then, we manually identify and structure the words and expressions related to these five concepts from a set of 265 review sentences, in order to discover the linguistic patterns for describing these five concepts in the online reviews. Next, to evaluate the performance of the linguistic patterns, we drafted annotation guidelines. Two human annotators are asked to manually structure the 265 review sentences with the help of the annotation guidelines. Finally, the inter-agreement among the human annotators' summarization results and our annotation results are calculated to evaluate the performance of the linguistic patterns in identifying user requirement words from online reviews.

II. Constructing the ontology

A. The key concepts in design models

Five key concepts describing user requirements were summarized from the current studies in design science and feature-based opinion mining. It means that during product development, designers were focused on the user requirements related to a product feature, perception, emotion, product affordance, and usage condition. Therefore, our proposed ontological data structuration model is based on these five key concepts (Figure 19).
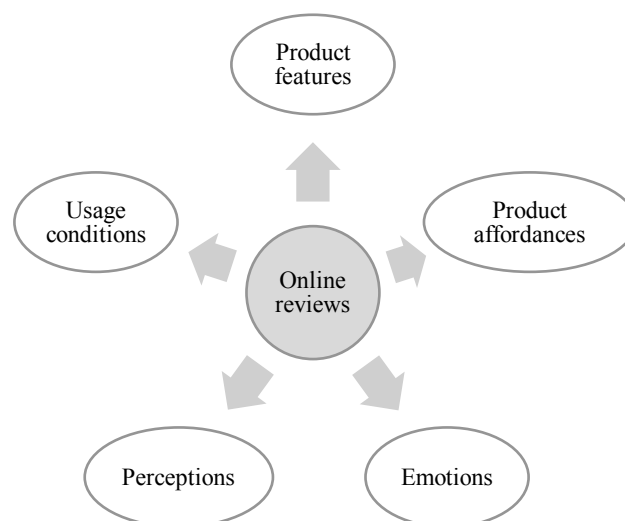
Figure 19. Our proposed data structuration model

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B. The affordance description form

Based on the literature review in Chapter 4, Section II, we propose the following affordance description form to structure the affordances in our study:

Afford the ability to [action word] [action receiver] [perceived quality] [usage condition]

This description form is derived from the basic affordance description forms summarized by Hu and Fadel (2012) (Table 9), based on our observation of the affordances of 11 products appeared in 13 papers of Maier and Fadel (Maier and Fadel 2002, Maier and Fadel 2003, Wang and Fesenmaier 2004, Maier and Fadel 2005, Maier and Fadel 2006, Sean and Maier Jonathan 2007, Maier and Fadel 2009, Maier and Fadel 2009, Maier, Fadel et al. 2009, Maier, Sandel et al. 2009, Nguyen, Fadel et al. 2012). The analysis results are shown in Appendix A. In the basic description forms, the indispensable element is the verb, namely *action word* in our proposed form, which defines the potential behavior between the product and another system (e.g. end user, postman). Alternative elements are the object of the verb, namely *action receiver* in our proposed form, which further defines the receiver of the behavior, and the suffix -ability, which shows that affordance is indeed a kind of potentiality. Two alternative elements, namely *perceived quality* and *usage condition*, are added to the basic form in order to capture more detailed information related to the product affordances. Perceived quality defines in which dimension, and how good the product can support potential behavior to happen (Mata, Fadel et al. 2015). For example, the ability to throw *high/low*, and the ability to throw *far/near*. A usage condition defines the physical surroundings in which the behaviors take place, such as geographical location, weather, etc. For example, the ability to read books *at night*. Specifying the usage condition enables designers to target easily the determining product features of the product affordance. For example, obviously, the determining features are different for the *ability to read books in dark* and the *ability to read books in bright light ambient*.

C. Data preparation

265 review sentences of Kindle Paperwhite 3 e-reader (hereafter referred to as KP3) are downloaded from Amazon.com. These sentences come from the first 10 reviews of the KP3. All 10 reviews were badged "verified purchase", which ensured their authenticity. The 265 sentences contain 4766 words in all. Table 13 gives detailed information for each review.

Table 13. Detailed information for each review

Review number	Number of sentences	Number of words	Star rating	Date published	Number of "helpful" votes
1	38	546	1	Jul 21, 2015	852
2	9	147	1	Jul 3, 2015	529
3	24	320	3	Oct 12, 2015	144
4	36	684	5	Jul 4, 2015	160
5	3	36	5	Oct 17, 2015	78
6	51	909	5	Jul 17, 2015	137
7	17	336	2	Jul 24, 2015	94
8	29	684	1	Jul 2, 2015	465
9	25	508	4	Jul 8, 2015	154
10	33	596	5	Aug 8, 2015	32

Before processing manual structuration, two basic rules were made for the sake of consistency: (i) articles "a(n)", "the" were not considered in the annotation, and (ii) pronouns such as "it", "them" were resolved and annotated when relevant to the concept.

D. A brief look at the structured data

The author processes the manual annotation of product feature, emotion, perception, and usage condition, as identifying the words concerning these concepts is relatively straightforward. The identification of affordance is processed by two experts in affordance-based design. The two experts make a consensus between them.

I used the free shipping but it was delivered very quickly after its official release.
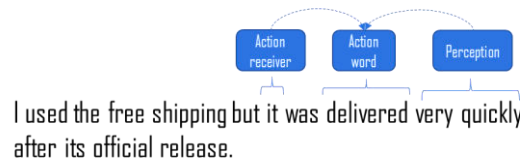
Figure 20. An example of human annotation
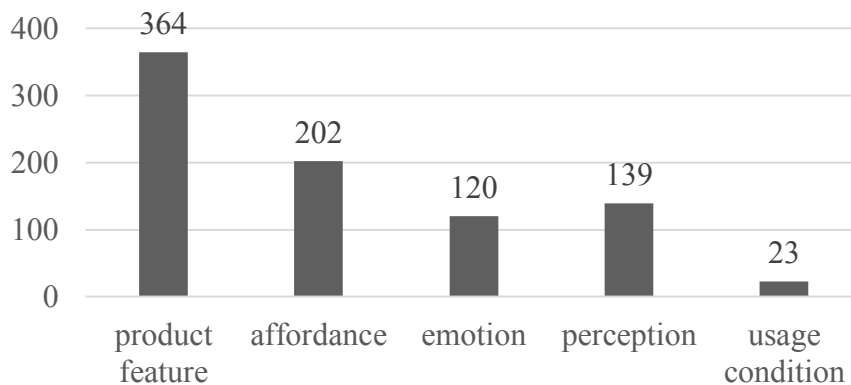
Figure 21. Descriptive statistics of the summarization result

Figure 20 shows an example of the human annotation. In the sentence, the expression "very quickly" is labeled as the perception of the reviewer towards the affordance "deliver it (Kindle)", in which "deliver" is the action word, and the word "it (Kindle)" is the action receiver. The results of the manual structuration of these 265 review sentences are shown in Appendix B. It can be seen from the statistical data (Figure 21) that besides product feature, large numbers of words are identified in the review data sample, showing that our summarization model does provide designers more information related to user needs, as, besides 364 words related to product features, 202 words concerning affordances, 120 words concerning emotions, 139 words concerning perception and 23 words concerning usage context are identified.

Table 14. Sample summarization results

Sentence	Structured data
However, as soon as I received it, I noticed a line of dead pixels right in the center of the screen (Note pic #1).	Product feature: {it, pixels, screen}, Affordance: {ability to receive it, ability to notice a line of dead pixels}, Perception: {dead (pixels)}
There's a significant amount of dust and unrecognizable particles under the screen.	Product feature: {significant amount of dust, unrecognizable particles, screen} Perception: {significant amount (dust), unrecognizable (particles)}
For those who hesitantly bought this device because of the boasted 300ppi screen and thought it would be on par with the Kindle Voyage, think again, it's not!	Product feature: {this device, 300 ppi screen, it, Kindle Voyage} Affordance: {ability to buy this device} Perception: {boasted (300 ppi)}
The setup is extremely easy.	Affordance: {ability to setup} Perception: {extremely easy (setup)}

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I am so excited to be able to finally read ebooks in the sun outside and to read in bed at night without killing my eyes or keeping the husband up.	Affordance: {ability to read ebooks, ability for I to read, ability for killing eyes, ability for keeping up husband} Emotion: {excited} Perception: {not (kill, keep)} Usage condition: {in sun outside (read), in bed at night (read)}

Table 14 shows the words summarized from five sentences. Multiple ways of visualizing the summarized data can be developed to gain insights for product design. For example, co-occurrence maps can be created to analyze the correlation among the extracted product features, product affordances, and usage conditions. In the map, the weight of the node represents the frequency of occurrence. The width of the edge represents the frequency of co-occurrence of two concepts at the sentence level. As illustrated in Figure 22, the most influential product feature for the affordance "read e-books" in general is the "resolution". Whereas the most influential product feature for the affordance "read in the dark" is the "brightness".
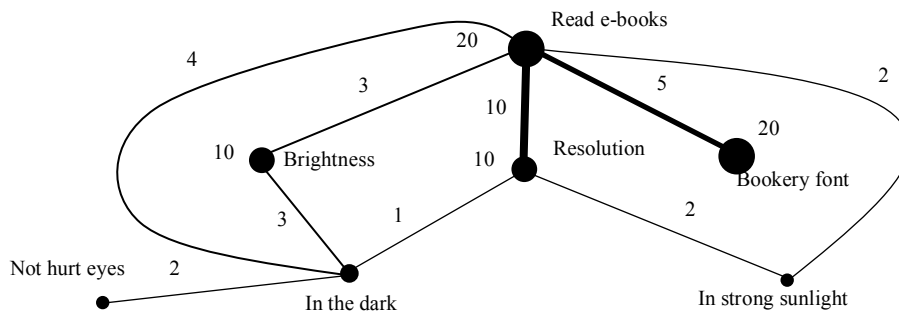
Figure 22. Correlation analysis among affordance, usage condition, and product feature

E. The proposed ontology

Based on the manual structured data, the proposed ontology is shown in Figure 23 and Table 15. The classes and their properties within the ontology are shown in Figure 23. The ontology consists of five classes, corresponding to the five concepts in user requirements.

In the online reviews, reviewers may have perceptions on product features, like "bad battery", or on product affordances, like "download fast", therefore, perception becomes the property of product feature and affordance. Meanwhile, usage context is generally associated with affordance, as both of them provide information on consumer's usage of the product. Therefore, it becomes a property of affordance. The affordance and the product feature appeared in the same sentence indicates that the product feature may influence the quality of the affordance. It suggests that improving the affordance requires modifying the corresponding product feature. Therefore, product feature becomes the property of affordance. In addition, the emotional word in the sentence may indicate reviewers subjective state when perceiving the product feature or the product affordance. Therefore, emotion becomes the property of the product feature and affordance.
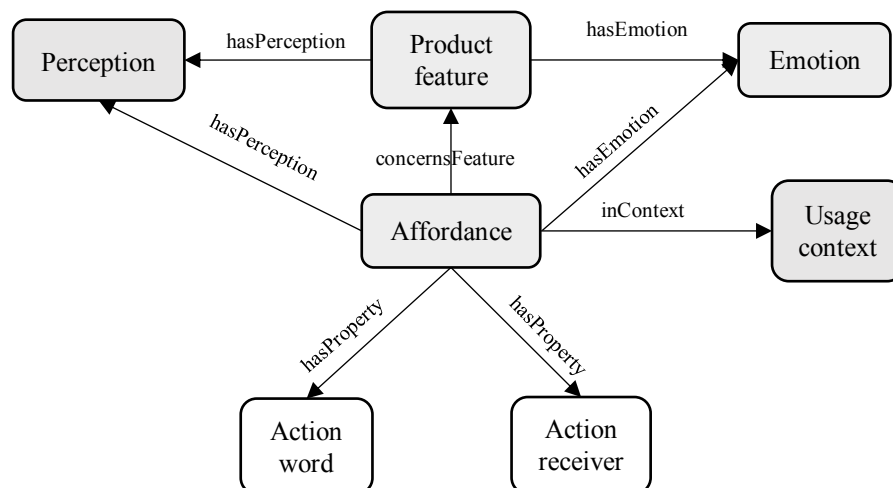
Figure 23. Online review structuration ontology

Our proposed ontological model is capable of answering the following types of logical inference questions (answers in parenthesis):

1) What affordances are associated with this product feature? (*concernsFeature*)

2) What are the product features related to this product affordance in this usage condition? (*concernsFeature* and *inContext*)

3) What are the usage conditions related to this product affordance? (*inContext*)

4) What perceptions do the reviewers have on this affordance and this product feature? (*hasPerception* + *concernsFeature*)

5) What emotion is generated from this product affordance? (*hasEmotion*)

Table 15. Online review structuration ontology classes and their properties

Class	Object properties	Data properties
Affordance	*hasPerception*	Action word
	InContext	Action receiver
	HasEmotion	
Product feature	*hasPerception*	
	HasEmotion	
Emotion		
Perception		
Usage context		

III. Linguistic pattern recognition

To identify words related to these concepts from online reviews, it is important to recognize the linguistic patterns when the reviewers describe these concepts in the review text. For example, the most widely used pattern for identifying product feature words is that product feature words are the nouns or noun phrases that are frequently appeared in the review text.

This section describes the linguistic patterns that we find out based on the ontology and the observation of the manual summarization result. Here, the linguistic pattern is defined as how the concepts are described syntactically and semantically (Zouaq, Gasevic et al. 2012).

1) Product feature

For product feature, two adjustments were made based on the two-level hierarchy model proposed by Liu (2012). First, the scope of component and attribute in the hierarchy model was

enlarged. The words describing things physically attached to the product (e.g. particles under the screen, cover of Kindle, e-books, Amazon account), or things produced by the product (e.g. defects, issues), or the dimension of the attribute (e.g. difference in clarity, variation of color) were all labeled as product feature. These chunks appeared frequently in the reviews and would help designers understand the summarized results. Second, whereas most research (Hu and Liu 2004, Liu 2012, Zhang, Sekhari et al. 2016) has only considered noun chunks as relevant to product features, in our summarization model, linking verbs were also taken into account. For example, in the sentence "This NEW Kindle looked great", "look" is labeled product feature as it referred to the appearance of the Kindle.

Therefore, the linguistic pattern for identifying product features are:

- *The nouns that describe product component and attribute;*

- *The linking verbs adjacent to a product name or product component.*

2) Affordance

Hu and Fadel (2012) summarized from the literature that the affordances can be described in three forms: "verb-ability", "verb + noun-ability", "verb (+ noun)". For example, a chair affords "sit-ability", an e-reader affords "read book-ability", a pen affords "write-ability. It can be seen that the verb is an indispensable element in the affordance description. However, first, we find that in the online reviews, nouns, and adjectives can also describe affordances, especially nouns and adjectives that are derived from verbs, having the suffix "-able", "-ible", "-ity(-ities)". For example, "movability of a chair", "transportability" of an e-reader. Second, not all verbs are product affordances, especially emotional verbs and stative verbs. Instead of a potential behavior between the user and the product, they describe solely the psychological state of the reviewer and the state of the product. For example, in the sentence "It looks nice", the word "looks" only describes the appearance of the product. In the sentence "I want to have the e-reader", the word "want" only describes the cognition of the reviewer. Third, we find that in the online reviews, reviewers talk not only about the product but also about logistics and after-sales service. These words are not affordances of the product, as the product is not involved in the action. For example, in the expression "I contact the after sales team", the word "contact" is not labeled as affordance.

Therefore, we use the description form "ability to [action word] [action receiver]" to structure the affordances described in online reviews. The linguistic patterns for identifying product affordances are:

- *The verbs are action words, except stative verbs, emotional verbs and the verbs describing an action in which the product is not involved;*

- *The nouns and adjectives, derived from verbs, having the suffix "-able", "-ible", "-ity(-ities)", are action words*

- *Action receiver is the object of the action word*

3) Emotion

As discussed in Chapter 4, Section V, various emotional lexicons were constructed in prior research (Bradley and Lang 1999, Strapparava and Valitutti 2004, Scherer 2005, Mohammad and Turney 2013). Therefore, identifying emotional word is relatively straightforward, as these lexicons can be directly used. We find that first, emotional words are not only adjectives. They can also be verbs and nouns. For example, in the sentence "I hope to have an e-reader for a long time", the word "hope" denoted the emotional state of the reviewer, i.e., desire. Second, as the emotional word describes the emotional state of human, the emotional word should be

adjacent to the words describing a human. For example, in the sentence "The color of the chair is exciting", the word "exciting" is not an emotional word, as it describes the property of the chair, i.e., color. However, in the sentence "The color of the chair makes me excited", the word "excited" is labeled as an emotional word.

Therefore, the linguistic pattern for identifying emotion is:

- *Words in emotional lexicons, adjacent to the words describing a human.*

4) Perception

Perception is defined as the way in which the product is regarded, understood, or interpreted by the reviewer. It means that when the reviewer describes their perception, there must be at least one object that receives the perception. Meanwhile, as summarized, perceptual words are adjectives paired with antonyms. Therefore, perceptual words are the adjectives adjacent to product features or the adverbs adjacent to product affordances, having antonyms. For example, in the expression "short battery life", the word "short" is the perception of the product feature "battery life". In the sentence "I can read the book easily", the word "easily" is annotated as the perception of the action word "read". In addition, perceptual words can be a negation. For instance, in the sentence, "I cannot listen to music", "cannot" is perception, meaning that the product does not have the ability to for the user to listen. However, not all adjectives are perceived configurations, especially those adjectives in proper nouns. For example, the word "internal" in "internal storage" does not describe a perception.

Therefore, the linguistic pattern for perception is:

- *Adjectives adjacent to product features, or adverbs adjacent to product affordances, having antonyms, except the adjectives and adverbs in a proper noun.*

5) Usage condition

Usage condition is defined as all the factors characterizing an application and the environment in which a product is used. Consequently, the words describing usage conditions are adjacent to product affordance.

Based on our observation, reviewers mainly talk about physical surroundings when they use the product. Therefore, the words describing usage conditions usually begin with the preposition of place, such as "on", "above", "in", "at". For example, "read book at night", "read book in bed". Therefore, the linguistic pattern for identifying usage condition is:

- *Prepositional phrases adjacent to product affordances, having preposition of place.*

IV. Evaluating the linguistic patterns

A. Data preparation and participants

We drafted annotation guidelines based on the linguistic patterns that we discovered from the manual summarization results. The guidelines contain linguistic patterns and examples to explain the annotation task. A Q&A section helps annotators quickly locate the answer to questions they may have during the annotation. The guidelines can be found in Appendix C.

To evaluate the linguistic patterns, two Ph.D. students in design science were asked to annotate carefully the 265 online KP3 reviews independently following the guidelines we drew up. After finishing the independent annotation, the two annotators compared their results and discussed the differences in their annotation results. If a difference was due to an error made by one annotator, then the annotators were asked to correct the result.

B. Evaluation metrics

The quality of the linguistic patterns was evaluated by the inter-agreement (Pustejovsky and Stubbs 2012) of the two student annotators' results and the authors' results. The inter-agreement denotes how often the annotators agree with each other. Obviously, high inter-agreement means that the annotators' results were precise and accurate in comparison with the authors' results, and thus signifies that the linguistic patterns were well established, and the annotation guidelines were clearly drafted. Fleiss's kappa (Fleiss 1971) is widely used to calculate the inter-agreement. The equation is:

$$K = \frac{Pr(a) - Pr(e)}{1 - Pr(e)}$$
Equation 1

where $Pr(a)$ is the relative observed agreement between annotators, and $Pr(e)$ is the expected agreement between annotators if each annotator was to randomly pick a category for each annotation. To interpret Fleiss's kappa, the scale proposed by Landis and Koch (1977) is used (Table 16).

Table 16. Interpreting Fleiss's kappa as proposed by Landis and Koch (1977)

K	Agreement level
<0	Poor
0.01 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Perfect

C. Results and discussion
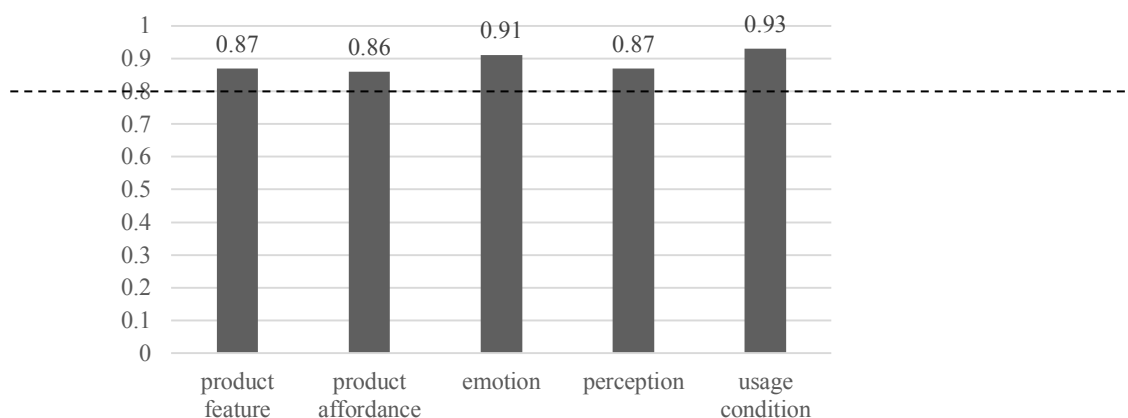
Figure 24. Fleiss's kappa for each concept

Figure 24 shows Fleiss's kappa for each concept. It can be seen that the inter-agreement for all the concepts exceeded 0.8, which means that our guidelines were "perfect" on the scale of Landis and Koch (1977).

We read the results of the two annotators and the results of the author. We particularly pay attention to the differences in the results and discuss the reasons for these differences. We found that firstly, some sentences were unclear owing to the indeterminacy of natural language. This often occurred when a reviewer expressed a perception in the interrogative form. For example, in the sentence, "Second: The 300dpi thing is quite meh (in comparison to 212 and even 167 of the pw1), I mean, is it better? Does it make much of a difference?", it is difficult to tell whether the reviewer thinks the resolution is better or not. Secondly, the annotators reported misspelling as one reason for disagreement in the annotation. These two disagreements cannot be eliminated by improving the guidelines, as the problem is inherent in the review sentence.

It is better to filter out these sentences before processing review summarization. Finally, annotators have different understandings of the concepts based on their knowledge. For example, one of the annotators considered that the word "setup" in the sentence "the setup is easy" was a product feature because the level of difficulty of the setup is an attribute of the software, while the other annotator regarded it as an action word that describes an affordance. Another example concerns the expression "be used to": whether it is an emotional word is still under discussion. These disagreements stem from the unclear definition of the concepts in design. With the development and clarification of the design models, they can be eliminated by fully listing the commonly-agreed lexicon related to each concept in the annotation guidelines (e.g. a database of affordances for each product).

V. Conclusion

In this chapter, we construct an ontological model to structure five aspects of user requirement from online reviews. An affordance description form is proposed based on the observation of affordance descriptions in the literature review. Then, linguistic patterns describing these five concepts are discovered based on a manual structuration of 265 online review sentences. An experiment shows the performance of these linguistic patterns in structuring online review data is high. These linguistic patterns can serve as rules in the study of automatized data structuration. The results of the experiment will serve as ground truth data to evaluate the performance of the automatic data structuration algorithm, i.e., the human-defined labels for each document that we are trying to match.

Chapter 7 A rule-based method for automatically structuring online reviews

I. Introduction

To be successful in today's market, learning customers' voice has become increasingly important for new product development (Liu, Jin et al. 2013, Tuarob and Tucker 2013, Jin, Liu et al. 2016). With the development of e-commerce, the large amount of online reviews has significantly influenced product sales and the way that customers make a purchase decision (Kim and Gupta 2009, Gao, Zhang et al. 2012, Jiménez and Mendoza 2013). These data could be a viable source for collecting user needs and preference for product development, especially for those designers who must continually renovate their products in the competitive market (Franke and Piller 2003).

In Chapter 6, we have constructed a data structuration model including multiple aspects of user requirements: product feature, product affordance, usage condition, user emotion, and perception. A manual structuration shows that a large number of meaningful words can be extracted from online review data. However, due to the large volume, it is impossible to process online review analysis with only human effort. Therefore, automatizing the data structuration process is needed (see Chapter 1, Section V).

As is discussed in Chapter 1, Section IV, supervised machine learning methods require a large amount of manually annotated data as training data. One of the disadvantages of this kind of methods is that they are domain specific. Changing a product category may require reconstructing the training data (Zhang, Sekhari et al. 2016, Kang and Zhou 2017). Therefore, in this chapter, to keep the availability of data structuration for all product categories, we develop a rule-based method to structure the online review data automatically. Rule-based methods are reported to have similar performance comparing with supervised machine learning methods (Kang and Zhou 2017) if the rules are well constructed.

We are particularly focused on how to extract product affordances and usage conditions, as little research has been conducted to extract the words concerning these two concepts automatically (Chou 2015). These concepts are widely used in design science (He, Hoyle et al. 2010, Mata, Fadel et al. 2015) to describe the potential behaviors between user and product. To do so, we firstly refine the linguistic patterns (i.e., adding rules) that we have discovered in Chapter 6 based on the natural language processing algorithms summarized in Chapter 5. Then, an experiment is conducted, showing that adding rules will iteratively improve the performance. At the end of the refinement, the performance is comparable to previous feature-based opinion mining methods.

II. Identification rules

In this section, we refine the rules that we have built in Chapter 6 to identify automatically the four elements in the affordance description form:

Afford the ability to [action word] [action receiver] [perceived quality] [usage condition]

which are action word, action receiver, perceived quality and usage condition. As an indispensable element in the description form, action words are firstly targeted. Alternative elements are then identified based on the identification of action words.

A. Identification of action word

Hu and Fadel (2012) suggested that action words are generally the verbs in the sentence. Inspired by the suffix "-ability", in our study, nouns having suffix "-ility" or "-ilities" that are derived from verbs are also considered as action word, like portability, transportability, etc. Similar to the nouns, the adjectives having suffix "-able" also describes potentiality of behavior, like noticeable, visible, etc. Hence the two rules for identifying action word:

- IF the word w is a <u>verb</u>, THEN w is labelled as an action word **(R-AW-1)**

- IF w is a <u>noun</u> or <u>adjective</u> AND w has the <u>suffix</u> -ility, -ilities, -able AND w is <u>derived from a verb</u>, THEN w is labelled as an action word **(R-AW-2)**

However, not all verbs are action words. The behavior described by the action word should involve two systems. Therefore, stative verbs, which describe the properties or the states of the product itself, like verb *be, have, seem, look, appear*, etc., and emotional verbs, which describe the state of the reviewer, like *hope, want, feel, wish* etc., should be exempted. Hence, the two pruning rules for cleansing the words identified by the previous two rules:

- IF the word w is a <u>stative verb</u>, THEN w is not labelled as an action word **(R-AW-3)**

- IF the word w is an <u>emotional verb</u>, THEN w is not labelled as an action word **(R-AW-4)**

B. Identification of action receiver

Generally, an action receiver was described by the object of the action word (Hu and Fadel 2012). However, we found two exceptions. First, in the case that the action word is in the passive voice, the action receiver is the subject of the action word. For example, in the sentence, "The new Kindle is delivered today", *new Kindle* is the action receiver of the verb *deliver*, which forms the affordance description: the *ability to deliver new Kindle*. Second, in the case that the action word is the verb in a clausal modifier of a noun, and the action word has its own subject, then the action receiver is the noun. For example, in the sentence, "The book that I read is interesting", the action receiver of the word *read* is the word *book*, which forms the affordance description: the *ability to read book*. Hence the three rules for identifying an action receiver:

- IF the word w is an <u>object</u> of its <u>headword</u> h, AND h is an action word, THEN w is labelled as an action receiver. **(R-AR-1)**

- IF the word w is a <u>subject in passive voice</u> of its <u>headword</u> h, AND h is an action word, THEN w is labelled as an action receiver. **(R-AR-2)**

- IF the word w is an action word <u>in a clausal modifier</u> of its <u>headword</u> h, AND w has its own <u>subject</u>, AND h is a <u>noun</u>, THEN h is labelled as an action receiver. **(R-AR-3)**

C. Identification of perceived quality

Perceived quality represents how customers perceive the affordance (Mata, Fadel et al. 2015). Generally, this element was defined by pairs of antonymous adjectives or adverbs which lie at either end of a qualitative scale (Petiot and Yannou 2004). The two antonymous words together define the dimension of the perceived quality. For example, for the affordance *ability to read books quickly*, *quickly* is the perceived quality. Its antonym is *slowly*, and these two words define the *speed* dimension of the affordance *ability to read books*. It conducts to the first two rules for identifying perceived quality.

Besides the adjectives and adverbs directly related to the action word in the dependency grammar of the sentence, the open clausal complement of action word in its infinitive form (i.e., to do) can also describe perceived quality. For example, in the expression "easy to read",

easy being the complement of the action word *read*, defines the quality of the affordance *ability to read* perceived by the reviewer. It conducts to the third identification rule.

It is common that the reviewers talk about some behaviors that have not been implemented in the product. For example, in the sentence, "I cannot listen to music with Kindle", the reviewer perceived that the product did not provide the user with the *ability to listen*. This kind of perceptions informs designers that new affordances deserve to be considered. Therefore, the existence of the affordance should also be considered as a dimension of perceived quality. Negations, like *not, no* signifies the non-existence of the affordance. It conducts to the fourth rule for identification of perceived quality.

- IF the word w is an <u>adverb</u> AND its <u>headword</u> h is an action word of <u>verb</u> or <u>adjective</u> form, AND w has an <u>antonym</u>, THEN w is labelled as a perception. **(R-P-1)**

- IF the word w is an <u>adjective</u> AND its <u>headword</u> h is an action word of <u>noun</u> form, AND w has an <u>antonym</u>, THEN w is labelled as a perception. **(R-P-2)**

- IF the word w is an <u>adjective</u>, AND it is the <u>open clausal complement</u> of its <u>headword</u> h, AND h is an action word, THEN w is labelled as a perception. **(R-P-3)**

- IF the word w is a <u>negation</u> of its <u>headword</u> h, AND h is an action word, THEN w is labelled as a perception. **(R-P-4)**

D. Identification of usage condition

A usage condition defines the physical surroundings (geographical location, sounds, weather, etc.) or temporal perspectives (the time of the day, the season of the year, the purchase time, etc.), in which the potential behaviors described by affordances can occur (He, Chen et al. 2012). We find that in the online reviews, usage condition is usually described with the words that are grammatically related to the action word through a positional preposition. For example, in the sentence "I can read books in the dark", the word *dark* is grammatically related to the action word *read* through the positional preposition *in*. Therefore, the sentence can be translated as the ability for reading books *in dark*. Hence the rule for identifying usage condition.

- IF the word w is a <u>positional preposition</u> AND w is the <u>head word</u> of h AND h is the an <u>object</u> of the <u>preposition</u> of w, THEN w is labelled as an usage condition. **(R-UC)**

III. Implementing the proposed rules with natural language processing programs

The rules we proposed in Chapter 7, Section II enable us to identify product affordances and usage conditions through linguistic features (underlined words in the identification rules in Section II). To summarize, the following linguistic features are needed: 1) word part-of-speech, to show whether a word is adjective, noun, verb, preposition, etc.; 2) grammatical dependency relation, to navigate in the dependency tree and to show grammatical structure of the sentence, such as object, subject, etc.; 3) word derivation, to show the original form of the word; 4) verb category, to show whether a verb is emotional verb or stative verb. The first two linguistic features are provided by many open-sourced NLP packages offering POS-tagging algorithm

and parsing algorithm, such as NLTK[1], Stanford CoreNLP[2], Spacy[3]. WordNet is used to capture the word derivation and verb category. WordNet is a large lexical database of English. It gives the derived form of every word (Fellbaum 1998). Meanwhile, the builder of WordNet has categorized verbs into fourteen groups, including emotional verb group and stative verb group[4]. Figure 25 shows the framework of the implementation.
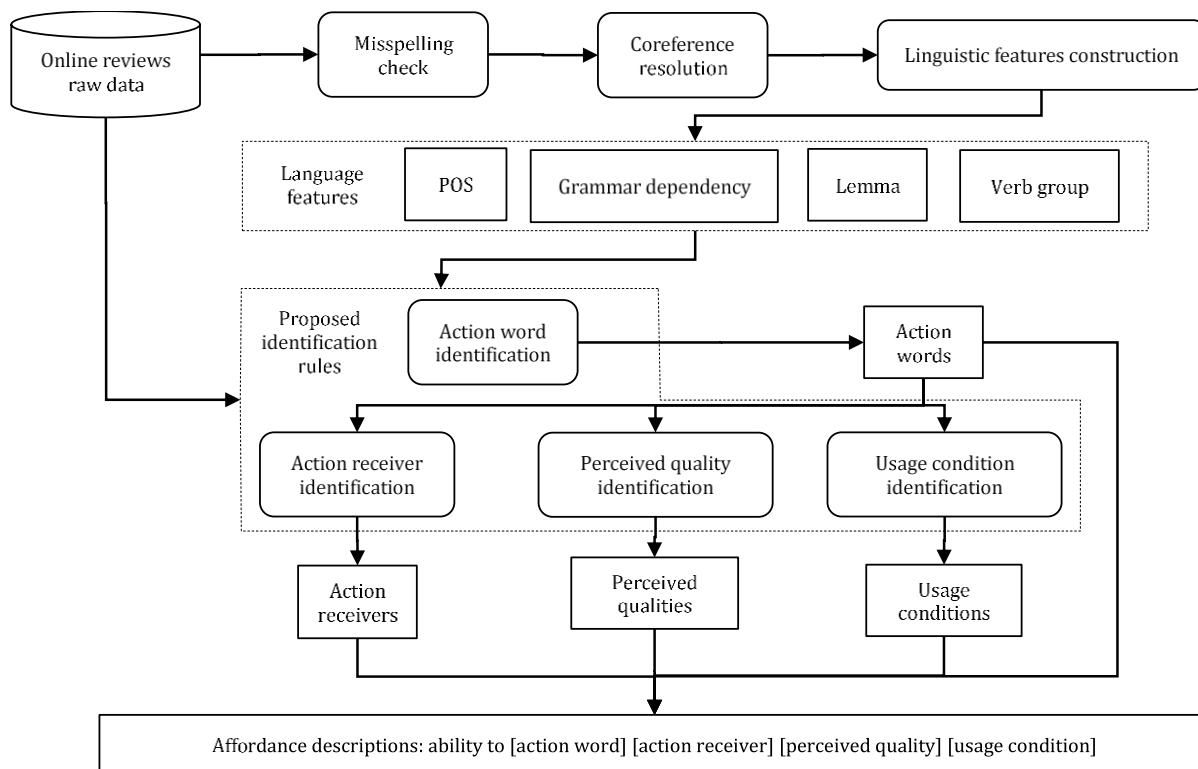
Figure 25. Synoptic of the proposed method

IV. Evaluating the performance

A. Data preparation

We test our proposed rule-based identification method using 265 online review sentences of Kindle Paperwhite 3 downloaded from the first page of the product on Amazon.com[5] (Same as the data used in Chapter 6). These 265 sentences come from 10 online reviews. Three researchers in design engineering are asked to carefully read the online review sentences and identify the elements in the proposed affordance description form. For each element, a list is created to show all the identified words. In the list, the words are in their original form. These word lists are used as *ground truth[6]* to evaluate the performance of the proposed method. To ensure the quality of the ground truth, annotators make consensus among them. The ground truth data are shown in Table 17.

Table 17. Ground truth data

Element	No. words	Word list

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[1] http://www.nltk.org/
[2] https://stanfordnlp.github.io/CoreNLP/
[3] https://spacy.io/
[4] https://wordnet.princeton.edu/
[5] https://www.amazon.com/Amazon-Kindle-Paperwhite-6-Inch-4GB-eReader/dp/B00OQVZDJM
[6] In data science, ground truth refers to the proper objective data. They are deemed as "real true".

Action word	78	adjust, beat, buy, charge, change, call, come, compare, connect, cover, create, define, deliver, display, distinguish, download, drop, eliminate, find, forget, get, give, guarantee, handle, happen, hurt, hold, hype, implement, improve, keep, kill, leak, light, load, look, make, manufacture, notice, order, pay, present, put, purchase, read, receive, recognize, refine, release, rent, replace, return, say, save, scratch, see, set, setup, send, show, ship, sign, slip, stare, subside, step, take, talk, test, try, turn, upgrade, use, variate, view, wait, weight, work
Action receiver	26	2GBs, brightness, comparison, device, difference, ebook, edge, eye, husband, improvement, kindle, leap, letter, lighting, model, Paperwhite, particle, pixel, product, PW, reading, resolution, screen, shadow, spot, warranty
Perceived quality	37	again, already, barely, basic, calmly, clearly, continually, easily, easy, evenly, far, fine, free, great, hard, hardly, have, hesitantly, high, immediately, impossible, lot, much, need, no, not, prematurely, quickly, shocking, should, simultaneously, straightforward, supposedly, surely, well, without, worthy
Usage condition	16	at Best Buy, at night, at UPS, in ambient, in bed, in bright, in dark, in light, in planes, in store, in sun, in sunlight, on display, outside, above clouds

B. Evaluation metrics and baseline

The performance of the automatic structuration method was commonly evaluated by counting the same items in the automatic structured word list and manual structured word list (i.e., ground truth). Three parameters were widely employed: precision, recall, and f-score (Figure 26). The precision is defined as the fraction of relevant items among the identified items. The recall is defined as the fraction of relevant items that have been identified over the total amount of relevant items. Generally, there is an inverse relationship between precision and recall. It is possible to increase one at the detriment to reducing the other. Therefore, the f-score is an evaluation of the overall accuracy. It is defined as the harmonic average of the precision and the recall (Equation 2). The performance for identifying each element in the affordance description form is evaluated separately with these three parameters.
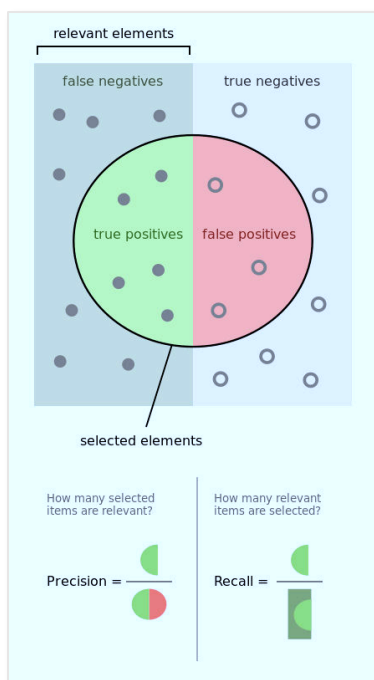
Figure 26. The definition of recall and precision

$$\text{F-score} = 2 \times \frac{recall \times precision}{recall + precision}$$ Equation 2

It has to be emphasized that one of the sources of the errors given by the proposed rule-based identification method is the imperfection of today's natural language processing packages (see Chapter 1, Section V.B). Errors cannot be completely avoided in linguistic feature construction, especially when the input text data comes from the internet as they contain a large amount of unexpected use of words (Bird and Loper 2004). To ensure that designers can manually correct the errors in the identification results in a timely manner, based on the recent studies of feature-based opinion mining (Table 18), we set the lowest tolerable value of f-score for assessing the relevance of our identification rules at 65%, which is the lowest f-score in the study of Zhang, Sekhari et al. (2016).

Table 18. Performance of existing text mining methods

Authors	Entity	Method	Performance
Zhang, Sekhari et al. (2016)	Product feature	Rule based	Recall: 65 – 71% Precision: 65 – 80% F-score: 67 – 75%
	Opinion word	Rule based	Recall: 74 – 86% Precision: 76 – 79 % F-score: 76 – 82%
	Opinion orientation	Rule based	Recall: 60 – 90% Precision: 75 – 98% F-score: 65 – 94%
Jin, Ho et al. (2009)	Product feature	Machine learning (HMM)	Recall: 65-97% Precision: 73-88%
Jakob and Gurevych (2010)	Product feature	Machine learning (CRF)	Recall: 29 – 44% Precision: 45 – 57% F-score: 37 - 49%

C. Procedure

The proposed method is implemented in Python using the open sourced natural language processing package Spacy. As can be seen from Table 11 and Table 12, it has the highest accuracy comparing with other packages. We iteratively add the identification rules to see whether they have a positive influence on the performance of the identification (Figure 25). The online review data are processed following the framework that is shown in Figure 25. As the identification rules and the implementation have been described, we focus on the pre-processing steps, which includes: 1) Misspelling check, allowing automatically identify spelling errors; 2) Lemmatization, giving the original form (i.e., lemma) of each word. For example, the lemma of the word *reading* is *read*; 3) Coreference resolution, specifying to what the pronoun refers. For example, the pronoun *it* in the sentence "The Kindle was delivered last night, and I receive it today" refers to *The Kindle*. In our implementation, Microsoft Word is used to check misspellings. The spelling errors are corrected manually. The open-sourced package Spacy provides lemmatization. NeralCoref is used for coreference resolution.

D. Results

375 affordance descriptions are identified. The performance of the proposed rule-based method is reported in Table 19 – Table 22. Each table shows an element in the affordance description form. As can be seen from the results, by iteratively adding the proposed rules in the identification, f-score gets higher, which means that all the proposed rules have a positive influence on the performance. The overall performance of our proposed method is comparable to the feature-based sentiment analysis method shown in Table 18. More specifically, for identifying action words, action receiver, perceived quality and usage conditions, the f-scores are higher than the lowest tolerable value previously set (65%).

Table 19. Performance of the proposed action word identification method

Rules	Recall	Precision	F-score
R-AW-1	82%	54%	65%
R-AW-1 + R-AW-2	85%	55%	67%
R-AW-1 + R-AW-2 + R-AW-3	**91%**	57%	70%
R-AW-1 + R-AW-2 + R-AW-3 + R-AW-4	90%	**74%**	**81%**

Table 20. Performance of the proposed action receiver word identification method

Rules	Recall	Precision	F-score
R-AR-1	72%	76%	74%
R-AR-1 + R-AR-2	78%	**76%**	77%
R-AR-1 + R-AR-2 + R-AR-3	**82%**	75%	**78%**

Table 21. Performance of the proposed perception word identification method

Rules	Recall	Precision	F-score
R-P-1	48%	**77%**	59%
R-P-1 + R-P-2	51%	76%	61%
R-P-1 + R-P-2 + R-P-3	53%	76%	62%
R-P-1 + R-P-2 + R-P-3 + R-P-4	**82%**	70%	**76%**

Table 22. Performance of the proposed usage condition expression identification method

Rules	Recall	Precision	F-score
R-UC	75%	67%	71%

Table 23. Automatically identified word list[1]

Element	Word list
Action word	adjust, beat, buy, charge, change, call, come, compare, connect, cover, create, define, deliver, display, distinguish, download, drop, eliminate, find, forget, get, give, guarantee, handle, hurt, hold, ~~hype~~, implement, improve, keep, kill, leak, light, ~~load~~, look, make, manufacture, notice, order, pay, present, put, purchase, read, receive, recognize, ~~refine~~, release, rent, replace, return, ~~save~~, scratch, see, set, ~~setup~~, send, show, ship, ~~sign~~, slip, stare, subside, step, take, talk, test, try, turn, upgrade, use, variate, view, wait, weight, ~~work~~, (ask, chat, choose, complain, contact, decide, deserve, dpi, go, happen, help, Kobo, list, pic, refurb, remain, request, say, sepia, stop, trade, up, wear, write)
Action receiver	2GBs, brightness, comparison, device, difference, ebook, ~~edge~~, eye, husband, improvement, kindle, ~~leap~~, ~~letter~~, lighting, model, Paperwhite, particle, pixel, product, ~~PW~~, ~~reading~~, resolution, screen, shadow, spot, warranty, (cloud, device, dud, kink, one, picture, thing)
Perceived quality	again, already, barely, ~~basic~~, calmly, clearly, continually, easily, easy, evenly, far, ~~fine~~, ~~free~~, great, hard, ~~hardly~~, ~~have~~, hesitantly, high, immediately, impossible, ~~lot~~, much, need, no, not, prematurely, quickly, shocking, should, simultaneously, straightforward, supposedly, surely, well, ~~without~~, worthy, (lol, luckily, meh, only, quick, this, Voyage)
Usage condition	~~at Best Buy~~, at night, at UPS, in ambient, in bed, in bright, in dark, in light, in planes, in store, in sun, in sunlight, on display, ~~outside~~, ~~above clouds~~ (at first, at all, at maximum, at price, at thing, in picture)

E.   Findings and analysis for potential improvement in the future

The errors in the automatic identification results are discussed in this section (Table 23). First, we find that our proposed method is incapable to eliminate the verbs that describe the actions other than the usage of the product. For example, in the sentence "I contacted the after sales …", the word *contact* is added to the action word list automatically. However, the action of *contact* describes the behavior between the salesperson and the customer, where the product is not directly involved in the behavior. This kind of behaviors is considered as noise because it does not provide useful information for the designer. As the identification of other elements is

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[1] Words with strikethrough are relevant words unidentified; Words in parenthesis are non-relevant words identified

dependent on the identification of action word, these noises cause the loss of precision for the identification of both action word and other elements. Second, to remind, the existence of the affordance is considered as a dimension of perceived quality. However, our proposed method is incapable to identify the words implicitly describing negation, such as "hardly", "without", "stop doing", etc., which cause the loss of the recall for identifying perceived quality. Third, we find that the performance of our proposed method is relatively low in identifying usage condition. In fact, some expressions corresponding to the linguistic rule R-UC do not describe a usage condition, such as *at first*, *at maximum* etc., which cause the loss of precision in the identification results. Besides, some usage conditions are not described with an expression having a preposition, such as *outside*, etc., which cause the loss of recall in the identification results. These findings suggest that more rules concerning words' semantic meaning may be added to improve the performance.

Another reason for the loss of precision and recall, as is discussed, is that the NLP programs for linguistic feature construction are not perfect. The POS-tagging and parsing make significantly more mistakes when processing long sentences (Bird and Loper 2004). Therefore, the performance can be improved by using more accurate natural language processing programs.

V. Conclusion

In this section, based on the manual structuration processed in Chapter 6, we propose a method to automatically structure the words related to affordances, usage conditions and the associated perceptions mentioned be reviewers. This method is essential to continue our research. An experiment shows that the performance of the proposed method is comparable to the recent research in feature-based opinion mining, which means that the errors caused by our automatic data structuration algorithm can be manually corrected in an acceptable time. The method can be easily extended to the online reviews of other kinds of products, like the cell phone, the home appliance, etc.

Part IV Data analytics to gain insights for product improvement and innovation

Chapter 8. Identifying novel affordances to gain insights for product innovation

I. Introduction

Today's online review analysis methods provide different insights for product development, such as lead user identification (Tuarob and Tucker 2014), product improvement strategy (Zhang, Sekhari et al. 2016), consumption trends identification (Tucker and Kim 2011, Qi, Zhang et al. 2016, Suryadi and Kim 2016), etc. These methods were mainly focused on product features on which people express their opinions. However, people seldom express their opinion on the product components or attributes that do not exist on the product. Therefore, although these methods gave insights for product improvement, they did not provide inspirations for innovation, i.e., favoring the way of using the product which was barely considered before, or integrating new functions into the product.

Identifying novel affordances can inspire innovative ideas (Shu, Srivastava et al. 2015). Research has shown that affordance modeling can more appropriately be used to guide innovation in the redesign of "mature" products (Sean and Maier Jonathan 2007, Maier and Fadel 2009). More specifically, when novel affordances are discovered and become important, they were often treated in isolation to stimulate innovation. Take vacuum cleaner as an example, it was initially designed to suck the dirt on the carpet. Therefore, it had the clean carpet-ability. Soon, customers began to use it to clean floors. However, its clean floor-ability was bad, as it was bulk at that time (Sean and Maier Jonathan 2007). Consequently, there came the upright vacuum cleaner. Another example concerns the evolution of the cellphone. Initially designed to make phone calls and send text messages, people later began to use it to watch videos, surf the internet, check emails frequently. That is one of the reasons why the screen of the cellphone is seen to be larger these days.

That is how novel affordances can provide insights into product innovation. Various methods have been proposed to identify affordances, such as pre-determination, direct experimentation, interview, online survey (Galvao and Sato 2005, Maier and Fadel 2006, Cormier, Olewnik et al. 2014, Hsiao and Yang 2016). However, the disadvantages of these methods are 1) pre-determination was only focused on the general affordances that the products should have. It does not allow to identify the affordances that are relatively novel; 2) other methods like the interview, the direct experimentation are time and resource consuming. Only a fraction of consumers has the potential to participate in these investigations. That makes the selection of innovative customers an early challenging task.

Our study of data structuration in Chapter 7 enables designers to identify and structure product affordances from online reviews in a highly automatized manner. In this chapter, we study how to identify the affordances that are relatively novel. Based on the literature review, we found a pattern for novel affordance identification: novel affordances are talked by fewer people (Chou and Shu 2014, Tuarob and Tucker 2014, Shu, Srivastava et al. 2015, Min, Yun et al. 2018). More specifically, the affordances that are talked by fewer people are more probable to be novel affordances than the affordances that talked by many people. Therefore, it is possible for designers to identify relatively novel affordances based on their frequency of occurrence and thus find innovation path.

Therefore, we propose in this chapter a method to automatically cluster similar affordances in the structured data to reduce information redundancy. In fact, many affordances given by the automatic structuration method are similar. For each cluster, a label is automatically given to represent the affordances in the cluster. The clusters are then ranked based on their frequency of occurrence in all the review data. Finally, an experiment is conducted to evaluate the performance of the proposed method in similar affordance classification. The results show that the performance of our clustering method is comparable to the recent research in feature-based

opinion mining. The advantage is that our method is able to cluster similar affordances, which has never been studied before to the best of our knowledge.

II. Literature review

A.   Definition of novel affordance

In the research of Chou (2015), the authors defined the novelty of affordance by the distance from intended function. They were generally "unexpected" by product designers, which means that they could not be easily inferred from the list of product features or specifications. Therefore, this kind of affordances can provide designers with ideas for innovation. The authors conducted an explorative study on how to identify novel affordances from online reviews based on several cue phrases, such as "as opposed to". However, on the one hand, they did not provide a method to extract novel affordance in a highly automatized manner. On the other hand, as pointed out in their research, the definition of the novelty of affordance was ultimately subjective. The notion of novelty was different for different people. Even their co-authors could not agree on the novelty of certain affordances.

Although there was no commonly agreed definition on novel affordance, the word "novelty" was defined in the dictionary as "the quality of being new, or following from that, of being striking, original or unusual". It can be deduced that novel things are perceived by fewer people because they are unusual. Therefore, we define the statistical pattern to identify novel affordance, i.e., novel affordances are talked by fewer people. This observation corresponds to the definition of "novelty" in the research of Tuarob and Tucker (2014) and Min, Yun et al. (2018). In the research of Tuarob and Tucker (2014), the authors defined the lead user as an innovative user, who faces needs that will be general in a marketplace but faces them months or years before the bulk of that marketplace encounters them. They proposed a method to identify lead users from online reviews based on the occurrence of product feature words mentioned by the reviewers. In the research of Min, Yun et al. (2018), the authors used the number of online reviews as an indicator of the novelty of user requirement.

B.   Semantic similarity evaluation between product features

Among the previous studies, the research in the objective of clustering the product feature words identified from online reviews is most closely related to our study. Therefore, we focused on these studies. There are two main kinds of similarity measuring methods, those relying on pre-existing knowledge resources, and those relying on distributional properties of the words in corpora.

For the methods relying on pre-existing knowledge resources, dictionaries like Thesaurus, WordNet (Fellbaum 1998) are employed. In the research of Carenini, Ng et al. (2005), the authors found that the categorization of information should not only aim at reducing the redundancy of the information, but also expressing the information in a way that is meaningful for designers. Therefore, they proposed a framework to categorize the feature words into user-defined product feature taxonomy. The hierarchical relationships between features could be introduced and exploited in organizing and presenting the extracted information. For example, the effective pixels and aspect ratio were two sub-features of camera resolution. In the meantime, such information was framed in a way that the user envisions the product to be described and reviewed.

Their proposed framework consists of two steps. First, the taxonomies were defined by designers manually with their professional domain knowledge. Second, the similarity between the user-defined features and the crude features, i.e., the features that were identified from online reviews, were evaluated. The similarity was measured in two levels. Three word-level

similarity metrics and two term-level similarity metrics were proposed respectively (Table 24). WordNet was used as a critical basis for word similarity evaluation.

Table 24. Similarity metrics (Carenini, Ng et al. 2005)

Word similarity metrics (w₁: the word in the crude feature, w₂: the word in the user-defined feature)	Word matching:	$Similarity(w_1, w_2)$ $= \begin{cases} 1 & if\ w_1\ matches\ w_2 \\ 0 & otherwise \end{cases}$
	WordNet Synset[1]:	$Similarity(w_1, w_2)$ $= \begin{cases} 1 & if\ Synset(w_1) \cap Synset(w_2) = \emptyset \\ 0 & otherwise \end{cases}$
	Similarity scores:	*The function provided with WordNet corpus (Patwardhan and Pedersen, 2003)*
Term similarity metrics (w₁: the word in the crude feature, w₂: the word in the user-defined feature)	Maximum word similarity score:	$Similarity(t_1, t_2) = max_{i,j}(w_i, w_j)$
	Average word similarity score:	$Similarity(t_1, t_2) = \dfrac{\sum_{i,j}(w_i, w_j)}{n}$

An experiment was conducted to evaluate the effectiveness of the framework in clustering feature words using the similarity metrics in Table 24. The ground truth was generated by human taggers, including 101 crude features and 86 user-defined features for digital camera and 110 crude features and 38 user-defined features for the DVD player. The authors proposed two parameters for the evaluation: the average placement distance and the reduction in redundancy. The placement distance of a crude feature was defined as the minimum number of edges between where the crude feature is placed by the mapping algorithm and where it was placed by the ground truth. The smaller the placement distance, the more accurate the mapping. Measuring accuracy in this way reflected how a user might scan results during the user revision process: a misplacement one edge away was easier to revise than the one that three edges away.

The redundancy was defined as follows:

$$Reduction\ in\ Redundancy = \frac{Placed\ crude\ features - Non\ empty\ user\ defined\ features}{all\ crude\ features}$$

This parameter measures how many crude terms were too similar to be considered as the same user-defined features and could, therefore, be thought of as redundant. Note that this measure penalized crude features that were mapped to multiple user-defined features by increasing non-empty user-defined features. Obviously, a higher reduction in redundancy was good for the user, as more repetitive information was removed.

The results of the experiment show that the average placement distance was less than 0.6, the reduction in redundancy could reach 50%. Thus, the inclusion of user-specific prior knowledge about the evaluated entity was necessary and valuable.

Later, Zhai, Liu et al. (2011) proposed a semi-supervised machine learning method for feature word categorization. Their method did not require a user-defined structure, only the number of clusters was necessary. They found that using similarity metrics might induce problems. First, many words and phrases that were not synonyms in a dictionary might refer to the same feature in an application domain. For example, "appearance" and "design" were not synonymous, but

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[1] A Synset is a set of cognitive synonyms in WordNet (https://wordnet.princeton.edu/)

they indicate the same feature, which is "design". Second, many synonyms were domain dependent. For example, "movie" and "picture" were synonymous in movie reviews, but not in camera reviews. Therefore, they insisted that using fully rule-based method might not be appropriate for feature categorization.

Their method relied on three common knowledge. First, feature words that ever co-occurred in the same sentence were unlikely to belong to the same group. Second, sharing words is an important clue for feature clustering. Third, lexical similarity based on WordNet is widely used in natural language processing to measure the similarity between two words. Note that the above three common knowledge could be violated in some conditions, they are regarded as soft-constraints.

The method consists of two phases: generating labeled data and semi-supervised learning using the expectation-maximization (EM) algorithm. For the first phase, the algorithm first connected feature words using sharing words, like customer service, customer support, service. Secondly, the lexical similarity based on WordNet was considered. The similarity of two words was evaluated using the method proposed by Jiang and Conrath (1997) because it was proved to be the best formula in their experimentation. Thirdly, the similarities were ranked, and the first k groups were merged, where k is the number of clusters that the user predefined. Finally, the largest k groups were selected as training data.

For the second phase, each feature word was represented with a document consisting of the context words, which was defined by the surrounding words of a feature expression in a text window of [-15 to 15]. Then, the EM algorithm proposed in prior work was modified to adapt the training data, as the labeled data might not be fully correct. The E step was firstly performed with initially defined classifier f_0 using training data on all the data. The M step was then performed to learn a new naïve Bayesian classifier from all the data. The E and M step were repeated until the classifier parameters stabilize.

The method was then evaluated with experiment. Five devices are used: home theater, insurance, mattress, car, and vacuum. The ground truth was obtained from the company, which is annotated by human taggers. The results were compared with other 13 clustering methods like K-mean, LDA (Latent Dirichlet Allocation), etc. Results showed that the proposed method outperformed other 13 clustering methods. The intuitive common knowledge was proved to be useful.

C. Limitations and other methods of semantic similarity evaluations

As discussed in the research of Zhai, Liu et al. (2011), dictionary-based semantic evaluation methods have limitations. On the one hand, not all words in the online reviews can be found in the dictionary, especially the words describing product name, such as "Nokia", "Samsung". On the other hand, many domain-dependent similar words were not regarded similar, as the dictionary was domain independent, such as *resolution* and *screen*.

To overcome these issues, distributional similarity assumed that words with similar meaning tend to appear in similar context. As such, this kind of methods fetched the surrounding words as context for each term. Similarity measures such as Cosine, Jaccard, etc. can then be employed to compute the similarities between contextual words and phrases. In the study of Rana and Cheah (2015), Google similarity distance (Cilibrasi and Vitanyi 2007) was used to cluster the product aspects that were extracted from online reviews. Google similarity distance used the world wide web as the source of data and Google search engine to find the similarity distance between words and phrases. Comparing with traditional dictionary-based similarity evaluation, Google similarity distance used larger text corpora. However, it was still domain independent.

Another tool that is widely used in today's distributional similarity evaluation is word2vec, which can overcome all the above-mentioned issues (Mikolov, Chen et al. 2013). It takes a large corpus of text as inputs and produces a large dimension vector space, in which each word in the corpus is represented as a vector. It uses two-layer neural networks to reconstruct the linguistic context of words. Therefore, the vector produced by word2vec was the distributional representation of the word in the linguistic context. The semantic similarity between two words could then be quantified by the cosine of the two vectors.

III. The definition of the similarity between affordances

A. The definition in practice

As product affordances are various, a large number of affordance descriptions can be identified from online reviews (see Table 26 as an example, 635 affordance descriptions are extracted from 7922 reviews). Many affordances are similar semantically.

However, similarity has different metrics. For example, "car" and "bus" are similar as they both belong to "vehicle", while "car" and "road" could also be regarded similar as they both describe "transport". Whether two words are similar depends on the user of the data. Our research is designer-oriented. Designers are focused on what the relations between product components/attributes and product affordances are so that they can modify the product components/attributes to meet user requirements on the affordances. Therefore, we define that two affordances are similar if they concern similar product components or attributes. For example, for an e-reader, "the ability to hurt eyes" mainly concerns the background light of the screen, while "the ability to hurt hands" mainly concerns the weight and the shape of the e-reader. Therefore, these two affordances are different. "The ability to buy e-reader" and the ability to purchase e-reader" both concern the price of the e-reader. Therefore, these two affordances are similar.

B. The definition at the linguistic level

To avoid the problem of independence caused by the dictionary (see Chapter 8, Section II.B), word2vec is used to evaluate the semantic similarity. However, Word2vec can only be used to evaluate the semantic similarity between words. In our proposed affordance description form, affordance description has two properties: action source and action receiver. Therefore, only evaluating the similarity between words cannot tell the similarity between two affordance descriptions. The way to calculate the semantic similarity between two affordance descriptions based on the semantic similarity between two words must be defined at the linguistic level. Meanwhile, the definition at a linguistic level must be in accordance with the definition in practice (see Chapter 8, Section III.A). We manually evaluate pair by pair the similarity of 10 affordance descriptions that are extracted from the online reviews of Kindle Paperwhite 3. The results are shown in Table 25. "0" means that the two affordances are different, "1" means that the two affordances are similar.

Table 25. Manually evaluated affordance similarity

List of affordances	Take kindle	Charge kindle	Listen music	Hurt eyes	Hurt hands	Buy Kindle	Purchase kindle	Read book	Read paper	Download book
Take kindle		0	0	0	0	0	0	0	0	0
Charge kindle	0		0	0	0	0	0	0	0	0
Listen music	0	0		0	0	0	0	0	0	0
Hurt eyes	0	0	0		0	0	0	0	0	0

Hurt hands	0	0	0	0		0	0	0	0	0
Buy Kindle	0	0	0	0	0		1	0	0	0
Purchase kindle	0	0	0	0	0	1		0	0	0
Read book	0	0	0	0	0	0	0		1	0
Read paper	0	0	0	0	0	0	0	1		0
Download book	0	0	0	0	0	0	0	0	0	

We find that to define the semantic similarity between two affordance descriptions, the logic AND of the similarity of action words and the similarity of action receivers can be employed. It means that only when the action words are similar and the action receivers are similar, the affordance descriptions are similar. For example, as is discussed, "the ability to hurt eyes" and "the ability to hurt hands" are practically different. At the linguistic level, although they both have the action word "hurt", the action receivers "hands" and "eyes" are different. "Buy kindle" and "purchase kindle" are similar practically. While at the linguistic level, the action words "buy" and "purchase" are similar. "Read book" and "Read paper" are similar practically, while the action receivers "book" and "paper" are similar.

Therefore, in this research, we choose to use the harmonic mean of the similarity between the two action words and the similarity between the two action receivers to quantify the semantic similarity between two affordances:

$$S_a = 2 \times \frac{S_w \times S_r}{S_w + S_r}$$

Equation 3

In Equation 3, S_a denotes the semantic similarity between the two affordance descriptions. S_w denotes the semantic similarity between the two action words. S_r denotes the semantic similarity between the two action receivers. S_a, S_w, S_r vary from 0 to 1, where 0 means totally different, 1 means exactly the same. The harmonic mean of two numbers is one of several kinds of average metrics in mathematics. It equals to 0 when one of the number is 0, and equals to 1 only when the two numbers are 1.

IV. Clustering similar affordances

In this section, we cluster similar affordances based on S_a. In the research of Zhai, Liu et al. (2012) and Chen, Zhao et al. (2016), K-means clustering and hierarchical clustering are used to cluster the product feature words identified from online reviews. The difference is that K-means clustering requires the number of groups as input. While hierarchical clustering does not necessarily need this parameter. Instead, it requires a threshold s as input. In the case that the similarity between the two groups is higher than the threshold s, the two groups are fused. In our study, as we do not use a pre-define template to cluster affordances, we do not know how many groups the clustering method should create. Therefore, the K-means method is not appropriate for our study.

We use a traditional hierarchical clustering method to cluster the affordance descriptions (Guha, Rastogi et al. 1999). The principles of the hierarchical clustering were that if the similarity between two affordance descriptions, or between two clusters of affordance descriptions, is larger than a threshold s ($s \in [0,1]$), then they are grouped together. In the method, the similarity between two clusters $c_i = \{a_1^i, a_2^i, a_3^i \dots a_n^i\}$ and $c_j = \{a_1^j, a_2^j, a_3^j \dots a_m^j\}$ is calculated by the following equation:

$$S_c(c_i, c_j) = \frac{\sum_{p=1}^{n} \sum_{q=1}^{m} S_a(a_p^i, a_q^j)}{n \times m}$$

Equation 4

In Equation 4 S_a and S_c vary from 0 to 1. After clustering, each group is given a label to mark the general meaning of the affordances in the group. In this research, the label is the affordance description in the group that appears the most frequently in the online review data.

V. Case study

A. Data preparation

In the case study, we take Kindle Paperwhite 3 (hereafter denoted as KP3) as our research object. The statistics of the online reviews of KP3 are shown in Table 26. All the online reviews of KP3 published from July 2015 to June 2018 on Amazon.com are downloaded. As online markets are reported to have the problem of fake reviews (Qi, Zhang et al. 2016), we are only focused on the reviews having more than one helpful vote. 7922 online reviews of KP3 are collected. 60266 affordance descriptions are annotated, summarized to 635 different affordance descriptions. Note that the natural language processing algorithms are not perfect, errors cannot be avoided in the identification results. Therefore, the author checked the 635 affordance descriptions. If the description is not readable or understandable, the description is eliminated; for example, "one time", "take try", "beat book". Finally, 496 different affordances are prepared for semantic similarity evaluation.

Table 26. descriptive statistics of the dataset

Nb. of reviews downloaded	56634
Nb. of reviews selected	7922
Nb. of affordance descriptions extracted	60266
Nb. of different affordance descriptions extracted	635
Nb. of different affordance descriptions extracted (after manual correction)	496
Example of affordance descriptions (10 most frequently appeared affordance descriptions)	read book, get Kindle, use kindle, work kindle, make difference, find book, say that, try Kindle, turn page

B. Process

We apply the Word2vec to the 7922 reviews to convert each word into a vector. The similarity S between two words w_1 and w_2 are calculated based on the cosine of the two vectors $\vec{V}(w_1)$ and $\vec{V}(w_2)$ given by the Word2vec algorithm (In the Word2vec algorithm, $S \in [0, 1]$). $S = 0$ means that the two vectors are orthogonal and w_1 and w_2's context words are totally different, while $S = 1$ means that the two vectors are parallel and w_1 and w_2's context words are exactly the same. For each pair of the 496 affordance descriptions, their similarity is calculated using Equation 3 (Table 28). Hierarchical clustering is then applied. In this case study, by comparing the manually and automatically evaluated similarity results (Table 25 and Table 27), we define the threshold $s = 0.8$. Next, the most frequently appeared affordance in the cluster is considered as the label of the cluster. The results are finally ranked with their frequency in the 7922 reviews.

Table 27. Sample of automatized similarity evaluation results

List of affordances	Take Kindle	Charge kindle	Listen music	Hurt eyes	Hurt hands	Buy Kindle	Purchase Kindle	Read book	Read paper	Download book

Take Kindle	1.00	0.55	0.41	0.39	0.47	0.76	0.73	0.53	0.59	0.53
Charge Kindle	0.55	1.00	0.58	0.37	0.47	0.73	0.63	0.68	0.61	0.50
Listen music	0.41	0.58	1.00	0.42	0.59	0.68	0.57	0.53	0.47	0.56
Hurt eyes	0.39	0.37	0.42	1.00	0.74	0.66	0.57	0.35	0.47	0.55
Hurt hands	0.47	0.47	0.59	0.74	1.00	0.67	0.63	0.55	0.58	0.40
Buy Kindle	0.76	0.73	0.68	0.66	0.67	1.00	<u>0.96</u>	0.57	0.44	0.49
Purchase Kindle	0.73	0.63	0.57	0.57	0.63	<u>0.96</u>	1.00	0.66	0.74	0.60
Read book	0.53	0.68	0.53	0.35	0.55	0.57	0.66	1.00	<u>0.91</u>	0.70
Read paper	0.59	0.61	0.47	0.47	0.58	0.44	0.74	<u>0.91</u>	1.00	0.71
Download book	0.53	0.50	0.56	0.55	0.40	0.49	0.60	0.70	0.71	1.00

C. Evaluation of clustering

We evaluate the performance of similar affordance descriptions clustering. Two human annotators are asked to check the results of affordance clustering. They compared each affordance description in the one cluster with the label of the cluster. If an affordance description is not correctly clustered, then it is put in the correct cluster. To avoid the subjectivity in the evaluation, the two annotators make a consensus between them.

The performance of similar affordance descriptions clustering is evaluated by purity. This parameter is widely used in evaluating the clustering results. It is defined by the following equations:

$$\text{purity}(A) = \frac{1}{N-1} \sum_k \max_j |a_k \cap m_j|$$

where $A = \{a_1, a_2 \dots a_n\}$ is the set of clusters that are to be evaluated. $M = \{m_1, m_2 \dots m_n\}$ is the set of clusters in ground truth. N is the number of clusters. Purity is a simple and transparent evaluation measure. It simply means the percentage of the affordance descriptions that are correctly clustered. A bad clustering has a purity close to 0, a perfect clustering has a purity of 1.

We compare the performance of our proposed clustering method with the previous studies of Zhai, Liu et al. (2012), where the average purity is 55%, and the research of Chen, Zhao et al. (2016), where the average purity is 90%. These two studies are closely related to our research. The objective of these two studies was to cluster similar product features extracted from online reviews.

D. Results and discussions

The 496 descriptions are clustered into 70 clusters. Table 28 shows the descriptive statistics and the purity on the twenty most frequently appeared clusters. Detailed results can be found in Figure 27 and Appendix F. The average purity is 88.5%, which is much higher than 55%. However, as the difference between our work and the previous studies is that their research objective is to cluster similar words, while our research objective is to cluster similar affordance expressions. It adds to the difficulties in similarity evaluation and explains the reason why the performance of our proposed framework is slightly lower than 90%, i.e. the performance of recent study conducted by Chen, Zhao et al. (2016).

We observe the affordance descriptions that are not correctly clustered. We find that first when action word has multiple meanings in the dictionary, the purity of the cluster is relatively low. For example, the purity of the cluster "do job" is only 65.0%. The affordance descriptions that are mistakenly categorized are "use book", "use dictionary", "use touch", "use touchscreen", "use battery", "use light" and "do update". That is because when the action word is "do" or "use", the meaning of the affordance expression mainly depends on the action receiver. This

observation suggests that considering the information entropy carried by the action word may be a way to improve the performance of clustering affordances in future research.

Table 28. A brief look at the clustering results (20 most frequently appeared clusters)

Cluster label	Number of descriptions	Typical descriptions	Number of occurrences	Purity
Read book	27	See book, see screen, see page	6469	83.3%
Receive paperwhite	23	Get kindle, get model, get paperwhite	1522	75.9%
Give star	3	Give rating, get stars	1467	100.0%
Download book	42	Add book, open book, show book	1414	93.0%
Purchase kindle	24	Buy kindle, buy paperwhite, choose paperwhite	1056	84.6%
Charge kindle	11	Charge device, charge paperwhite, plug kindle	915	100.0%
Make difference	16	Make improvement, upgrade kindle, replace kindle	799	77.8%
Do job	15	Work kindle, use kindle, operate kindle	699	65.0%
Turn page	12	Swipe page, turn kindle, change page	608	90.9%
Know word	5	Learn word, review word, use dictionary	494	66.7%
Hurt eye	9	Strain eye, age eye, bother eye	481	100.0%
Touch screen	9	Touch page, touch word, tap screen	364	100.0%
Carry book	12	Take book, use book, carry library	358	72.7%
Sleep husband	4	Sleep wife, bother husband, bother wife	356	100.0%
Recommend reader	7	Recommend kindle, recommend paperwhite, recommend device	336	100.0%
Adjust size	4	Increase size, reduce size, change size	312	100.0%
Light screen	5	Glare screen, use screen, illuminate screen	303	100.0%
Click button	11	Press button, hit button, push button	290	100.0%
Pay extra	18	Offer discount, remove ad, justify cost	277	94.1%
Understand problem	23	Fix problem, cause problem, solve problem	273	100.0%
Total				**88.5%**
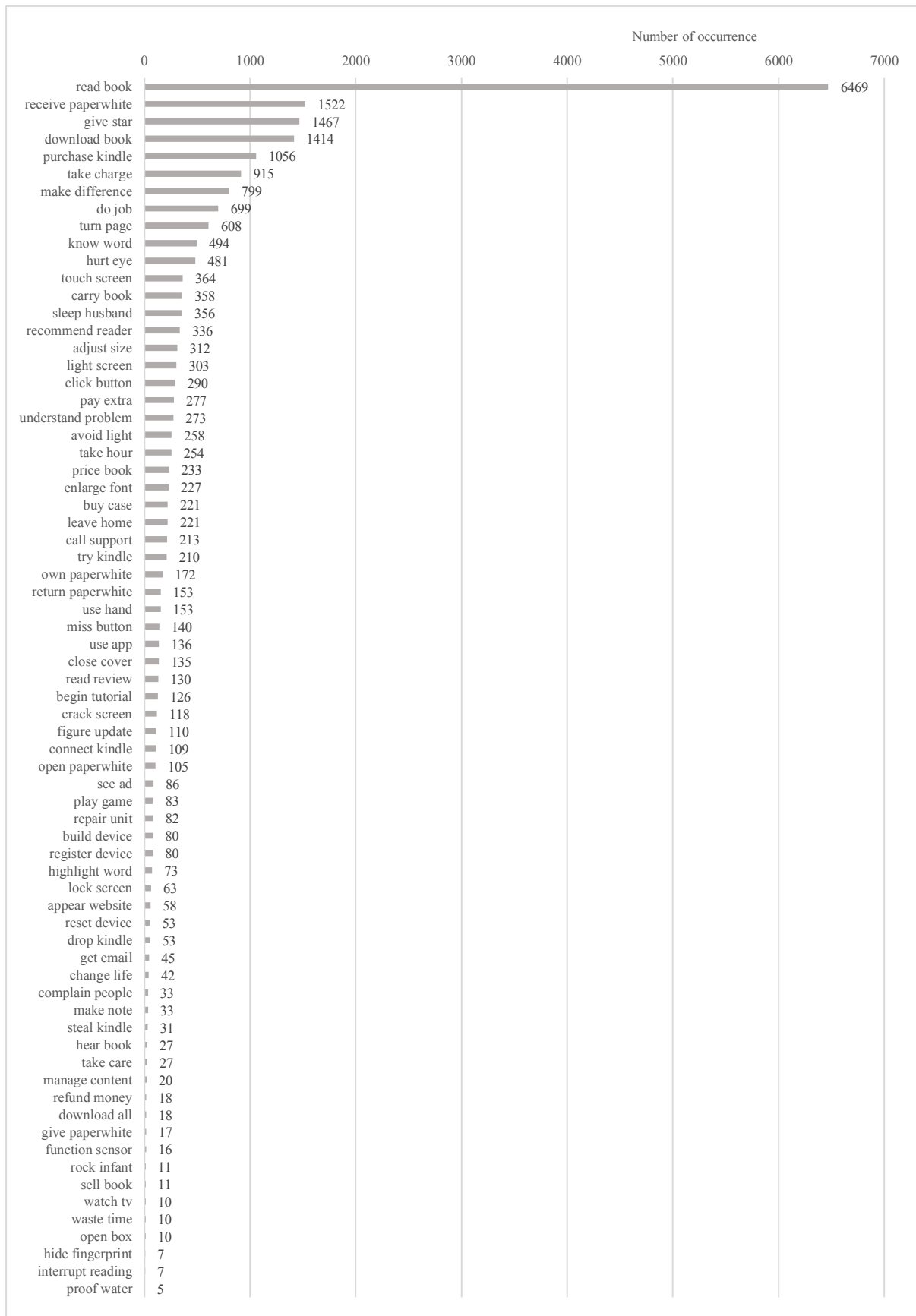
Figure 27. The distribution of the clustered affordance descriptions

VI. Product innovation path

Based on our discussion on the definition of novel affordance, we find that one of the factors that define the novelty of affordance is its frequency of occurrence. Therefore, it is easier to seek out innovation path from the affordances that are mentioned by relatively fewer people than from the affordances that are frequently mentioned.

We use the structured and clustered data given by our proposed clustering method (See Table 26 for the descriptive of statistics of the dataset). For each cluster, its number of occurrence in the 7922 online reviews are counted. Table 29 lists the ten least frequently appeared clusters. These affordances are rather "unintended" when the designer was developing the product, and thus might carry innovative ideas for the design of next-generation e-reader, or even for designing new products. For example,

- "Proof water" suggests that e-readers that can be used in the bathtub may be developed.
- "Interrupt reading" suggests that e-readers should prevent users from being interrupted by real-time push notifications, like messages, emails, etc.
- "Waste time" suggests that a device that can help the user manage their time may be developed.
- "Watch TV" suggests that an audio or video function can be added to the product.
- "Sell book" suggests that a second-hand digital book market can be created.
- "Rock infant" suggests that a device that is specially designed for parents having babies may interest consumers.

It has to be emphasized that the innovation track listed above are indicative. Their practicability needs further discussions and demonstration.

Table 29. Ten least frequently appeared clusters

Affordance description	Number of occurrences
Give paperwhite	17
Function sensor	16
Rock infant	11
Sell book	11
Watch Tv	10
Waste time	10
Open box	10
Hide fingerprint	7
Interrupt reading	7
Proof water	5

VII. Conclusion

A. Theoretical implications

Today, people talk about text data analytics (Wamba, Akter et al. 2015). However, comparing with traditional data, if nothing new can be discovered from big data, why should we proceed to online review analysis? Therefore, the value of the text data added to product design depends on their statistical features. In our research, we find that one of the characters that define the novelty of product affordances is the frequency of occurrence: novel affordances are mentioned by fewer people. That is where our research begins. From our research trial, we generalize this aspect for online review analysis in perspective of design, i.e., we must discuss what the relationship is between the statistical features of the online review data and their practical meanings.

B. Practical implications

Online review analysis: how to get useful information for product improvement and innovation

Online reviews provide a large amount of data to mine how the consumers use the product. Our research provides a framework to identify relatively novel affordances from online reviews to guide product innovation. We rank the affordances by their frequency of occurrence, as novel affordances are easier to be identified from the affordances that appear less frequently. However, many affordances are semantically similar. We need to categorize them before ranking them. To do so, we define the similarity between two affordances in practice and at the linguistic level. To the best of our knowledge, we are the first to study the semantic similarity between affordances and to use it to categorize similar affordances.

We conduct an experiment to evaluate the performance of the proposed clustering method. The experiment shows that the performance of our proposed method is comparable to previous research in feature-based opinion mining. A set of innovation leads can be identified from the online reviews of Kindle Paperwhite downloaded from Amazon.com. This method can be easily applied to online product reviews of other product categories, like the cellphone, the wearable devices, the home appliances, etc.

Chapter 9. Mining the changes of user preference to gain insights for product improvement

I. Introduction

Online reviews provide opportunities for designers to capture a large amount of information concerning user requirements and preference. Comparing with traditional user requirements identification methods, such as focus group exercises or surveys based on physical prototypes, the large amount of readily accessible review data enables designers to acquire the full spectrum of customer needs in a timely and efficient manner (Tuarob and Tucker 2013). Meanwhile, online reviews are updating in real-time, enabling designers to monitor the changes in the user preference at all times. This unprecedented characteristic was summarized as the velocity of big data (Wamba, Akter et al. 2015). It provides designers with the opportunity to draw new knowledge about the market structure and competitive landscape that cannot be provided by traditional user requirement identification methods. The companies that could capture the changes and trends of user preference early would gain a strong competitive advantage in today's competitive market.

However, few studies in design-oriented online review analysis were focused on profiting from the velocity of the online review data. Therefore, in this chapter, we provide a method to capture the dynamic changes of user preference in different time-spans. The proposed method can be applied to evaluate and develop product improvement strategies.

To do so, we firstly download the online review data of Kindle e-readers posted on amazon.com from the year 2013 to 2018. These online reviews concern two consecutively released products: Kindle Paperwhite 2 and Kindle Paperwhite 3. The online review data are structured using our proposed automatized data structuration method (see Chapter 7). Product affordance, usage conditions, and the associated perceptions are extracted. Then, we are focused on the affordances and usage conditions on which people have opposite perceptions. For example, for an e-reader, some reviewers perceived that it is easy to carry with hands, while others reported that it is hard to carry with hands. For each kind of perception, its weight on the star rating is quantified using an ordered logit model. Next, the five product attribute categorizations in the Kano model are used to interpret the results of the conjoint analysis. Finally, by applying the proposed method on the online reviews posted in different time-spans, the dynamic changes of user preference are captured.

II. Literature review

A. Profiting from the velocity of online review data for product design

Velocity hinges on processing incoming data at high frequency (Wamba, Akter et al. 2015). Based on this characteristic, it is possible to capture changes in data by comparing the current data against the data in the past, which is why the computation of dated review data holds so much promise.

Tuarob and Tucker (2013) attempted to predict product market adoption by analyzing the correlation degree of correlation between product longevity and product sales using online social media data in a series of time-spans. Product longevity was defined based on the number of positive statements and negative statements in social media data. Suryadi and Kim (2016) found that frequency of occurrence of different product features has different influences on sales rank. Online reviews could thus be used to highlight the product features that have the biggest influence on sales rank. Zhang, Sekhari et al. (2016) analyzed the correlation between the strength of sentiment of each product feature and product sales and used the correlation to devise a method for target product features that need to be improved. Min, Yun et al. (2018) studied the dynamic change in the number of positive reviews and negative reviews on mobile applications over time. They used the Kano model to explain the dynamic patterns of change.

Previous scholarship has mainly focused on what trends can be concluded by analyzing the correlation between frequency of occurrence of product features and the product's sales, but without providing information on how user preference evolves over time, which is critical for guiding product improvement.

B. Conjoint analysis

Conjoint analysis is a survey-based statistical technique used in market research that helps determine how people value different attributes that make up an individual product or service (Green and Srinivasan 1978). The objective of the conjoint analysis is to determine what combination of a limited number of attributes have the strongest influence on respondent choices or decision-making (Green, Carroll et al. 1981). A controlled set of potential products or services is shown to survey respondents, and by analyzing their different preference levels to these products, the implicit valuation of the individual elements making up the product or service can be determined. These implicit valuations can be used to create market models that estimate market share, revenue, and even the profitability of new design (Yannou, Yvars et al. 2013).

C. The Kano model

The Kano model is a seminal theory for product development and customer satisfaction (Figure 28) (Kano 1984). It classifies product features into five "attribute" categories based on the correlation between customer preferences and quality or intensity of the feature:

1) *Must-be* attributes, which consist of the basic and indispensable product attributes. Customers would be extremely dissatisfied if these attributes are not fulfilled, although fulfillment will not increase satisfaction level because customers take their presence for granted.

2) *Performance* attributes, which when present increase satisfaction levels but when absent decreases satisfaction levels proportionally. This type of attribute provides customer loyalty for firms.

3) *Attractive* or *must-have* or *exciter* attributes, which usually act as a weapon to differentiate companies from their competitors because their functional presence generates absolutely positive satisfaction whereas customers will not be dissatisfied at all without it.

4) *Indifferent* attributes, which make little contribution to customer satisfaction regardless of whether they are present or absent in a product.

5) *Reverse* attributes, which should be removed from a product because their functional presence is actually detrimental to customer satisfaction.
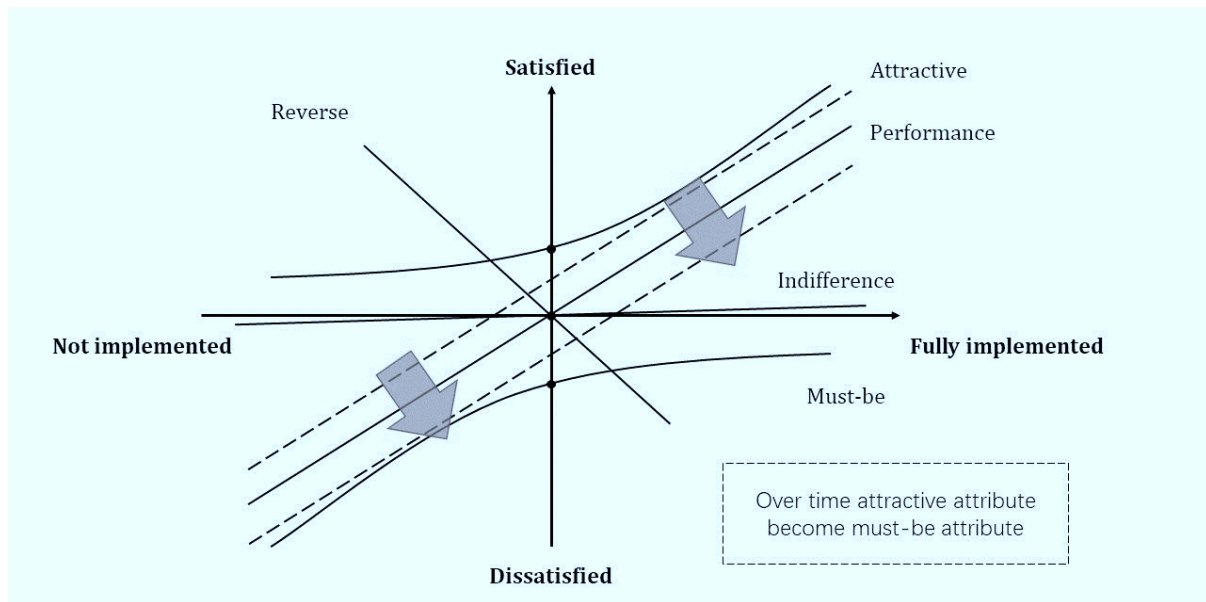
Figure 28. Mapping the attributes to the Kano model (Kano 1984)

To do so, a Kano survey is used to ascertain the customer satisfaction classification of an attribute (Figure 29). During the survey, customers are asked pairs of questions. For each attribute, each participant is asked to rate their satisfaction level if 1) the attribute is present on the product, and 2) the attribute is absent on the product. Then, a Kano evaluation matrix is constructed based on the survey results. Finally, for each attribute, the designers count the number of participants for each category in the Kano model, and the count number can determine one or several dominant categories.
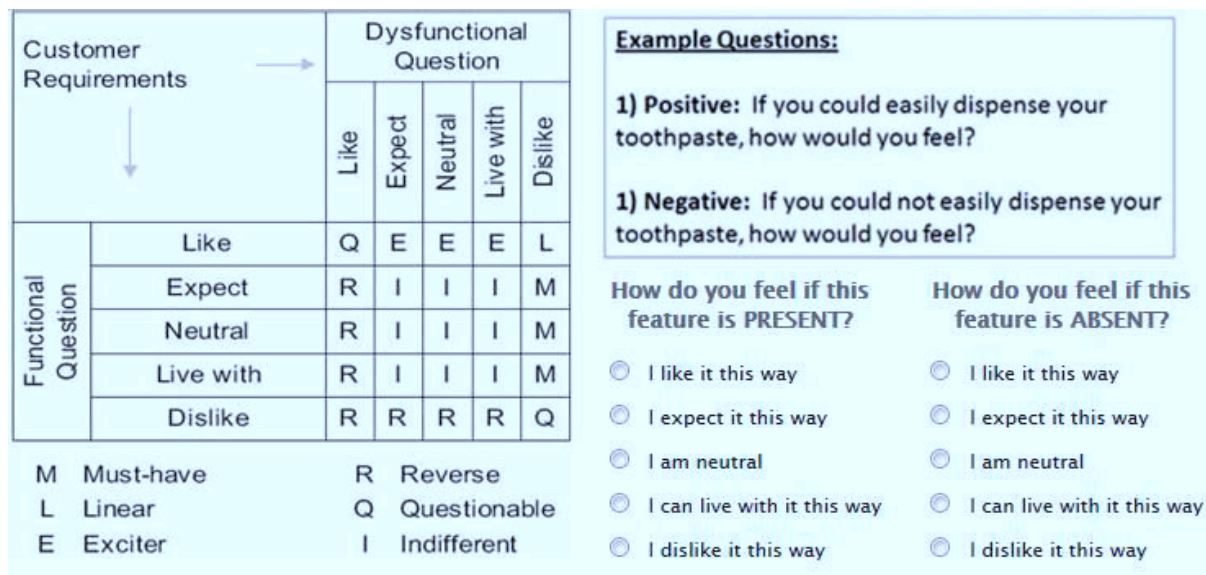
Figure 29. the Kano survey questions and the Kano evaluation matrix

III. Clarifying the definition of user preference and perception

Previous feature-based sentiment analysis has generally confused the concept of preference with the concept of perception. The scholarship had implicitly assumed that the perceptual words associated with product features indicated whether customers liked or disliked it. Studies used sentiment lexicon to determine the polarity of the sentiment expressed through perceptual words (Liu 2010, Raghupathi, Yannou et al. 2015, Ravi and Ravi 2015, Zhang, Sekhari et al.

2016). However, we find that this assumption is a rough approximation. Preference refers to whether the customer likes or dislikes the product. Perception refers to the way in which the product is regarded, understood or interpreted (Schütte 2005, Poirson, Petiot et al. 2007, Petiot, Salvo et al. 2008, Jomaa 2013, Poirson, Petiot et al. 2013). For example, the word low in "low battery capacity" is considered a derogatory term in many sentiment lexicons such as Vader1, SentiWordNet2, DAL3, but it does not necessarily mean that the customer disliked the battery. A customer who is used to carrying a power bank can tolerate this feature and thus give a 5-star rating to the product, which suggests that the low battery capacity has little influence on the customer's (dis)like of the product.

Inspired by this observation, here we use conjoint analysis to quantify the weight of different perceptions on reviewers' overall preference for the product. We then use the Kano model to explain the result of the conjoint analysis. It is actually commonplace to see the people posting online reviews have different perceptions on the same affordance, and people having the same perception can nevertheless give different star-ratings. For example, for the affordance "ability to read book" offered by the Kindle Paperwhite 3, the perception of some customers was that they could use the product to read books, while others reported they could not read books with Kindle due to the bad screen quality, battery, or other reasons. We pay particular attention to this kind of affordance, i.e. on which people have opposite perceptions. By quantifying the weight of each perception in the product star-rating, designers can determine which category the affordance belongs to in the Kano model. By analyzing the online reviews from different spans of time, designers can capture the dynamic changes in the categorization of product affordances in the Kano model.

IV. The proposed method

A. Conjoint analysis with the ordered logit model

We take each different review text as a conjoint-analysis survey response and the star rating, R, given by the reviewer as the reviewer's own choice, i.e., preference level. As star-rating is an ordinal discrete value, to estimate the weight of each perception mentioned in the review text to the star rating, we use ordered logit regression (Wang and Chen 2015, Wang, Chen et al. 2015). The ordered logit model was derived from a logit model. Logit models are widely used in cases where the dependent variable is binary, e.g., 0 and 1, whereas ordered logit models apply when the dependent variable has more than two values, and the values are ordinal.

The ordered logit model is based on the proportional odds assumption, which means the relationship between each pair of outcome groups is the same. In other words, it assumes that the coefficients that describe the relationship between the lowest value versus all higher values of the dependent variable are the same as those that describe the relationship between the next lowest value and all higher values. Conventionally, this assumption is tested by the significance of the parallel test (>0.05).

The star-rating R has five ordinal values: 1 star, 2 stars, 3 stars, 4 stars, and 5 stars. The logit model is therefore described by the following equations:

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[1]https://github.com/cjhutto/vaderSentiment
[2]http://sentiwordnet.isti.cnr.it/
[3]https://www.god-helmet.com/wp/whissel-dictionary-of-affect/index.htm

$$Pr\left(R = 5 \middle| X_i^{(1)}, X_i^{(2)}\right) = \frac{exp\left(\varepsilon_1 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}{1 + exp\left(\varepsilon_1 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}$$

$$Pr\left(R \geq 4 \middle| X_i^{(1)}, X_i^{(2)}\right) = \frac{exp\left(\varepsilon_2 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}{1 + exp\left(\varepsilon_2 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}$$

$$Pr\left(R \geq 3 \middle| X_i^{(1)}, X_i^{(2)}\right) = \frac{exp\left(\varepsilon_3 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}{1 + exp\left(\varepsilon_3 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}$$ Equation 5

$$Pr\left(R \geq 2 \middle| X_i^{(1)}, X_i^{(2)}\right) = \frac{exp\left(\varepsilon_4 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}{1 + exp\left(\varepsilon_4 + \sum_i\left(\alpha_i X_i^{(1)} + \beta_i X_i^{(2)}\right)\right)}$$

$$Pr\left(R \geq 1 \middle| X_i^{(1)}, X_i^{(2)}\right) = 1$$

where $X_i^{(1)}$ and $X_i^{(2)}$ represent the opposite perceived quality that the reviews have on the i-th affordance X_i. Usually, $X_i^{(1)}$ denotes the absence/non-existence of the affordance, or relatively low affordance quality in human cognition, like "slow", "low", "traditional", etc., while $X_i^{(2)}$ denotes the presence/existence of the affordance, or relatively high affordance quality, like "fast", "high", "modern", etc. The value of $X_i^{(1)}$ and $X_i^{(2)}$ is binary: 0 or 1. $X_i^{(1)} = 1$ means that the reviewer perceived the quality of X_i as relatively low, or X_i is absent; $X_i^{(2)} = 1$ means that the reviewer perceived the quality of X_i as relatively high, or X_i is existent. Both $X_i^{(1)}$ and $X_i^{(2)} = 0$ means that the reviewer does not mention X_i, and he/she does not care about the quality of the affordance. α_i and β_i denote the weights of the opposite perceived qualities of X_i in the star rating. Their practical meaning can be explained by the following equation:

$$Ln\left(\frac{Pr_j}{1 - Pr_j}\right) = \varepsilon_j + \sum_i\left(\alpha_i X_i^{(1)} + \beta X_i^{(2)}\right)$$ Equation 6

where $Pr_j = Pr(R \geq j | X_i^{(1)}, X_i^{(2)})$, and j is the number of stars given by the reviewer. For example, when $X_i^{(1)}$ changes from 0 to 1, the odds of the reviewer giving more than j-star (i.e. higher star-rating) $\frac{Pr_j}{1-Pr_j}$ are multiplied by $exp(\alpha_i)$.

B. Explaining the coefficients with the Kano model

After α_i and β_i are calculated, each pair of coefficients α_i and β_i are plotted in the Cartesian coordinate system by two points: $A_i = (-1, \alpha_i)$ and $B_i = (1, \beta_i)$. As $X_i^{(1)} = 1$ mainly denotes the absence or the low quality of affordance, $\alpha_i < 0$ means that the absence (low quality) reduces the possibility of the reviewers giving a higher rating, whereas $\alpha_i > 0$ indicates that the absence (low quality) increases the possibility the reviewers giving a higher rating. The same holds for the coefficient β_i and the presence (high quality) of the affordance $X_i^{(2)}$.

As illustrated in Figure 28, in the Kano model, the curves representing performance attribute and indifference attribute are relatively close to the origin (0, 0). The difference is that the performance attribute has a larger slope. The curves representing attractive attribute and must-be attribute are relatively far from the origin. The attractive attribute is situated above the horizontal axis and must-be attribute is situated below it. Based on this observation, we categorize the affordance X_i in the Kano model based on the slope $K_i = \frac{\beta_i - \alpha_i}{2}$ and the intercept

$M_i = \frac{\alpha_i + \beta_i}{2}$ of segment $\boldsymbol{A_i B_i}$ (Figure 30) with the following rules (Table 30): if K_i is negative, then the affordance X_i is categorized as a reverse attribute. If K_i is positive and is lower than the threshold k $(k > 0)$, if $-m \le M_i \le m(m > 0)$, then X_i is categorized as an indifferent attribute. If $M_i > m$ or $M_i < -m$, X_i is categorized as a questionable attribute. If K_i is higher than the threshold k, $M_i > m$, $-m \le M_i \le m$ and $M_i < -m$ mean that X_i is an attractive attribute, a performance attribute and a must-be attribute, respectively.
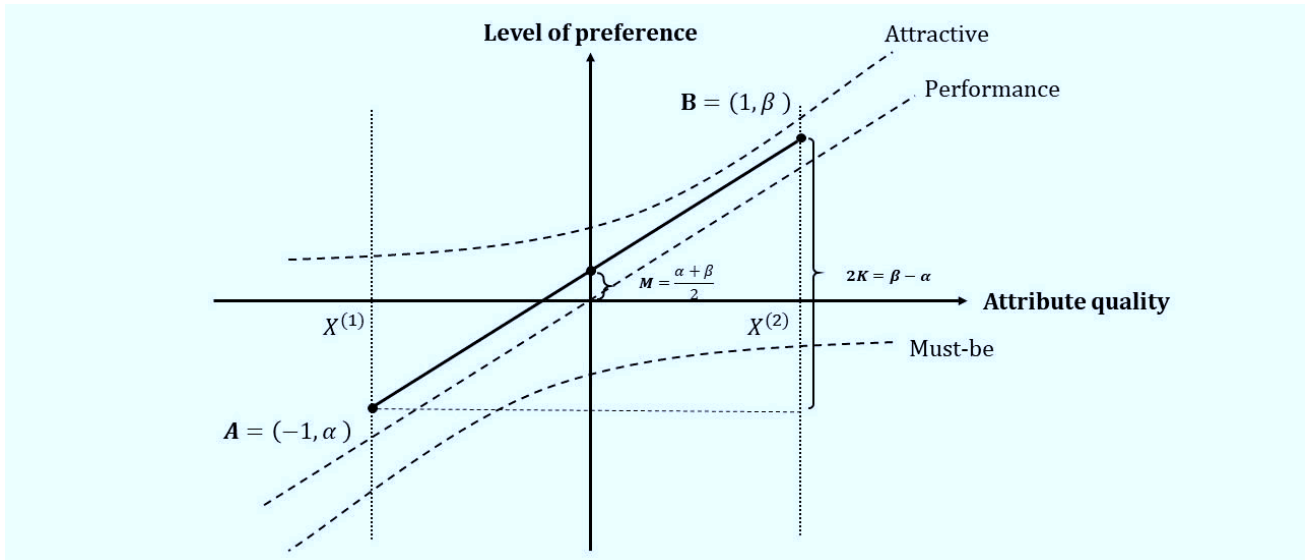
Figure 30. The parameters K and M illustrated on the Kano model

Table 30. Categorization rules according to the parameters K, M on the Kano model

K	M	Categorization
$K < 0$		Reverse attribute
$0 < K < k$	$M < -m$ or $M > m$	Questionable attribute
	$-m < M < m$	Indifferent attribute
	$M < -m$	Must-be attribute
$K > k$	$-m < M < m$	Performance attribute
	$M > m$	Attractive attribute

The differences between our method of using the Kano model and the original Kano survey comes from the unstructured nature of online review data (Figure 31). In a Kano survey, each participant is required to give his/her choices in two conditions, i.e. the absence of attribute and the presence of the attribute, whereas in our study, as online review data is unstructured, reviewers do not have to mention every affordance of the product in their review text. In the same way, when one reviewer expresses his/her preference for the presence of an affordance, he/she is not asked to express his preference in case of absence of the affordance. Consequently, our method cannot be applied to individual reviewers. The categorization of affordance is based on the aggregated preference of the reviewer group. In addition, the responses in the Kano survey represent the absolute value of user preference level for the absence and presence of the attribute. However, in our study, the coefficients α_i and β_i describe the odds of the reviewer giving a higher star-rating in cases where the reviewer mentions the absence/presence of the affordance $(X_i^{(1)} = 1$ or $X_i^{(2)} = 1)$, compared with the case that the reviewer does not mention the absence/presence of the affordance $(X_i^{(1)} = 0$ or $X_i^{(2)} = 0)$. These compromises have to be made due to the unstructured nature of online review data.
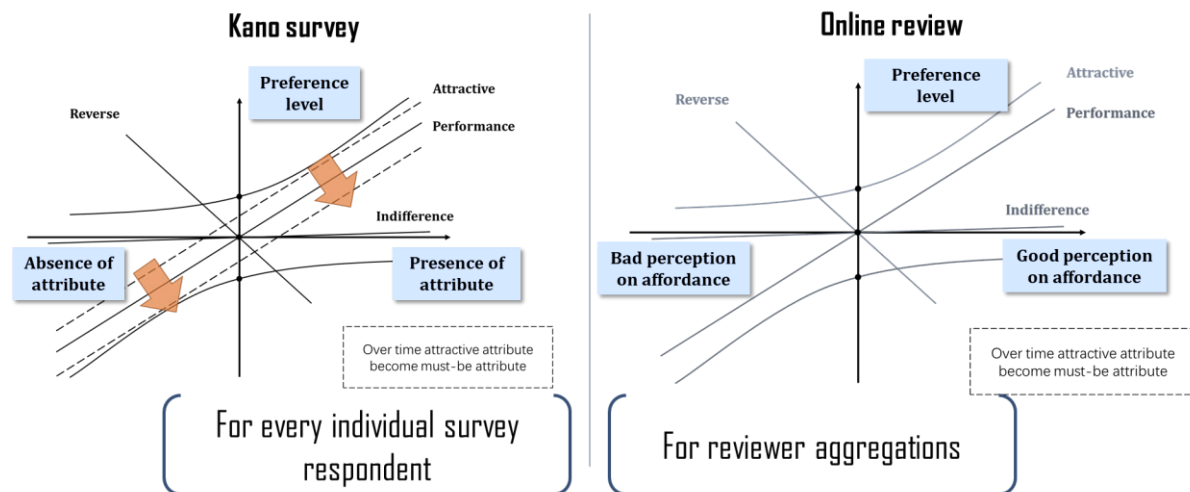
Figure 31. The differences between our method of using the Kano model and the original Kano survey

C. Analyzing online reviews of different spans of time

By applying the proposed conjoint analysis method to the online reviews published in different spans of time, designers can observe the changes in the categorization of product affordances in the Kano model at different times. In fact, in this step, online reviews can be collected from the products of different brands or versions in the same product category. That is because in our approach, the attribute quality, i.e. the horizontal axis in the Kano model, represents the user-perceived quality instead of the real quality of the attribute. For example, it is known to all that an e-reader does provide readability. However, due to user incapability or user misuse, the perception of some reviewers is that they cannot read with it. Therefore, as long as reviewers have opposite perceptions on the same affordance in the different spans of time, our proposed conjoint analysis method can be applied to capture the dynamic changes of user preference on the affordance, even though the products are different.

V. Case study

Based on our discussion in Section 5, we demonstrate our proposed conjoint analysis method with the online review data on the Kindle Paperwhite 21 (hereafter referred to as KP2) and Kindle Paperwhite 32 (hereafter referred to as KP3). KP2 was launched on September 2013 and was replaced by KP3 in September 2015 (Table 31). They have similar market targets as they were priced at the same level. We collect the online reviews of KP2 published from September 2013 to August 2015 and the online reviews of KP3 published from September 2015 to now[3].

Table 31. Product features of Kindle e-readers and descriptive statistics of online review data

Product name	On-shelf period	Price	Typical features	Average rating	Number of reviews
Kindle Paperwhite 2	Sep. 2013 - Jun. 2015	Around $150	Thickness:9.1mm; weight: 205g; screen: 212 ppi, 6 inches, 4 LEDs; battery: 8 weeks; storage: 4GBs	4.5	45829

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[1]https://www.amazon.com/Amazon-Kindle-Paperwhite-eReader-Previous-Generation-6th/dp/B00AWH595M
[2]https://www.amazon.com/Amazon-Kindle-Paperwhite-6-Inch-4GB-eReader/dp/B00OQVZDJM
[3] April 2018

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Kindle Paperwhite 3	Jul. 2015 – Now	Around $150	Thickness:9.1mm; weight: 205g; screen: 300 ppi, 6 inches, 4 LEDs; battery: 6 weeks; storage: 4GBs	4.5	56634

A. Data preparation

The data are prepared in the following steps. The statistics for each step are shown in Table 32. Detailed data can be found in Appendix D and E. First, the credible reviews, which have at least one useful vote and badged with *verified purchase*, are fed to our proposed rule-based affordance identification method. The method gives a large number of affordance descriptions. Second, the authors carefully read the affordance descriptions that appear more than a threshold (10 in our case study). The incorrect or unintelligible identification results are eliminated. Third, the affordances on which reviewers have opposite perceptions are selected. Frequently mentioned affordance is assumed to be more influential for the star rating. Therefore, the 50 most frequently appeared affordance descriptions are chosen, which means that the conjoint analysis is based on these 50 affordance descriptions. 30 of them appeared in both products, which means we can observe the dynamic changes of user preference on these 30 affordances from 2013 to now.

Table 32. Descriptive statistics of the dataset

Steps	Statistics	2013-2015 (KP2)	2015-2018 (KP3)
Raw data	Nb. of reviews	45829	56634
Step 1	Nb. of reviews selected	8715	7922
Step 1	Nb. of affordance descriptions extracted	62681	60266
Step 2	Nb. of affordance descriptions extracted (appeared in more than 10 reviews)	618	770
Step 2	Nb. of affordance descriptions extracted (after manual correction)	565	680
Step 3	Nb. of affordance descriptions having opposite perceptions	516	535
Step 3	Example of affordance descriptions having opposite perceptions	read book turn page use kindle buy kindle use kindle buy one buy paperwhite tell people download book buy this	read book get one use kindle work kindle make difference find book say that try kindle turn page
Step 3	Nb. of affordance descriptions in common	30	

B. Results and representations on the Kano model

SPSS is used to calculate the coefficients α_i and β_i. In our case study, $k = 0.2$ and $m = 0.2$. Table 33 illustrates the results of the conjoint analysis. 80% (96/120) of the coefficients are statistically significant. The significance in a parallel test for the KP2 and KP3 data is 0.054 and 0.105, respectively, which means the parallel assumption is validated (Section 5.2). Most of the opposite perceptions are non-existent and existent only for connect WIFI-ability, and reviewers particularly perceive the speed of the connection, i.e. slow and fast.

Table 34 and Figure 32 illustrate the categorization of affordances on the Kano model. For KP2, ten affordances are categorized as must-be attributes, including as *work kindle-ability, turn page-ability*. Seven affordances are categorized as performance attributes, such as *read book-ability, change page-ability*. Three affordances are categorized as attractive attributes, such as

touch screen-ability, *travel a lot-ability*. Eight affordances are categorized as indifferent attributes, such as *find book-ability*, *know word-ability*. *Return kindle-ability* is categorized as a reverse attribute and *try kindle-ability* is categorized as a questionable attribute. For KP3, fourteen affordances are categorized as must-be attributes, including *work kindle-ability*, *turn page-ability*. Four affordances are categorized as performance attributes, such as *read book-ability*, *take kindle-ability*. Seven affordances are categorized as indifferent attributes, such as *use kindle-ability*, *know word-ability*. Three affordances are categorized as reverse attributes, such as *upgrade kindle-ability*, *pay extra-ability*. Finally, *carry book-ability* is categorized as an attractive attribute, and *try kindle-ability* is always a questionable attribute.

Table 33. Estimated results of the parameters[1]

Affordance descriptions	Opposite perceptions (p_1/p_2)	2013-2015 (KP2)						2015-2018 (KP3)					
		α	Std.err	sig	β	Std.err	sig	α	Std.err	sig	β	Std.err	sig
read book	Non-existent/existent	-1.36	0.10	**	1.02	0.05	**	-1.38	0.11	**	0.99	0.05	**
get kindle	Non-existent/existent	-0.24	0.13	**	0.00	0.07	0.33	-0.19	0.12	*	-0.11	0.06	**
use kindle	Non-existent/existent	-0.17	0.15	*	0.21	0.07	**	0.01	0.13	0.30	0.12	0.06	**
work kindle	Non-existent/existent	-0.83	0.12	**	-0.11	0.08	*	-0.85	0.13	**	-0.38	0.08	**
turn page	Non-existent/existent	-0.30	0.20	**	-0.19	0.08	**	-0.56	0.23	*	-0.12	0.09	**
find book	Non-existent/existent	-0.18	0.16	*	-0.19	0.09	**	-0.29	0.15	**	-0.17	0.08	**
know word	Non-existent/existent	0.00	0.13	0.33	0.35	0.11	*	-0.15	0.13	*	0.24	0.11	*
try kindle	Non-existent/existent	-0.35	0.21	**	-0.21	0.09	**	-0.38	0.22	**	-0.29	0.09	**
buy kindle	Non-existent/existent	-0.91	0.22	**	0.01	0.10	0.31	-0.96	0.38	**	-0.08	0.17	0.22
download book	Non-existent/existent	-0.78	0.25	**	0.16	0.12	*	-1.03	0.23	**	0.17	0.11	*
charge kindle	Non-existent/existent	-0.99	0.27	**	-0.24	0.12	**	-0.49	0.23	**	-0.30	0.12	**
upgrade kindle	Non-existent/existent	-0.88	0.20	**	-0.61	0.14	**	-0.62	0.22	**	-0.48	0.13	**
take kindle	Non-existent/existent	0.12	0.43	**	0.24	0.13	*	-0.23	0.24	*	0.32	0.10	**
light screen	Non-existent/existent	0.00	0.47	0.33	0.38	0.15	**	-0.80	0.57	*	0.36	0.16	**
read book at night	Non-existent/existent	-0.83	0.26	*	0.24	0.15	*	-1.42	0.34	0.56	-0.05	0.16	0.74
buy one	Non-existent/existent	-0.55	0.30	**	0.06	0.14	0.24	-0.88	0.17	**	-0.03	0.08	0.25
compare kindles	Non-existent/existent	-0.43	0.44	*	0.13	0.15	*	-0.83	0.38	0.29	-0.14	0.15	*
change page	Non-existent/existent	0.12	0.35	0.73	0.42	0.14	**	-0.30	0.30	*	0.12	0.13	0.28
connect WIFI	Slow/fast	-0.65	0.34	**	-0.30	0.19	*	-1.44	0.34	**	-0.29	0.18	*
pay extra	Non-existent/existent	-0.26	0.34	*	0.15	0.17	**	-0.13	0.31	*	-0.55	0.15	**
touch screen	Non-existent/existent	0.19	0.35	0.20	0.69	0.15	**	-0.24	0.37	0.31	-0.03	0.16	*
add book	Non-existent/existent	-0.58	0.67	0.19	0.24	0.18	*	-0.85	0.45	*	0.08	0.16	0.20
travel lot	Non-existent/existent	-0.08	0.51	0.29	0.79	0.19	**	-0.84	0.50	**	1.10	0.20	**
own kindle	Non-existent/existent	-0.27	0.58	**	0.08	0.20	0.71	-0.20	0.37	*	0.17	0.18	0.05
return kindle	Non-existent/Existent	-0.32	0.47	*	-1.86	0.17	**	-0.03	0.33	0.31	-1.55	0.12	**
leave charger	Non-existent/existent	-0.89	0.65	*	-0.25	0.18	*	-0.01	0.42	0.19	-0.05	0.18	0.77
carry book	Non-existent/existent	0.73	1.08	*	1.56	0.25	**	0.16	0.59	**	0.29	0.19	**
adjust size	Non-existent/existent	-1.26	0.51	**	0.92	0.21	**	-1.45	0.81	**	0.99	0.19	**
replace kindle	Non-existent/existent	-0.36	0.57	0.18	0.18	0.18	**	-0.57	0.40	*	-0.31	0.14	**
receive paperwhite	Non-existent/existent	-0.95	0.63	**	-0.17	0.21	*	-0.67	0.48	*	-0.17	0.18	*

Table 34. Categorization of affordance in the Kano model[2]

Affordance descriptions	Opposite perceptions (p_1/p_2)	2013-2015 (KP2)					2015-2018 (KP3)				
		α	β	K	M	Kano	α	β	K	M	Kano
read book	Non-existent/existent	-1.36	1.02	1.19	-0.17	P	-1.38	0.99	1.19	-0.19	P
get kindle	Non-existent/existent	-0.24	0.00	0.12	-0.12	I	-0.19	-0.11	0.04	-0.15	I
use kindle	Non-existent/existent	-0.17	0.21	0.19	0.02	I	0.01	0.12	0.05	0.07	I
work kindle	Non-existent/existent	-0.83	-0.11	0.36	-0.47	M	-0.85	-0.38	0.24	-0.61	M
turn page	Non-existent/existent	-0.30	-0.10	0.10	-0.20	M	-0.56	-0.12	0.22	-0.34	M
find book	Non-existent/existent	-0.18	-0.19	-0.01	-0.19	I	-0.45	-0.02	0.22	-0.24	M
know word	Non-existent/existent	0.00	0.35	0.17	0.18	I	-0.15	0.24	0.20	0.04	I
try kindle	Non-existent/existent	-0.35	-0.21	0.07	-0.28	Q	-0.38	-0.29	0.05	-0.34	Q
buy kindle	Non-existent/existent	-0.91	0.01	0.46	-0.45	M	-0.96	-0.08	0.44	-0.52	M
download book	Non-existent/existent	-0.78	0.16	0.47	-0.31	M	-1.03	0.17	0.60	-0.43	M
charge kindle	Non-existent/existent	-0.99	-0.24	0.38	-0.61	M	-0.25	-0.04	0.11	-0.15	I
upgrade kindle	Non-existent/existent	-0.12	0.21	0.17	0.05	I	-0.06	-0.48	-0.21	-0.27	R
take kindle	Non-existent/existent	0.12	0.24	0.06	0.18	I	-0.23	0.32	0.28	0.05	P
light screen	Non-existent/existent	0.00	0.38	0.19	0.19	I	-0.80	0.36	0.58	-0.22	M
read book at night	Non-existent/existent	-0.83	0.24	0.54	-0.30	M	-1.42	-0.05	0.68	-0.74	M
buy one	Non-existent/existent	-0.55	0.06	0.31	-0.25	M	-0.88	-0.03	0.43	-0.46	M
compare kindles	Non-existent/existent	-0.43	0.13	0.28	-0.15	P	-0.83	-0.14	0.35	-0.48	M
change page	Non-existent/existent	-0.12	0.42	0.27	0.15	P	-0.30	0.12	0.21	-0.09	P
connect WIFI	Slow/fast	-0.65	-0.30	0.18	-0.47	Q	-1.44	-0.29	0.57	-0.87	M
pay extra	Non-existent/existent	-0.26	0.15	0.21	-0.06	P	-0.13	-0.55	-0.21	-0.34	R
touch screen	Non-existent/existent	0.19	0.69	0.25	0.44	A	-0.24	-0.03	0.11	-0.14	I
add book	Non-existent/existent	-0.58	0.24	0.41	-0.17	P	-0.85	0.08	0.47	-0.38	M
travel lot	Non-existent/existent	-0.08	0.79	0.43	0.36	A	-0.84	1.10	0.97	0.13	P
own kindle	Non-existent/existent	-0.27	0.08	0.17	-0.10	I	-0.20	0.17	0.19	-0.02	I
return kindle	Non-existent/Existent	-0.32	-1.86	-0.77	-1.09	R	-0.03	-1.55	-0.76	-0.79	R

[1] For KP2, R^2=0.0908, sig = 0.054, for KP3, R^2=0.1069, sig=0.105. Significance level: **, * are statistical significant at the 0.01, and 0.05 level, respectively

[2] "P" means "performance attribute", "I" means "indifferent attribute", "M" means "must-be attribute", "A" means "attractive attribute", "R" means "reverse attribute", "Q" means "questionable attribute"

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leave charger	Non-existent/existent	-0.89	-0.25	0.32	-0.57	M	-0.05	-0.01	0.02	-0.03	I
carry book	Non-existent/existent	0.73	1.56	0.42	1.15	A	0.16	0.29	0.07	0.23	A
adjust size	Non-existent/existent	-1.26	0.92	1.09	-0.17	P	-1.45	0.99	1.22	-0.23	M
replace kindle	Non-existent/existent	-0.36	0.18	0.27	-0.09	P	-0.57	-0.13	0.22	-0.35	M
receive paperwhite	Non-existent/existent	-0.95	-0.17	0.39	-0.56	M	-0.67	-0.17	0.25	-0.42	M

read book — KP2: P / KP3: P

get one — KP2: I / KP3: I

use kindle — KP2: I / KP3: I

work kindle — KP2: M / KP3: M

turn page — KP2 / KP3

find book — KP2: I / KP3: M

know word — KP2: I / KP3: I

try kindle — KP2: Q / KP3: Q

buy kindle — KP2: M / KP3: M

download book — KP2: M / KP3: M

charge kindle

upgrade kindle

take kindle

light screen

read book at night

buy one

compare kindles

change page

connect -PRON-

pay extra
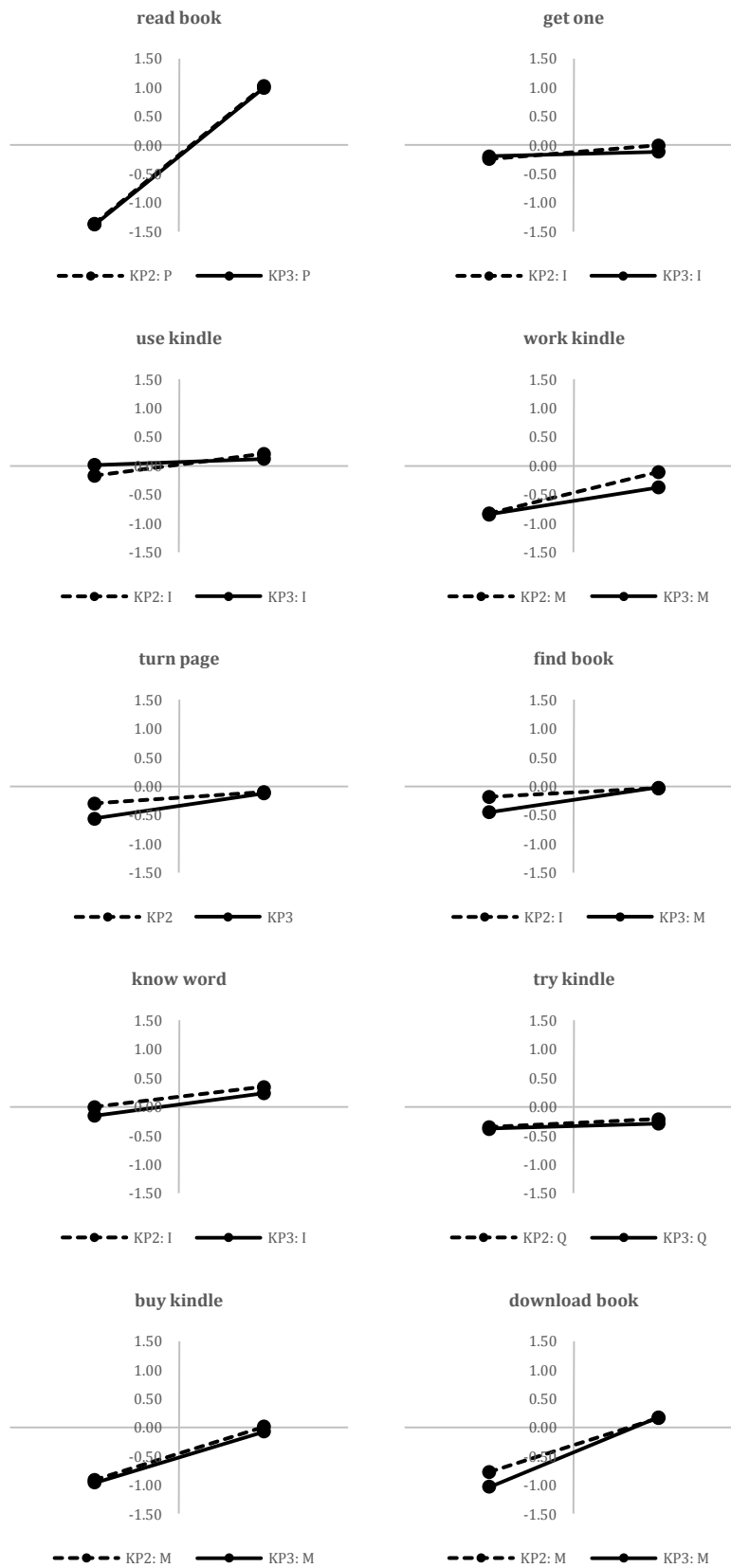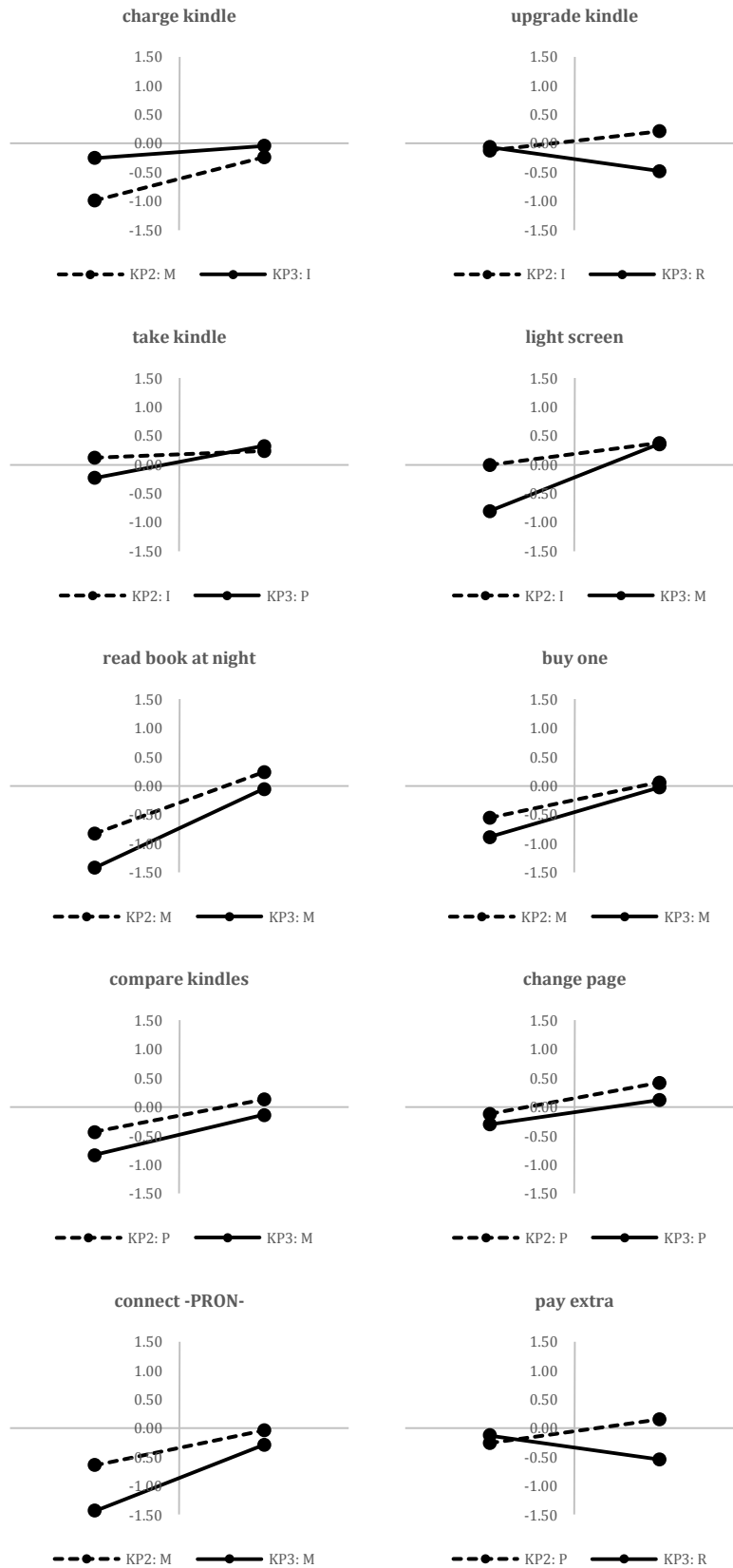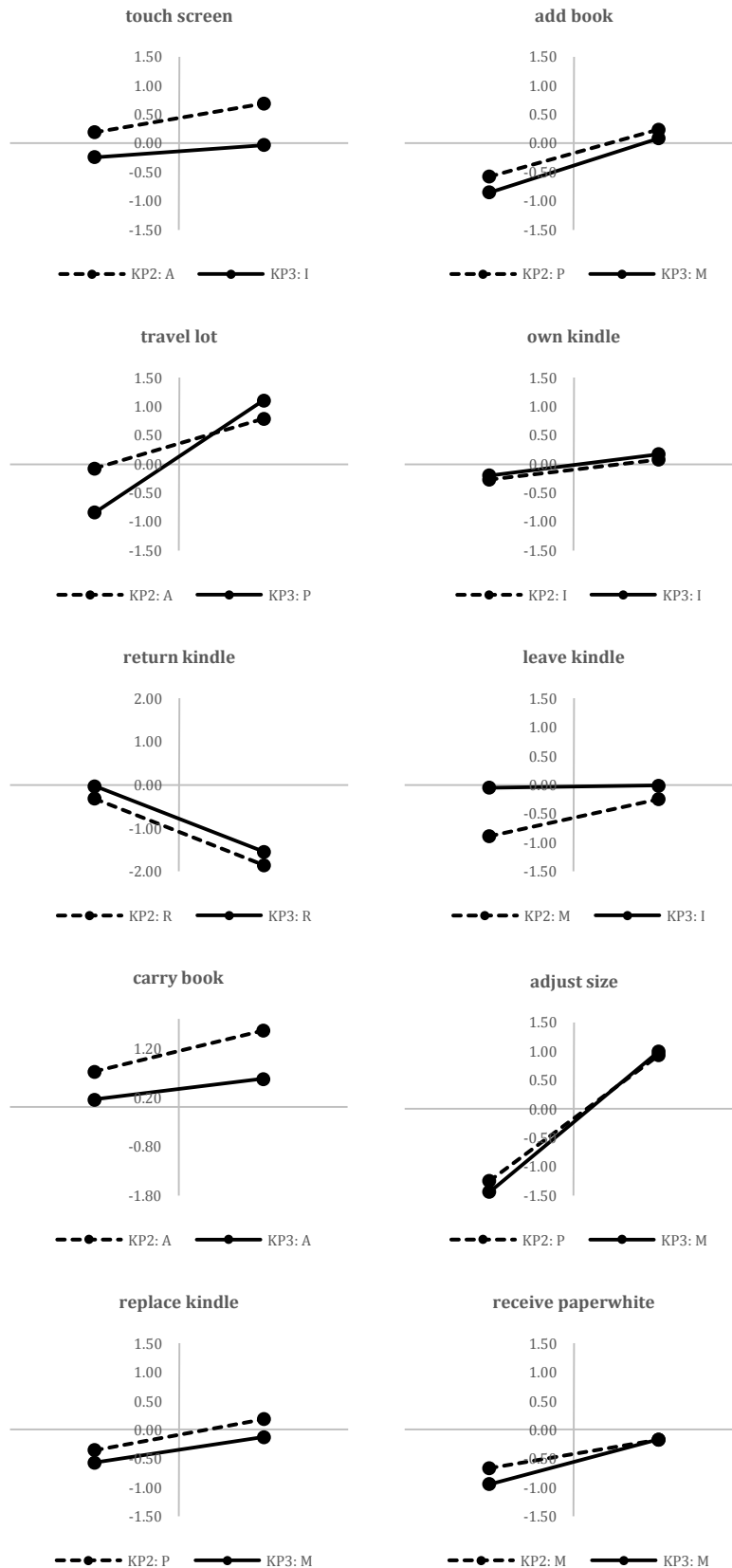
Figure 32. Representation of product affordances on the Kano model

C. Analysis of the results and product improvement strategies

Kano (1984) observed that in the Kano model, product attributes should appear as attractive and evolve towards must-be after a few years on the market. This observation globally corresponds to our findings, as for 25 out of the 30 affordances, the segments representing the affordances of KP3 (solid line) are below the segments representing the affordances of KP2 (dotted line) in Figure 32.

For the affordances that do not change their categorization in our analysis results, *read book-ability* and *change page-ability* have always been performance attributes from 2013 to now. It is obvious that an e-reader with good readability constantly provides high-level customer loyalty (Section 2.5). Note, however, that unlike *read book-ability*, the existence of *read book at night-ability* does not produce much satisfaction, which suggests that improving *read book-ability* in other usage contexts may have a more positive influence on user satisfaction.

Get kindle-ability, *use kindle-ability*, *own kindle-ability* are constantly categorized as indifferent affordances because these affordances are too general in meaning. User preferences on these affordances are randomly distributed. For example, people may use the Kindle to read or to do other things. *Know word-ability* is categorized as an indifferent affordance, which means customers pay less attention to it. Therefore, the implementation of a dictionary in the operating system is not essential.

Work kindle-ability, *turn page-ability*, *buy kindle-ability*, *download book-ability*, *read book at night-ability*, *buy one-ability*, *connect WIFI-ability*, and *receive paperwhite-ability* are constantly categorized as must-be affordances for both products. *Buy kindle-ability* and *buy one-ability* are synonymous affordances, so it is reasonable for them to be categorized in the same group.

Only *carry book-ability* remains an attractive affordance. However, as shown in Figure 32, it is much less "attractive" recently. *Try kindle-ability* is always a questionable attribute. This means that customers get unsatisfied whether they try kindle or not before purchase. We find that in the online reviews, when reviewers talk about try kindle, they either express their regret for not having tried the e-reader at the store or tend to criticize the difference between the e-reader they had tried in the store and the e-reader they had received.

For the affordances that change categories, unsurprisingly, *travel lot-ability* changed from an attractive attribute to a performance attribute. *Compare kindles-ability*, *add book-ability*, *adjust size-ability*, and *replace kindle-ability* changed from performance attributes to must-be attributes. *Find book-ability* and *light screen-ability* turned from indifferent attributes to must-be attributes. *Take kindle-ability* changed from indifferent attribute to performance attribute. These trends support the study of Kano (1984).

Interestingly, we found that *upgrade kindle-ability* was an indifferent attribute that is fast becoming a reverse attribute. In fact, according to Amazon's marketing strategy, each version of the Kindle e-reader is sold in two different configurations: one with advertisements and one without advertisements. The cheaper one constantly shows advertisements on the e-reader home screen. From the year 2014, customers have the option to upgrade kindle by paying an extra 20 dollars to stop getting advertisements. From 2013 to 2015, this was an attractive option, which means that customers are satisfied if they can upgrade the kindle. However, since 2015, customers are voicing dissatisfaction even if they can remove the advertising. We read the reviewers concerning this affordance, and we found that today's customers are tired of this marketing strategy. They reported that the upgrade option is just a trick to make them pay more money. This observation is supported by its synonymous affordance *pay extra-ability*, which shifts from a performance attribute to a reverse attribute.

Meanwhile, we observe that *charge-kindle ability* tends to become an indifferent affordance as the parameter M gets higher. Our assumption is that compared with today's other electronic products, like smartphones, e-readers have a much larger battery capacity for ordinary use (i.e. about one month). However, it is also getting easier to find Kindle Paperwhite-compatible battery chargers as the micro-USB connector is becoming increasingly common on electronic products. This assumption is supported by its synonymous affordance *leave charger-ability*, which is also changing from a must-be attribute to an indifferent attribute. This means that for KP2, if users cannot/do not leave the charger at home or at other places that they used to go to, then they are unsatisfied. However, for KP3, charger availability is less of an issue for users.

The move from KP2 to KP3 marked an increase in screen resolution and a decrease in battery capacity (Table 31). As *read book-ability* remains an important performance attribute while *charge kindle-ability* is becoming less of a must-be attribute, these upgrades respond to the dynamic changes in user preference found in our analysis. Our study suggests that for next-generation e-readers, designers should pay less attention to battery and storage capacity, and more attention to their market strategy. Selling the *with advertisements-version* is a questionable strategy. Also, *read book-ability*, in general, is a performance attribute, while *read book at night-ability* is a must-be attribute, which suggests that improving reading experience in other usage contexts—such as reading *in the sun*, *on plane*, *on the beach,* for example—may help improve user satisfaction.

D. Robustness check

In the previous section, for the online reviews posted from 2015 to 2018, i.e., the online reviews of KP3, 7922 reviews are selected as our research object. To test the robustness of our proposed method in capturing the evolution of user preference, we divide the online reviews into five proportions of samples. The five proportions are constructed with the following steps:

1) The online reviews are sorted chronologically,

2) The online reviews are numbered,

3) The online reviews are divided into three groups based on the remainder of the review number n divided by 5. The first proportion contains the reviews where the review number n is divisible by 5 with no remainder. The second group contains the reviews where the reminder equals 1. The third group contains the reviews where the reminder equals 2, and so on.

In this way, the online reviews are evenly distributed into five proportions chronologically. The underlying assumptions are that if our conjoint analysis is robust, the categorization results based on the five proportions of data should be similar.

Each of the five proportions contains 1584 reviews (two of them contains 1585 reviews). The five proportions are added to the input data iteratively. Then, we compare the categorization of affordances in the Kano model for each iteration. The number of different categorization results comparing with the results given by all five proportions is counted. As Table 35 illustrates, as the samples added in, the number of different categorization in the Kano model decreases, and the categorization of affordances becomes increasingly stable, which means that our conjoint analysis is robust.

Table 35. Comparison of the results of the conjoint analysis

Affordance descriptions	Opposite perceptions (p_1/p_2)	Proportion 1	Proportion 1 and 2	Proportion 1, 2 and 3	Proportion 1, 2, 3 and 4	Proportion 1, 2, 3, 4 and 5
read book	Non-existent/existent	**M**	P	P	P	P
get kindle	Non-existent/existent	**M**	I	I	I	I
use kindle	Non-existent/existent	I	I	I	I	I
work kindle	Non-existent/existent	M	M	M	M	M
turn page	Non-existent/existent	M	M	M	M	M

find book	Non-existent/existent	M	M	M	M	M
know word	Non-existent/existent	**P**	**P**	I	I	I
try kindle	Non-existent/existent	Q	Q	Q	Q	Q
buy kindle	Non-existent/existent	M	M	M	M	M
download book	Non-existent/existent	M	M	M	M	M
charge kindle	Non-existent/existent	I	I	I	I	I
upgrade kindle	Non-existent/existent	R	R	R	R	R
take kindle	Non-existent/existent	**I**	P	P	P	P
light screen	Non-existent/existent	M	M	M	M	M
read book at night	Non-existent/existent	M	M	M	M	M
buy one	Non-existent/existent	M	M	M	M	M
compare kindles	Non-existent/existent	M	M	M	M	M
change page	Non-existent/existent	**M**	**M**	**M**	P	P
connect WIFI	Slow/fast	M	M	M	M	M
pay extra	Non-existent/existent	**I**	R	R	R	R
touch screen	Non-existent/existent	**Q**	I	I	I	I
add book	Non-existent/existent	M	M	M	M	M
travel lot	Non-existent/existent	P	P	P	P	P
own kindle	Non-existent/existent	I	I	I	I	I
return kindle	Non-existent/Existent	R	R	R	R	R
leave charger	Non-existent/existent	I	I	I	I	I
carry book	Non-existent/existent	**Q**	A	A	A	A
adjust size	Non-existent/existent	M	M	M	M	M
replace kindle	Non-existent/existent	M	M	M	M	M
receive paperwhite	Non-existent/existent	M	M	M	M	M
Number of different categorization in the Kano model		8	3	1	0	-

VI. Conclusion

A. Theoretical implications

Online reviews have been studied by many researchers in product design due to their rich content and high reliability. To draw new insight from the data, data analyzers must begin with the unprecedented characteristics of the data. In the research of this chapter, we are focused on the velocity of the data, from which it is possible to capture the dynamic changes of user preference in real-time.

Meanwhile, classical design models should be reformed in the context of online review data. The Kano model, for example, has been widely used in product development for many years. Kano model analysis has always been based on physical prototypes and focus groups. The answers given by participants are structured, as people are guided by the questions. In our study, we reform the model due to the unstructured nature of the review text.

B. Practical implications

Online reviews provide large amounts of data for mining user requirements and preferences. Our research provides a method for processing data analytics. In particular, a conjoint analysis method is proposed to quantitatively categorize the automatically structured affordances into the Kano model. We demonstrated with a case study that, using our proposed method, designers are able to find unexpected changes in user preference for product affordances. It is thus convenient to evaluate the improvement strategies in previous generations of product and to propose new strategies for designing the next generation of the product. Our approach can be easily and usefully extended in various industries for different kinds of popular products, from mobile phones and wearable devices to electrical household appliances.

General conclusion

I. Practical contributions

In this research project, we investigate how to use online reviews to provide insights into product design. An approach implemented in Python is provided to designers, which can be used directly in industry. We simulate a real research context: Amazon wants to get insights from for the design of their next generation Kindle e-reader. The case study based on this simulation evaluates the performance and practicability of the proposed approach. In the big picture, our research enables industries to integrated big data analytics in the background of the big data.

The major contributions of the present work are:

Contribution 1: A list of challenges in today's online review analysis.

Through an analysis of the state of the art in online review analysis, we identify three challenges in online review analysis: 1) the challenge in data acquisition, 2) the challenge in data structuration, and 3) the challenge in data analytics. This analysis of challenges provides directions for future studies of data analytics. Entering the big data era, people are more aware of the security of data. Web scraping becomes more and more difficult these days. Therefore, in the research of online review analysis, the publicly available data are precious. Meanwhile, as online reviews are text data, the unstructured nature is one of its property. People can talk about everything in the text and people only talk about the thing that they care. That is why comparing with other kinds of data, text data must be structured before further analysis. Although today's natural language processing technology enables the computer to understand natural language at a certain extent, the variety in the usage of words, the sarcasm, the ambiguity in the sentence, etc. still prevent us from obtaining an automatized data structuration with 100% accuracy. Last but not least, the data analytics requires to translate the statistical features of the data to practical meaning, which requires that data analyzer must have strong domain knowledge.

Contribution 2: An ontological model for structuring user requirements and preference from online reviews. This model is a solution proposed for our research question 1.

Customer needs are measures of customer value, actionable and controllable through product design, predictive of success, independent of a solution or technology. Having a full set of customer needs impacts all aspects of innovation, the way markets are segmented and sized, the way product and pricing strategies are formulated, and the way ideas are constructed, tested and positioned.

However, what kind of words describe user requirements? There is a lack of a standard formalism shared between researchers in online review analysis. Previous studies were mainly focused on the product feature, while we have observed that product feature cannot cover all the aspects of requirements.

To tackle this problem, an ontological model is constructed in this research to structure the words related to multiple aspects of user requirement. Besides product feature, the proposed model includes the concept of affordance, usage condition, emotion, and perception. A case study shows that many words related to these concepts can be identified from online reviews. Structuring the online reviews based on the proposed model can help designers understand more aspects of user requirements and manage the knowledge extracted from online review data.

Contribution 3: A method is proposed to automatically identify and structure product affordances, usage conditions and the associated perceptions mentioned by reviewers. The

performance of the automatic structuration method is comparable to recently proposed feature-based opinion mining methods. This proposed method is a solution to research question 2.

Due to the large volume of data, it is impossible for designers to manually analyze the online reviews one by one. With the help of the natural language processing technique, we proposed a method to automatically identify meaningful words based on the linguistic features of the text data. As our method does not rely on training data, theoretically, it can be used to structure the online reviews of every product category. An experiment shows that the performance of the proposed method is comparable to previous studies.

Contribution 4: A method is proposed to automatically cluster similar affordances. The performance of the clustering method is comparable to recently proposed product feature clustering methods.

Using the proposed automatic data structuration method, a large number of affordances can be extracted from online reviews. However, designers still have difficulties in reading these affordances due to its quantity. These structured data need to be organized in a way that is more readable. We discuss the definition of similarity between two affordances. Based on the discussion, a method is proposed to evaluate the semantic similarity between affordances. An algorithm is then used to cluster similar affordances automatically.

Contribution 5: A data analytics method is proposed to identify novel affordances from the structured data. This method is our proposed solution to research question 3.

Identifying novel affordances is important, especially for the designers who must continually renovate their product in the competitive market. These novel affordances can provide insights for product innovation, i.e. adding the affordances that have not been implemented in previous versions, to make the product perfect, or even to develop new products.

Based on a discussion on the definition of novel affordance, we use the frequency of occurrence of affordance as an indicator of the novelty and originality of affordance. The affordances that are mentioned by fewer people is regarded as more novel. This translation of statistical feature in practice is theoretically reasonable. A case study shows the practicability of the method in inspiring innovation.

Contribution 6: A data analytics method is proposed to capture the changes of user preference on product affordance-based on the structured data. This method is our proposed solution to research question 4.

As one of the unprecedented characteristics of the online review data, the velocity enables designers to capture the dynamic changes of user preference. It is difficult for traditional user requirement identification methods to investigate trends, especially trends in user preference because they cannot revert the information of user preference at a certain time in the past.

In our research, we proposed a method using conjoint analysis to capture the dynamic changes of user preference. A case study shows the practicability of our proposed method. Using this method, designers can set up new strategies for product improvement, or evaluate their strategies over the past.

Contribution 7: An implementation of the whole design-oriented online review analysis approach is realized in this study.

Through our research study, we simulate a research context in practice. The case study that we processed based on the research context requires to implement the proposed method to provide meaningful insights. The implementation can be used in industry in a direct manner.

Contribution 8: A set of strategies are provided for designing the next generation e-reader. These strategies are our solution proposed to the practical research context that we simulated.

For adding innovative functions, designers can consider making the product waterproof, less interrupting, preventing the user from wasting time, etc. For improving existing product features, designers can consider conserving the battery and storage capacity, removing the e-readers with the advertisement from the market, improving the readability in the environment other than *in the dark*.

II. Theoretical implications

Through our research, we summarize the following theoretical implications. These implications can guide future research in design-oriented online review analysis, or more generally, in big data analytics.

First, the value of the big data added to data analytics depends on their linguistic and statistical features. Before processing data analytics, how to translate these features in practice must be discussed. To do so, data analyzer must have enough domain knowledge. In our research, one of our data analytics is based on the reasonable assumption: novel affordances are talked by fewer people.

Second, people talk about text data analytics (Wamba, Akter et al. 2015). However, comparing with traditional data, if nothing new can be discovered from big data, why should we proceed to online review analysis? In our research, comparing with traditional user requirement and preference identification methods, such as questionnaire, interview and focus group, we found that online data differs from traditional data at 3Vs: volume, velocity, and veracity, which are important to create actionable new insights for decision making. As the volume and the veracity have been deeply studied in previous research, we are focused on what insights can be drawn by using the real-time characteristics of the data. That is where data analytics should begin.

Third, we must use the correct domain theory to change the unstructured text data to structured data before further analysis of text data. Feature-based opinion mining dominates the previous online review analysis for product design, which involves product feature words extraction, opinion words extraction, and sentiment orientation determination. However, both product feature and opinion lack a theoretical basis in design engineering. As previous research found, product features alone cannot cover all the significant issues addressed in customer reviews. Users are not only focused on product features but also the usage of the product and the usage conditions of the product, which correspond to the affordance-based design proposed in design science. That is why we introduce the concept of affordance to structure the text data.

Fourth, Qi, Zhang et al. (2016) insisted that the classical design models should be reformed under the context of online review data. Our research supports Qi et al.'s opinion. For example, traditionally, the Kano survey only considered users' preference to the absence/presence of the attribute, while does not consider whether the user cares the attribute or not. It investigated the absolute value of user preference level to the absence and the presence of the attribute. Also, traditionally the Kano survey requires each participant to rate their preference level to both the absence and the presence of the attribute. In our study, we reform the Kano survey under the context of online review data. Our research brings to the Kano model, conjoint analysis and affordance-based design a new vitality in the context of big data.

III. Research perspectives

The open perspectives of this research project are listed in this section.

Perspective 1: For automatic data structuration, the performance of data structuration still has room to improve. In fact, in the research, human efforts are needed to manually check and correct the mistakes caused by natural language processing algorithms. Using more accurate natural language processing algorithm can largely reduce the time of manual correction. Based on our analysis of structuration results in Chapter 7, Section IV.E, introducing more domain knowledge can also potentially improve the performance.

Perspective 2: Also, for affordance clustering, the performance of data structuration still has room to improve. Based on our analysis of clustering results in Chapter 8, Section V.C, considering the entropy of information carried by the action word may be a way to improve the performance of clustering affordances in future research.

Perspective 3: Our research only involves the online review data downloaded from amazon.com. These reviews are in English. Future studies can be focused on analyzing online reviews in other languages. By comparing the analysis results in different countries, the influence of geography on design engineering can be deduced.

Perspective 4: In our data analytics, we have proposed two methods for monitoring the dynamic changes of user preference and for gaining innovative insights. Managerial implications have been concluded. However, one of the difficulties in design-oriented online review analysis is that the insights are difficult to further evaluate and validate in practice. As is discussed, the strategies proposed in our research project are indicative, not decisive. Further studies and demonstration are needed to evaluate the practicability of these strategies.

Therefore, future works could strengthen the proposed strategies by involving user studies and examining diverse case studies of different product domains. Combining the anonymous online review data and the nominative data provided by interviews, focus groups is a potential way to support the implications drawn from online reviews.

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Appendices

Appendix A: Analyzing the affordance descriptions in literature review

Affordance example	Relevant	Complete description	Action source	Action	Action receiver
Ladder					
elevate-ability	affordance	ability for the ladder to elevate user	ladder/user	elevate	user
elevation	affordance	ability for the ladder to elevate user	ladder/user	elevate	user
support-ability	affordance	ability for the ladder to support user	ladder/user	support	user
support	affordance	ability for the ladder to support user	ladder/user	support	user
storage-ability	affordance	ability for user to store the ladder	user	store	ladder
storage	affordance	ability for user to store the ladder	user	store	ladder
transport-ability	affordance	ability for user to transport the ladder	user	transport	ladder
transportation	affordance	ability for user to transport the ladder	user	transport	ladder
stable-ability	not affordance				
Falling-ability	affordance	ability for user to fall	user	fall	
falling	affordance	ability for user to fall	user	fall	
electrocuting-ability	affordance	ability for the ladder to electrocute user	ladder/user	electrocute	user
electrocution	affordance	ability for the ladder to electrocute user	ladder/user	electrocute	user
cutting-ability	affordance	ability for the ladder to cut user	ladder/user	cut	user
cutting	affordance	ability for the ladder to cut user	ladder/user	cut	user
collapse-ability	affordance	ability for user to collapse the ladder	user	collapse	ladder
collapse	affordance	ability for user to collapse the ladder	user	collapse	ladder
pinch-ability	affordance	ability for the ladder to pinch user	ladder/user	pinch	user
pinching	affordance	ability for the ladder to pinch user	ladder/user	pinch	user
working surface	affordance	ability for user to work	user	work	
comfort	affordance	ability for user to feel comfort	user	feel	
aesthetics	not affordance				
customizable	affordance	ability for user to customize the ladder	user	customize	ladder
manufacture	affordance	ability for manufacturer to manufacture the ladder	manufacturer	manufacture	ladder
maintenance	affordance	ability for engineer to maintain the ladder	engineer	maintain	ladder
sustainability	affordance	ability for engineer to sustain the ladder	engineer	sustain	ladder
frustration	affordance	ability for user to feel frustrated	user	feel	
degradation	affordance	ability for user to degrade the ladder	user	degrade	ladder
Automatic window switch in vehicle					
all windows accessible to passengers	affordance	ability for passengers to access windows	passengers	access	windows
accessibility to all window to user	affordance	ability for passengers to access windows	passengers	access	windows
flushed surface	not affordance				
use same hand for shifting, radio control, as for window control	affordance	ability for user to shift gear with the same hand as window control	user	shift	gear
usability of same hand for shifting, radio control and window control	affordance	ability for user to control radio with the same hand as window control	user	control	radio

frustrating user by unnatural mapping (up/down)	affordance	ability for user to feel frustrated	user	feel	
frustrating user by unnatural mapping to window locations	affordance	ability for user to feel frustrated	user	feel	
difficult reaching	affordance	ability for user to reach the switch	user	reach	switch
accidental up activation	affordance	ability for user to activate the switch	user	activate	switch
ability to accidentally activation of window up operation	affordance	ability for user to activate the switch	user	activate	switch
reduced weight	not affordance				
collecting dirt	affordance	ability for the switch to collect dirt	switch	collect	dirt
become stuck	affordance	ability for other things to stuck the switch	other things	stuck	switch
Steering wheel					
turn-ability	affordance	ability for user to turn the steering wheel	user	turn	steering wheel
turn-ability	affordance	ability for user to turn the steering wheel	user	turn	steering wheel
see through-ability	affordance	ability for user to see through the steering wheel	user	see through	steering wheel
street view-ability	affordance	ability for user to view street	user	view	street
speed view-ability	affordance	ability for user to view speed	user	view	speed
hand rest-ability	affordance	ability for user to rest hand	user	rest	hand
protect-ability	affordance	ability for the steering wheel to protect user	steering wheel/user	protect	user
protect ability	affordance	ability for the steering wheel to protect user	steering wheel/user	protect	user
power transmission	affordance	ability for the steering wheel to transmit power	steering wheel	transmit	power
grasp ability on the wheel	affordance	ability for user to grasp the steering wheel	user	grasp	steering wheel
grasp comfort ability	affordance	ability for user to grasp the steering wheel	user	grasp	steering wheel
clean ability	affordance	ability for user to clean the steering wheel	user	clean	steering wheel
Camera					
port-ability	affordance	ability for user to carry the camera	user	carry	camera
hold-ability	affordance	ability for user to hold the camera	user	hold	camera
stability	not affordance				
exposure-ability	affordance	ability for user to expose the camera	user	expose	camera
screen view-ability	affordance	ability for user to view screen	user	view	screen
Hair dryer					
drying hair	affordance	ability for user to dry hair	user	dry	hair
hair dry ability	affordance	ability for user to dry hair	user	dry	user
drying paint chips	affordance	ability for user to dry paint chips	user	dry	paint chips
transportation	affordance	ability for user to transport the hair dryer	user	transport	hair dryer
electronic shock if drop in water	affordance	ability for the hair dryer to electronic shock user if drop in water	hair dryer/user	electronic shock	user
electronic shock if drop in water	affordance	ability for user to drop the hair dryer	user	drop	hair dryer
electronic shock ability	affordance	ability for the hair dryer to electronic shock user	hair dryer/user	electronic shock	user
portability	affordance	ability for user to carry the hair dryer	user	carry	hair dryer

reliability	affordance	ability for user to trust the hair dryer	user	trust	hair dryer
comfortability	affordance	ability for user to feel comfortable	user	feel	
provide user adjustment	affordance	ability for user to adjust the hair dryer	user	adjust	hair dryer
adjustable for user	affordance	ability for user to adjust the hair dryer	user	adjust	hair dryer
annoying user with noise	affordance	ability for user to feel annoyed	user	feel	
annoying user with different operation	affordance	ability for user to feel annoyed	user	feel	
costing user's money to operate	affordance	ability for the hair dryer to cost money	hair dryer/user	cost	money
costing user's money to operate	affordance	ability for user to operate the hair dryer	user	operate	hair dryer
burn user	affordance	ability for the hair dryer to burn user	hair dryer/user	burn	user
cut or pinch user	affordance	ability for the hair dryer to cut user	hair dryer/user	cut	user
cut or pinch user	affordance	ability for the hair dryer to pinch user	hair dryer/user	pinch	user
provide attachment	affordance	ability for user to attach the hair dryer	user	attach	hair dryer
conduct electricity	affordance	ability for the hair dryer to conduct electricity	hair dryer	conduct	electricity
transmit power	affordance	ability for the hair dryer to transmit power	hair dryer	transmit	power
transfer heat	affordance	ability for the hair dryer to transfer heat	hair dryer	transfer	heat
provide temperature dependent voltage	affordance	ability for the hair dryer to change voltage	hair dryer	change	voltage
clogging airway	affordance	ability for something to clog airway	something	clog	airway
damage by overheating	affordance	ability for user to damage the hair dryer	user	damage	hair dryer
damage by overheating	affordance	ability for the hair dryer to overheat	hair dryer	overheat	
Shaver					
ergonomics	not affordance				
close shave-ability	affordance	ability for user to shave	user	shave	
clean out-ability	affordance	ability for user to clean out the shaver	user	clean out	shaver
shave-ability	affordance	ability for user to shave	user	shave	
hold-ability	affordance	ability for user to hold the shaver	user	hold	shaver
hydrate-ability	affordance	ability for user to hydrate the shaver	user	hydrate	shaver
pleasing user with aesthetics	affordance	ability for user to feel pleased	user	feel	
ability to shave precisely	affordance	ability for user to shave precisely	user	shave	
annoying user with noise	affordance	ability for user to feel annoyed	user	feel	
electronic shock ability	affordance	ability for the shaver to electronic shock user	shaver/user	electronic shock	user
cutting user	affordance	ability for the shaver to cut user	shaver/user	cut	user
accidentally turn off vibration	affordance	ability for user to turn off vibration accidentally	user	turn off	vibration
pinching user	affordance	ability for the shaver to pinch user	shaver/user	pinch	user
irritating user skin	affordance	ability for the shaver to irritate user skin	shaver/user	irritate	skin
transportability	affordance	ability for user to transport the shaver	user	transport	shaver
rusting	affordance	ability for the shaver to rust	shaver	rust	
Ball					
Throwability	affordance	ability for user to throw the ball	user	throw	ball
throwing	affordance	ability for user to throw the ball	user	throw	ball

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bouncing	affordance	ability for user to bounce the ball	user	bounce	ball
Monitor stand					
the use of up to 21-inch CRT monitor	affordance	ability for user to use monitor	user	use	monitor
access to buttons and ports on PC and docking station	affordance	ability for user to access to buttons and ports on PC and docking station	user	access	buttons and ports
human use	affordance	ability for user to use the monitor stand	user	use	monitor stand
manufacture	affordance	ability for manufacturer to manufacture the monitor stand	manufacturer	manufacture	monitor stand
aesthetics	not affordance				
improvement	affordance	ability for engineer to improve the monitor stand	engineer	improve	monitor stand
maintenance	affordance	ability for engineer to maintain the monitor stand	engineer	maintain	monitor stand
retirement	affordance	ability for user to retire the monitor stand	user	retire	monitor stand
sustainability	affordance	ability for engineer to sustain the monitor stand	engineer	sustain	monitor stand
additional weight onto the laptop	not affordance				
interference to the portable computer and docking station beneath it	affordance	ability for the monitor stand to interfere portable computer and docking station	monitor stand	interfere	portable computer and docking station
damage when a monitor is dropped from a height of three inch on it	affordance	ability for user to damage monitor	user	damage	monitor
damage when a monitor is dropped from a height of three inch on it	affordance	ability for user to drop monitor	user	drop	monitor
human injury	affordance	ability for the monitor stand to injure user	monitor stand/user	injure	user
frustration	affordance	ability for user to feel frustrated	user	feel	
product degradation	affordance	ability for user to degrade the monitor stand	user	degrade	monitor stand
a view of the monitor vertically as close as possible to its height on the desk without monitor stand	affordance	ability for use to view the monitor	user	view	monitor
Vehicle					
transportation of occupants	affordance	ability for the vehicle to transport occupant	vehicle/user	transport	occupants
transportation of cargo	affordance	ability for the vehicle to transport cargo	vehicle/user	transport	cargo
comfort to human	affordance	ability for user to feel comfortable	user	feel	
entertainment of occupants	affordance	ability for occupants to entertain themselves	occupants	entertain	themselves
communication with others	affordance	ability for user to communicate with others	user	communicate	
injuring occupants	affordance	ability for the vehicle to injure occupants	vehicle/user	injure	occupants
injuring others	affordance	ability for the vehicle to injure others	vehicle/user	injure	others
aesthetics to buyers and occupants	not affordance				
improvement to owners and occupants	affordance	ability for owner or occupant to improve the vehicle	owner/occupant	improve	vehicle
maintenance to owners and workers	affordance	ability for owner or worker to maintain the vehicle	owner/worker	maintain	vehicle
retirement	affordance	ability for user to retire the vehicle	user	retire	vehicle

sustainability	affordance	ability for engineering to sustain the vehicle	engineer	sustain	vehicle
degradation of itself	affordance	ability for the vehicle to degrade	vehicle	degrade	
frustration to occupants	affordance	ability for user to feel frustrated	user	feel	
damaging other vehicles	affordance	ability for user to damage other vehicles	vehicle/user	damage	other vehicles
pollution to the environment	affordance	ability for the vehicle to pollute the environment	vehicle	pollute	environment
Vacuum cleaner					
maneuverability	affordance	ability for user to maneuver the vacuum cleaner	user	maneuver	vacuum cleaner
pleasing user with aesthetics	affordance	ability for user to feel pleased	user	feel	
ability for user to reach different surface	affordance	ability for user to reach different surface	user	reach	surface
ability for user to clean effectively with suction ability	affordance	ability for user to clean something	user	clean	something
injuring user by electronic shock	affordance	ability for the vacuum cleaner to injure user	vacuum cleaner/user	injure	user
injuring user by electronic shock	affordance	ability for the vacuum cleaner to electronic shock user	vacuum cleaner/user	electronic shock	user
annoying user with noise	affordance	ability for user to feel annoyed	user	feel	
annoying user by clogging	affordance	ability for user to feel annoyed	user	feel	
costing the user with power consumption	affordance	ability for the vacuum cleaner to cost user	vacuum cleaner/user	cost	user
costing the user with power consumption	affordance	ability for the vacuum cleaner to consume power	vacuum cleaner	consume	power
transitional move ability	affordance	ability for user to move the vacuum cleaner transitionally	user	move	vacuum cleaner
transport ability	affordance	ability for user to transport the vacuum cleaner	user	transport	vacuum cleaner
cutting user	affordance	ability for the vacuum cleaner to cut user	vacuum cleaner/user	cut	user
drapes clean ability	affordance	ability for the vacuum cleaner to clean drapes	vacuum cleaner/user	clean	drapes
loss of clean ability by blocked airflow path	affordance	ability for the vacuum cleaner to loss clean ability	vacuum cleaner	loss	clean ability
loss of clean ability by blocked airflow path	affordance	ability for something to block airflow path	something	block	airflow path
blowing dirt in front of machine	affordance	ability for the vacuum cleaner to blow dirt	vacuum cleaner	blow	dirt
overheating	affordance	ability for the vacuum cleaner to overheat	vacuum cleaner	overheat	
Chair					
affords support	affordance	ability for the chair to support user	chair/user	support	user
affords sitting	affordance	ability for user to sit	user	sit	
Glass					
affords seeing through	affordance	ability for user to see through the glass	user	see through	glass
affords breaking	affordance	ability for user to break the glass	user	break	glass
Turning					
turning	affordance	ability for user to turn the knob	user	turn	knob

Appendix B: Manually structured online reviews

1. I've been a LONG time Amazon customer, but this is the first time I've written a review so needless to say, I feel very strongly about this.

   - Ability to write a review. (quality: existing)
   Whether customer can or cannot write a review depends on the online market website. Thus, it is regarded as indirect affordance. Quality: existing

   - Ability to feel [strongly] [about writing a review]. (quality: strongly)
   "Strongly" is a human feeling. Therefore, this is an experience affordance.

2. I was one of the customers that *pre-ordered* this new Kindle Paperwhite.

   - Ability to pre-order new kindle paperwhite. (quality: existing)

   - *Physical property: new kindle paperwhite*

3. I've wanted a Kindle and this NEW Kindle looked great!

   - Ability to want a kindle (quality: existing)
   Like the word "strongly", "want" means human's desire. Therefore, it is an experience affordance.

   - *Physical property: great appearance*

4. I used the free shipping but it was delivered very quickly after its official release.

   - Ability to use free shipping. (quality: existing)
   Whether customer can or cannot use free shipping does not depend on product itself. Therefore, we regard it as indirect affordance.

   - Ability to deliver kindle [quickly]. (quality: existing)

   - Ability to release kindle [officially]. (quality: existing)

   - *Physical property: free shipping, official release*

5. However, as soon as I received it, I noticed a line of dead pixels right in the center of the screen (Note pic #1).

   - Ability to receive kindle. (quality: existing)

   - Ability to notice dead pixels [in the center of the screen]. (quality: existing)
   Whether user can or cannot notice dead pixels totally depends on the product.

   - *Physical property: dead pixels, screen*

   - *Usage condition: as soon as user receive kindle*

6. I online chatted with Danyielle who was incredibly helpful!

   - Ability to chat with tech support [online]. (quality: existing)
   Whether the user can or cannot chat with tech support does not depend on product. Therefore, we regard it as indirect affordance.

   - *Physical property: helpful tech support*

7. She suggested that I return the old one and buy a new one to guaranteed a new model (instead of a possible refurb).

   - Ability to return the old kindle. (quality: existing)

   - Ability buy new kindle. (quality: existing)

   - Ability to guarantee new model. (quality: existing)

   - *Physical property: old kindle, new kindle*

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8. She even upgraded my new Kindle free 2-day shipping.

   - Ability <u>person</u> to upgraded new Kindle [free 2-day shipping]. (quality: existing)

   - *Physical property: free shipping, 2-day shipping*

9. I was pleased.

   - Ability to <u>feel</u> [pleased]. (quality: pleased) (polarity: beneficial)
     "Pleased" is a feeling brought by the product or the service. Therefore, it is an experience affordance.

10. Product defects happen but at least Amazon's customer service is top notch!

    - Ability defects to happen. (quality: existing)
      It is regarded as artifact-artifact affordance because it describes a change process by the product itself.

    - *Physical property: top notch service*

11. Then comes the 2nd Kindle... (see pic #2)

    - Ability kindle to come [<u>to user</u>]. (quality: existing)

12. As soon as I received it, I noticed very uneven lighting throughout the screen and some light leaks at the bottom of the screen (where light comes in) which created spots of shadow throughout the bottom of the screen.

    - Ability to receive <u>kindle</u>. (quality: existing)

    - Ability to notice uneven lighting. (quality: existing)

    - Ability to leak [at the bottom of the screen]. (quality: existing)

    - Ability to create spots. (quality: existing)

    - *Physical property: uneven lighting, screen*

    - *Usage condition: as soon as user receive kindle*

13. I even compared it to my first Kindle (with the dead line of pixels) and confirmed the lighting was definitely uneven on this 2nd Kindle.

    - Ability to compare <u>kindle</u> [to user's first kindle]. (quality: existing)

    - Ability to confirm uneven lighting [definitely]. (quality: definitely)
      It is better to be described as "ability to notice uneven lighting.

    - *Physical property: dead pixels, uneven lighting*

14. I look at screens every day living so it might be easier to notice these things than others.

    - Ability to look at screens [every day]. (quality: existing)

    - Ability to notice <u>uneven lighting</u> [easier]. (quality: easier)

    - *Physical property: screen, <u>uneven lighting</u>*

15. I was very bummed.

    - Ability to <u>feel</u> [bummed]. (quality: bummed) (polarity: harmful)

16. I went online and requested a refund.

    - Ability to go [online]. (quality: existing)

    - Ability to request a refund. (quality: existing)

17. And I ordered a 3rd Kindle, because I really want a Kindle!

    - Ability to order a 3rd kindle. (quality: existing)

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- Ability to want a kindle [really]. (quality: really)

18. Then comes the 3rd Kindle yesterday...(see pic #3)

    - Ability kindle to come [to user]. (quality: existing)

19. It's definitely not a charm.

    - *Physical property: not charm kindle*

20. There's a significant amount of dust and unrecognizable particles under the screen.

    - Ability to <u>recognize</u> particles [under the screen]. (quality: non-existing)

      This affordance is described by an adjective "unrecognizable" derived from the verb "recognize". As it is an implicit description, we mark the verb with underline.

    - *Physical property: significant amount of dust, unrecognizable particle*

    - I've read other reviewers talk about this but it's pretty shocking to see it to read other reviewers talk about <u>dust</u>. (quality: existing)

    - Ability to feel [shocked] [to see it]. (quality: shocked)

    - Ability to talk [about <u>dust</u>]. (quality: existing)

    - Ability to see <u>dust</u>. (quality: existing)

    - *Physical property: <u>dust</u>*

21. The 3rd Kindle has already been dropped off at UPS to be returned.

    - Ability to drop off kindle [at UPS to return kindle]. (quality: existing)

    - Ability to return <u>kindle</u>. (quality: existing)

22. Now Amazon's customer service is incredible and deserves a 5-star rating.

    - Ability service deserve a 5-star rating. (quality: existing)

    - *Physical property: incredible service*

23. But I am not sure this product is up to par.

24. Kindle is an incredible product and makes reading so much more enjoyable.

    - Ability to <u>feel</u> [enjoy]. (quality: enjoy) (polarity: beneficial)

    - *Physical property: incredible product*

25. But who wants to stare at the screen when all you can notice is dead pixels, or dark shadows, or unknown particles under the screen.

    - Ability to stare [at the screen (quality: existing)

    - Ability to notice dead pixels, or dark shadows, or unknown particles [under the screen]. (quality: existing)

    - *Physical property: dead pixels, dark shadows, unknown particles*

26. I am not sure if Amazon was trying to make a deadline so this product was prematurely released.

    - Ability to release kindle [prematurely]. (quality: prematurely)

27. I've never owned a Kindle so I can't compare it to previous models.

    - Ability to compare <u>kindle</u> [to previous models]. (quality: existing)

28. I'd REALLY like to own a Kindle - but I am scared to order a fourth one that's defective again.

    - Ability to like [to own a kindle] [really]. (quality: really)

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- Ability to feel [scared]. (quality: scared)

- Ability to order a fourth <u>kindle</u>. (quality: existing)

- *Physical property: defective kindle*

29. As easy as Amazon makes the return process, it's still a huge inconvenience.

  - Ability to return <u>kindle</u> [easily]. (quality: easily)

  - *Physical property: huge inconvenience*

30. I am also losing confidence that a fourth one would have a proper screen brand new product.

  - Ability to lose confidence. (quality: existing)

  - *Physical property: proper screen, new <u>kindle</u>*

31. This has been incredibly disappointing.

  - Ability to feel [disappointed]. (quality: disappointed)

32. The is not a worthy upgrade... Uneven, and even dimmer lighting, no noticeable difference in text clarity or sharpness!

  - Ability to upgrade <u>kindle</u> [worthy]. (quality: worthy)

  - Ability to notice <u>difference</u> [in text clarity or sharpness]. (quality: existing)

  - *Physical property: not worthy upgrade, uneven lighting, dimmer lighting, text clarity, text sharpness.*

33. As a matter of fact, at full brightness, last years version looks brighter and crisper, where the new unit looks dull, with blotchy and uneven lighting!

  - *Physical property: <u>old</u> version, new <u>version</u>, dull appearance, blotchy lighting, uneven lighting, not bright appearance, not crisper appearance.*

  - *Usage condition: at full brightness*

34. I am so not impressed!

  - Ability to feel [impressed]. (quality: not impressed)

35. Even with the new font, there is NO noticeable improvement!

  - Ability to <u>notice</u> improvement. (quality: non-existing)

  - *Physical property: new font*

36. The only thing that has been supposedly upgraded on this unit, this one has 4GBs of storage, compared to last years 2GBs!

  - Ability to upgrade kindle. (quality: existing)

  - *Physical property: 4GB storage, 2GB storage.*

37. Otherwise, this unit is an actual downgrade compared to last years model!

  - Ability to <u>downgrade</u> kindle. (quality: existing)

  - Ability to compare kindles. (quality: existing)

  - *Physical property: old model*

  - Just look at a comparison of the two units and decide to compare <u>kindles</u>. (quality: existing)

  - Ability to decide <u>which kindle to buy [</u> (quality: existing)

38. Which one do you think looks brighter, crisper, more evenly lit...

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- Ability to light kindle [evenly]. (quality: not evenly)

- *Physical property: brighter appearance, crisper appearance*

39. I have the new paperwhite and love it.

    - Ability to love <u>kindle</u>. (quality: existing)

    - *Physical property: new paperwhite*

40. I just ordered one husband and the display is NOT the same.

    - Ability to order kindle [husband]. (quality: existing)

    - *Physical property: not same display*

41. It does not have the vivid bright white background like mine does.

    - *Physical property: not vivid background, not bright background, not white background*

42. It has a sepia background.

    - *Physical property: sepia background*

43. This is with the brightness turned all the way up and it's on any page, in a book, home screen, etc.

    - Ability to turn up the brightness. (quality: existing)

    - *Physical property: brightness*

44. I asked replacement.

    - Ability to ask <u>after sales</u> [(quality: existing)

45. I received it today and it's the exact same thing.

    - Ability to receive kindle [today]. (quality: existing)

    - *Physical property: <u>sepia background</u>*

46. I talked to the kindle tech person and he acted like he almost didn't believe me.

    - Ability to talk [to kindle tech person]. (quality: existing)

    - Ability tech person to believe user. (quality: existing)

47. I have taken pictures of both kindles side by side with my Paperwhite(that I've had few months), but he didn't want me to email them to him.

    - Ability to take pictures [of both kindles side by side]. (quality: existing)

    - Ability to email kindle tech person. (quality: existing)

48. Maybe they don't have a way to view an email?

    - Ability tech person to view an email. (quality: non-existing)

49. Not sure, but now they are sending me a 3rd one.

    - Ability to send user a 3rd kindle. (quality: existing)

50. 1 day shipping...which I appreciate greatly, as this was an anniversary gift husband.

    - Ability to appreciate 1-day shipping [greatly]. (quality: greatly)

    - *Physical property: 1-day shipping*

    - *Usage condition: this was an anniversary gift husband*

51. If the 3rd one is the same, then I give up and I'll just give my husband my paperwhite that does have the bright

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white background and I'll keep the defect one, even though it's not as easy on the eyes to read.

- Ability to give up <u>kindle</u> (quality: existing)

- Ability to give kindle to her husband. (quality: existing)

- Ability to keep <u>kindle</u>. (quality: existing)

- Ability <u>book</u> [easily]. (quality: easily)

- *Physical property: sepia background, not bright background, not white background, defect <u>kindle</u>*

52. I'm going to assume that reason, amazon is manufacturing kindle paperwhites without the bright white background anymore.

- Ability to manufacture kindle paperwhites [without the bright white background]. (quality: non-existing)

- *Physical property: bright background, white background*

53. I've included pictures of the 1st kindle I got him and the 2nd one.

- Ability to include pictures [<u>in review</u>]. (quality: existing)

54. Both are beside my kindle and both brightnesses are turned all the way up.

- Ability to turn up brightness. (quality: existing)

55. In the first pic, my kindle is on the left.

56. In the 2nd pic, my kindle is on the right and you can see the brightness levels are exactly the same

- Ability to see same brightness. (quality: existing)

- *Physical property: same brightness*

57. I got the Paperwhite 2014 (6th generation as indicated on the back of its box, 212 ppi) last month and was very pleased with it.

- Ability to get paperwhite. (quality: existing)

- Ability to <u>feel</u> [pleased]. (quality: pleased) (polarity: beneficial)

58. However, a week later, Amazon advertised the release of the Paperwhite 2015 with 300 ppi resolution so I went ahead and pre-ordered so I can compare the two and decide.

- Ability to advertise the release. (quality: existing)

- Ability to pre-order <u>kindle</u>. (quality: existing)

- Ability to compare the two <u>kindles</u>. (quality: existing)

- Ability to decide <u>whether to buy new kindle</u>. (quality: existing)

59. I received the Paperwhite 2015 (7th generation per its box) and my initial reaction was similar to many –

- Ability to receive kindle 2015. (quality: existing)

- Ability to <u>feel</u> [similarly] [to many]. (quality: similarly)

60. This is so beige!

- *Physical property: beige kindle*

61. I put both devices away to let my initial disappointment settle down then went back to calmly compare the two.

- Ability to put away both device. (quality: existing)

- Ability to settle down disappointment. (quality: existing)

- Ability to <u>feel</u> [disappoint]. (quality: disappointed) (quality: existing)

- Ability to compare kindles [calmly]. (quality: calmly)

62. The 2014 model indeed has a more white screen and the 2015 has a hint of beige to it.

    - *Physical property: less white screen, beige screen*

63. However, it's just about one and a half to two hues of a difference (a few said it has a Sepia background but that's about at least 25x of an exaggeration).

    - *Physical property: sepia background*

64. I compared the two devices side by side with their brightness set at maximum.

    - Ability to compare <u>kindles</u>. (quality: existing)

    - Ability to set brightness [at maximum]. (quality: existing)

65. The first photo was taken inside a moderately-lit room (with natural light through the windows but balcony door blinds closed) and the second photo was taken outside.

    - Ability to take photo. (quality: existing)

    - *Usage condition: inside a moderately-lit room, outside*

66. There is hardly any difference when comparing the two devices outside.

    - *Usage condition: when comparing the two devices, outside*

67. Also, if you turn on the Paperwhite 2015 on its own, away and not next to the Paperwhite 2014, it will not even occur to you that it has a hint of beige to it.

    - Ability to turn on the paperwhite 2015. (quality: existing)

    - Ability to occur to user that it is beige. (quality: non-existing)
      It is better to be described as "ability to notice that kindle is beige"

      Physical property: beige kindle

    - *Usage condition: on its own, away and not next to the paperwhite 2014*

68. As a matter of fact, it looks white.

    - *Physical property: white <u>appearance</u>*

69. So I suggest to stop comparing them side by side because you will find yourself obsessing with the difference.

    - Ability to compare <u>kindles</u> [side by side]. (quality: existing)

    - Ability to feel [obsessing] [with the difference]. (quality: existing)

70. And do not even look at one, turn around, and look at the other because that's just like the same thing.

    - Ability to look [at <u>kindle</u>]. (quality: existing)

71. Put the two devices away, do something else few minutes, go back and turn on the Paperwhite 2015 only and Voila! It's white!

    - Ability to put away <u>kindle</u>s. (quality: existing)

    - Ability to turn on kindle. (quality: existing)

    - *Physical property: white kindle*

72. (If you'd think about it, you don't really plan on reading from two devices simultaneously nor side by side anyway.

    - Ability to read kindles [simultaneously]. (quality: not simultaneously)

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73. Besides, a typical actual paperback is a hundred times more brown than the PW 2015 screen.)

   - *Physical property: less brown screen*

74. The resolution is not grossly different but is noticeable to me.

   - Ability to <u>notice</u> the resolution is different. (quality: existing)

   - *Physical property: different resolution*

75. The letters on the PW 2015 are more crisp, refined, and the edges are more well-defined.

   - *Physical property: crisp letter, refined letter, well-defined edge.*

76. I do agree, though, that there is a little trade off on the contrast.

   - Ability to agree there is a little trade off on the contrast. (quality: existing)

   - *Physical property: contrast*

77. The letters are a little bit black/gray on the PW 2015 (which I actually find easier on the eyes) and more black-ish on the PW 2014.

   - *Physical property: black letters, gray letters, easier on eye letters*

78. However, when I wear any of my readers glasses, the contrast is better and more apparent.

   - Ability to wear readers glasses. (quality: existing)

   - *Physical property: better contrast, apparent contrast*

   - *Usage condition: when user wear reader glasses*

79. Also, when reading in the dark, I find that I set the brightness higher on the PW 2015 than what I did with the 2014.

   - Ability to set higher brightness. (quality: existing)

   - *Usage condition: when reading in the dark*

80. The shorter battery life is not an issue to me as I do not read long periods and I charge my device every few days.

   - Ability to read <u>kindle</u> [long periods]. (quality: non-existing)

   - Ability to charge kindle [every few days]. (quality: existing)

   - *Physical property: shorter battery life*

81. As new Bookerly font, I really don't care at all.

   - Ability to care <u>new font</u> [really] (quality: not really)

   - *Physical property: new font*

82. I chose the PW 2015 because of the higher resolution.

   - Ability to choose pw 2015. (quality: existing)
     In fact, this affordance describes a desire of customer. Therefore, we regard it as experience affordance.

   - *Physical property: higher resolution*

83. Plus I had purchased the extended 2-year warranty on the PW 2015 (only because it is new model and hasn't been tried and tested yet) so it's covered if anything goes wrong with it.

   - Ability to purchase the extended 2-year warranty. (quality: existing)

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- Ability to try and test kindle [before buying]. (quality: non-existing)

- Ability to cover repairing fee. (quality: existing)

- Ability to go wrong. (quality: existing)

- *Physical property: 2-year warranty, new model*

84. I didn't feel I needed to purchase warranty PW 2014 because that model has been tried, tested, and well-reviewed by many.

   - Ability to purchase a warranty. (quality: need)
   Apparently, need to do something is different from able to do something. In this example, the product affords a need to customer. Therefore, we regard "need" as affordance quality.

   - Ability to try, test and kindle. (quality: existing)

   - Ability to review kindle [well]. (quality: well)
   These three affordances are the affordances of last version's kindle paperwhite

   - *Physical property: warranty*

85. Bottom line, choose and decide based on whichever is important to you.

   - Ability to choose and decide whether to buy kindle or not. (quality: existing)

86. You can't go wrong either way.

   - Ability to go wrong. (quality: non-existing)

87. Happy reading!

   - Ability to feel [happy]. (quality: happy) (polarity: beneficial)

   - Ability to read kindle. (quality: existing)

88. Love love love this upgrade.

   - Ability to love this upgrade. (quality: existing)

   - Ability to upgrade kindle. (quality: existing)

89. This is my third kindle.

90. The backlit feature has an amazing amount of gradients, definitely easy on the eyes AND I can read in the dark.

   - Ability to read books [in the dark]. (quality: existing)

   - *Physical property: easy on eye backlit, amazing amount of gradients*

   - *Usage condition: in the dark*

91. *****UPDATE******It's been about 4 months since I got my Kindle Paperwhite and I still love this little beasty as much as I did the first day I got it!

   - Ability to love kindle [as much as the first day]. (quality: existing)

   - *Usage condition: 4 months since user got kindle paperwhite.*

92. She's holding up amazingly strong and I have absolutely no complaints at ALL!

   - Ability to hold up [strongly]. (quality: strongly)

   - Ability to complain kindle. (quality: non-existing)

93. My screen is still working just fine and has no color variation.

   - Ability to work [just fine]. (quality: fine)

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- Ability color <u>variate</u>. (quality: non-existing)

94. And umm...let me just praise the battery life of this contraption because it is absolutely AMAZING!

   - Ability to praise the battery life. (quality: existing)

   - Ability to <u>feel</u> [amazing] [about battery life]. (quality: amazing) (polarity: beneficial)

   - *Physical property: amazing battery life*

95. I have been reading on my Kindle A LOT.

   - Ability to read <u>book</u> [a lot]. (quality: a lot)

96. I mean at least 1-2 hours a day and every few days the long sits of 4-8 hours of reading occur, and STILL the battery life is great.

   - Ability to read <u>book</u> [at least 1-2 hours a day]. (quality: existing)

   - Ability to read <u>book</u> [every few days 4-8 hours]. (quality: existing)

   - *Physical property: great battery life*

97. Since getting my Paperwhite, I've only had to charge it 3-4 times.

   - Ability to charge <u>kindle</u> [only 3-4 times]. (quality: need)

   - *Usage condition: Since getting paperwhite*

98. I've had this thing 13 weeks now!

   - *Usage condition: since getting paperwhite 13 weeks*

99. That's amazing!

   - Ability to <u>feel</u> [amazing]. (quality: amazing)

100. I will never regret buying this.

   - Ability to regret [buying <u>kindle</u>]. (quality: non-existing)

101. Probably the best Amazon purchase I've ever made!

   - Ability to purchase <u>kindle</u>. (quality: existing)

102. *******************

103. Just got my kindle today birthday and I love it!

   - Ability to get kindle [today]. (quality: existing)

   - Ability to love kindle. (quality: existing)

   Usage condition: birthday

   - I was worried I wouldn't like it that much or that I'd get a dud like some have received but luckily that was not the case to <u>feel</u> [worry]. (quality: not worry) (polarity: beneficial)

   - Ability to like <u>kindle</u> that much. (quality: much)

   - Ability to get <u>kindle</u>. (quality: existing)

   - Ability to <u>feel</u> [lucky]. (quality: lucky) (polarity: beneficial) (polarity: beneficial)

104. This is my FIRST kindle and I am so excited I finally started giving ebooks a try.

   - Ability to <u>feel</u> [excited]. (quality: excited) (polarity: beneficial)

   - Ability to try e-books. (quality: existing)

105.I went to test the Paperwhite at Best Buy before buying it to make sure it was what I wanted.

- Ability to test kindle. (quality: existing)

- Ability to feel sure [about kindle]. (quality: sure)

- *Usage condition: before buying kindle*

106.The one on display seemed glitchy and had poor lighting on it that was blotchy.

- *Physical property: glitchy appearance, poor lighting, blotchy appearance.*

107.Made me extremely nervous to order one.

- Ability to feel [nervous]. (quality: nervous) (polarity: harmful)

- Ability to order kindle. (quality: existing)

108.But with how much reading I've been doing with ebooks, and the fact that my iPhone and laptops are making my stinking eyes feel like they want to bleed off of my face (yes, off of my face), I decided to take the leap.

- Ability to read many e-books (quality: existing)

- Ability to bleed off face. (quality: non-existing)

- Ability to decide [to take the leap]. (quality: existing)

- Ability to take the leap. (quality: existing)

109.SO glad that I did!

- Ability to feel [glad]. (quality: glad) (polarity: beneficial)

110.My kindle I received is perfect.

- Ability to receive kindle. (quality: existing)

- *Physical property: perfect kindle*

111.The colors are right where they should be, with no blotchy spots like some say and crispness between the white and black text.

- *Physical property: not blotchy spots, crisp text*

112.My kindle is SO much more responsive and faster than the one I tried on display.

- Ability to response user [fast]. (quality: fast)

- Ability try kindle [on display]. (quality: existing)

Physical property: responsive kindle, faster kindle.

113.If you are going to try them out in a store first, keep in mind they probably aren't as nice as the one you will get!

- Ability to try kindles [in a store]. (quality: existing)

- Ability to get kindle [as nice as in a store]. (quality: existing)

- *Physical property: nice kindle*

114.There's a night and day difference in the test one and the one I bought.

- Ability to buy a kindle. (quality: existing)

- Ability to test kindle. (quality: existing)

- *Physical property: night-and-day difference*

115.I am so excited to be able to finally read ebooks in the sun outside and to read in bed at night without killing

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my eyes or keeping the husband up.

- Ability to feel [excited]. (quality: excited) (polarity: beneficial)

- Ability to read e-books [in the sun outside]. (quality: existing)

- Ability to read e-books [in bed at night]. (quality: existing)

- Ability to kill my eyes. (quality: non-existing) (polarity: beneficial)

- Ability to keep up the husband. (quality: non-existing)

- *Usage condition: in the sun, outside, in bed, at night.*

116. The setup is extremely easy.

- Ability to setup kindle [easily]. (quality: easily)

- *Physical property: easy setup*

117. Once you connect to wifi, you can sign into your kindle/amazon account or it will already be signed in and boom, there are your books in your library!

- Ability to connect WIFI. (quality: existing)

- Ability to sign into amazon account. (quality: existing)

- Ability to sign in account. (quality: existing)

- *Usage condition: once user connect to WIFI*

118. The setup of it is also really easy and basic too, and steps you through it from the very beginning.

- Ability to step through the setup [from beginning]. (quality: existing)

- *Physical property: easy setup, basic setup.*

119. No idea why some people say it's confusing, because it is NOT.

- Ability to feel [confused]. (quality: not confused) (polarity: harmful)

120. If you can work a smart phone, you can surely work a simple Kindle lol.

- Ability to work a kindle. (quality: existing)

- *Physical property: simple kindle*

- *Usage condition: if user can work a smart phone.*

121. The only thing I am surprised and a little disappointed about is that it does feel heavier than I thought it would.

- Ability to feel [surprised]. (quality: surprised) (polarity: harmful)

- Ability to feel disappointed. (quality: disappointed) (polarity: harmful)

- *Physical property: heavier weight.*

122. It's nothing bad at all and I don't believe it will hurt my hands holding it up in bed, but I was hoping little less weight in a device so small.

- Ability to hurt hands. (quality: non-existing) (polarity: beneficial)

- Ability to hold up kindle [in bed]. (quality: existing)

- *Physical property: not bad kindle, less weight, small device.*

- *Usage condition: in bed*

123. But at the same time, the weight does make it feel very sturdy, and the entire thing is weighted evenly so

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there's no tipping one way or another with the device.

- Ability to feel [sturdy]. (quality: sturdy) (polarity: harmful)

- Ability to weight kindle [evenly]. (quality: evenly)

124. This Paperwhite is a dream, and I am so happy that I decided to give Kindles a chance.

- Ability to feel [happy]. (quality: happy) (polarity: beneficial)

- Ability to decide to give kindles a chance. (quality: existing)

125. If you're a firsts time Kindle buyer, DO IT!

126. I don't think you'll regret it one bit!

- Ability to regret. (quality: non-existing) (polarity: beneficial)

127. But even if you don't end up liking it, the worst that happens is you send it back.

- Ability to like kindle. (quality: existing)

- Ability to send back kindle. (quality: existing)

- Ability worst thing to happen. (quality: existing)

- *Usage condition: if user don't end up liking kindle*

128. But it's worth a shot definitely!

129. With how much you can save on books by downloading free ones from amazon (I have 234 books in my library and I have only bought 4 of them.

- Ability to save money [on books]. (quality: existing)

- Ability to download free books [from amazon]. (quality: existing)

- Ability to buy only 4 books. (quality: existing)

- *Physical property: free books*

130. Much of this is thanks to discovering bookbub.com that shows you free and marked down books from amazon) and the fact you can rent ebooks from your public library (I love to do this! No wait time between sequels either!!!) is amazing.

- Ability to discover bookbub.com. (quality: existing)

- Ability to show user free and marked books. (quality: existing)

- Ability to rent e-books. (quality: existing)

- Ability to love renting e-books. (quality: existing)

- Ability to feel [amazing]. (quality: amazing) (polarity: beneficial)

- *Physical property: free books, marked books*

131. So you pay $119 device and then BOOM: basically free books or books under $5 forever.

- Ability to pay $199 [device]. (quality: existing)

- *Physical property: free books, forever books under $5*

132. Give this wonderful, well made and fun device a chance!

- Ability to give kindle a chance. (quality: existing)

- *Physical property: wonderful kindle, well-made kindle, fun kindle.*

133. I'm happy that I did!

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- Ability to *feel* [happy]. (quality: happy) (polarity: beneficial)

134. (Note in the pictures that the lighting is perfect, no blotchyness, and up close it truly looks like a book page!)

- *Physical property: perfect lighting, blotchy kindle, book-like appearance*

135. So, I have two problems with this new kindle.

- *Physical property: new kindle*

136. First - The light is just too yellow in comparison to paperwhite 1 and 2 (as can be seen in the photos I'm providing).

- Ability to compare kindles. (quality: existing)

- Ability to see yellow light. (quality: existing)

- Ability to provide photo. (quality: existing)

- *Physical property: yellow light*

137. Also, the light is weaker, which makers not so good experience while reading in a bright lit ambient).

- Ability to read books [in a bright lit ambient]. (quality: non-existing)

- *Physical property: weaker light*

- *Usage condition: while reading in a bright lit ambient*

138. I'm not sure if my device is simply defective or if this new yellowish and weaker light is by design, if it is, I don't like it and think it should probably be advertised, maybe a change name to kindle paperyellow?

- Ability to be sure [of the device]. (quality: non-existing) (polarity: harmful)

- Ability to like new light. (quality: non-existing)

- Ability to advertise new light. (quality: non-existing)

- Ability to change name of kindle. (quality: non-existing)

- *Physical property: defective device, yellowish light, weaker light.*

139. Second: The 300dpi thing is quite meh (in comparison to 212 and even 167 of the pw1), I mean, is it better?

140. Yes, I guess it is but - Will it make much of a difference?

- Ability to guess 300dpi is better. (quality: existing)
- Ability to make much difference. (quality: not much)

141. Well, maybe if you read using the largest setting, but even then just a small difference...

- Ability to read books [using the largest setting]. (quality: existing)

- Ability to use the largest setting. (quality: existing)

- *Physical property: small difference*

142. Oh, also bookerly, it is a nice typeset, but I still prefer Caecilia and Palatino... A matter of taste, I know...

- Ability to prefer other fonts. (quality: existing)
- *Physical property: nice typeset*

143. Still, not much of a thing having this new typeset, even if one prefers it...

- Ability to prefer new font. (quality: existing)

144. Btw, why can't we just side-load our favored typesets as is some other brads reading devices?

- Ability to side-load users favored typesets. (polarity: non-existing)

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145. That would be an improvement.

   - Ability <u>to improve kindle</u>. (quality: non-existing)

146. And what I like about it?

   - Ability to like <u>kindle</u>. (quality: existing)

147. Well, the same I did like about the previous devices, it is still a good ereader and I could probably get used to it, but I still prefer the previous version, both one and two, in my opinion, make better overall reading experience.

   - Ability to like previous devices. (quality: existing)

   - Ability to get used to <u>new kindle</u> [probably]. (quality: probably)

   - Ability to prefer the previous version. (quality: existing)

   - Ability to make a better reading experience. (quality: existing)

   - Ability to read <u>kindle</u>. (quality: existing)

   - *Physical property: good e-reader, better experience.*

148. The photos.

149. They are, from left to right, Paperwhite 1, Paperwhite 3 (the current version), and Paperwhite 2.

150. For those who hesitantly bought this device because of the boasted 300ppi screen and thought it would be on par with the Kindle Voyage, think again, it's not!

   - Ability to hesitate. (quality: existing)

   - Ability to buy kindle. (quality: existing)

   - Ability to think kindle would be on par with kindle voyage. (quality: existing)

   - ability to think again. (quality: existing)

   - *Physical property: boasted 300ppi screen.*

151. It's nowhere close and not even in the same ballpark.

152. I too, bought this on a whim despite reading numerous reports of the cheap dull looking display and the washed out contrast because even though I already own a Voyage, I still like the feel of the Paperwhite and love the Onyx book style cover over the Origami.

   - Ability to buy kindle [on a whim.] (quality: existing)

   - Ability to read numerous reports. (quality: existing)

   - Ability to own a voyage. (quality: existing)

   - Ability to like the feel of paperwhite. (quality: existing)

   - Ability to love the Onyx book style. (quality: existing)

   - *Physical property: cheap display, dull display, washed out contrast.*

153. So I did, and boy I am ever disappointed!

   - Ability to feel [disappointed]. (quality: disappointed) (polarity: harmful)

154. First off all this device will be good enough masses, newbies, or those that aren't already spoiled by the quality of a Voyage.

   - Ability spoil user the quality of Voyage. (quality: non-existing)

155. Honestly if you really think the Paperwhite is good, you are really missing out by not getting a Voyage despite

the higher price.

- Ability to think the paperwhite is good. (quality: existing)

- Ability to get a voyage. (quality: existing)

156. Yes there have been previous issues with a two tone screen, but I believe Amazon has worked out those kinks on newer devices, the one I got is literally perfect (see picture).

- Ability to work out kinks. (quality: existing)

- *Physical property: two-tone screen, perfect <u>kindle</u>*

157. Upon receiving the Paperwhite, I immediately noticed a beige, sepia tone looking screen.

- Ability to notice beige, sepia tone screen [immediately]. (quality: immediately)

- *Physical property: beige screen, sepia screen*

- *Usage condition: upon receiving the paperwhite.*

158. I mean, it's an obvious yellow tint which takes away from the higher resolution.

- *Physical property: yellow tint, higher resolution*

159. This device should literally be called the Kindle Paperbeige or perhaps the Papersepia but definitely not a Paperwhite, because it's nowhere near having a white background.

- Ability to call kindle Paperbeige. (quality: non-existing)

- *Physical property: not white background*

160. The display also has blotches on the lower portion which still haven't been eliminated despite this being the 3rd generation PW.

- Ability to eliminate blotches. (quality: non-existing)

- *Physical property: blotches, display*

161. The text is grey, not black as in the previous PW2 due to the very low levels of contrast.

- *Physical property: grey text, not black text, low contrast*

162. So here we go, let's start off with a 5 star review and then decrease one star based upon abnormalities we find.

- Ability to decrease one star. (quality: existing)

- Ability to find abnormalities. (quality: existing)

163. * Dull beige looking display - Minus one-star

- Ability to minus on star. (quality: existing)

- *Physical property: dull display, beige display.*

164. * Blotches on lower portion of screen and shadows throughout (see pic) - Minus one star

- Ability to minus one star. (quality: existing)

165. * VERY low contrast with washed out grey fonts - Minus one star

- Ability to minus one star. (quality: existing)

- *Physical property: low contrast, washed out fonts, grey fonts.*

166. * Battery life is less than previous PW2 version - Minus one star

- Ability to minus one star. (quality: existing)

- *Physical property: less battery life*

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167.* The resolution is better over the previous version which you can barely notice due to the dull screen - Plus one star

- Ability to notice better resolution. (quality: existing)

- Ability to plus one star. (quality: existing)

- *Physical property: better resolution, dull screen*

168. Total equals 1 star our of a possible 5

169. This is how you properly grade a device.

- Ability to grade kindle [properly]. (quality: properly)

170. Even though I wanted to love this device because I love Amazon, I am not some ego invested fanatic that isn't honest and will simply rate this device 5 stars with all the obvious flaws just because I bought it.

- Ability to love kindle. (quality: existing)

- Ability to love amazon. (quality: existing)

- Ability to simply rate 5 stars. (quality: simply)

- Ability to buy kindle. (quality: existing)

171. I feel like I would be doing a disservice to others by not being completely honest.

- Ability to feel [dishonest]. (quality: dishonest) (polarity: harmful)

172. These are all facts without any bias involved.

- Ability to involve bias. (quality: non-existing)

173. I am simply listing truths here.

- Ability to list truth. (quality: existing)

174. I won't get into the cheap looking matte design Amazon implemented with this new version which scratches easily although I will say it's not as elegant as the glossy piano finish the PW2 had with the ink embedded Amazon logo.

- Ability to get into the design. (quality: non-existing)

- Ability to scratch matte [easily]. (quality: easily)

- Ability say kindle is not elegant. (quality: existing)

- Ability to embed ink. (quality: existing)

- *Physical property: cheap matte, elegant matte.*

175. Check out the photo I uploaded comparing the Kindle Voyage (left) side by side with the new Paperwhite (right) and the differences are astonishing.

- Ability to upload photo. (quality: existing)

- *Physical property: astonishing differences.*

176. Fore $80 more on the Voyage you get a slimmer, sleeker device with better quality materials, you get page turn sensors that work, you get auto brightness and you get a superior flush glass display that feels much better than the sand paper rough type display you get on a Paperwhite.

- Ability to get voyage [more]. (quality: existing)

- Ability turn sensor to work. (quality: non-existing)

- Ability change [automatically]. (quality: not automatically)

- Ability to feel [better]. (quality: not better) (polarity: harmful)

- *Physical property: not slimmer device, not sleeker device, not better quality materials, not auto brightness, not flush glass display, rough display.*

177. For $80 more, you get MUCH better contrast where the fonts look pitch black and not grey.

- Ability to get better contrast. (quality: non-existing)

- *Physical property: not better contrast, not black font, grey font*

178. You get a whiter background and superior lighting that is actually white and not a sepia tone color.

- Ability to get a whiter background kindle. (quality: non-existing)

- *Physical property: not whiter background, not superior lighting, not actually white lighting, sepia tone color.*

179. The Kindle Paperwhite 3 (released in 2015) is again a good ereader that could have been just a little better.

- *Physical property: good e-reader.*

180. The GOOD.

181. • PW3's text seems to be one shade of gray less dark than that of the PW2.

- *Physical property: less dark text*

182. This is another source of eyestrain, and it is why I gave away my Kobo Aura.

- Ability to hurt eye. (quality: non-existing) (polarity: beneficial)

- Ability to give away kobo. (quality: existing)

183. It might be that the bluish tinted frontlight is responsible apparent lightening of the text.

- Ability user to lighten text apparently. (quality: apparently)

- *Physical property: bluish tinted front light, apparent lightening text.*

184. Edit: The bold font face on the PW3 is almost impossible to distinguish from the normal weight font face, a possible unintended result of the higher resolution.

- Ability to distinguish bold font [from normal weight font face]. (quality: non-existing)

- *Physical property: higher resolution.*

185. • PW3's battery (1320 mAh) is about 10% less capacious than PW2's (1470 mAh).

- *Physical property: less capacious battery.*

186. It's probably still good hours' continuous use.

- Ability to use kindle [continually 24 hours]. (quality: continually)

187. The NEUTRAL.

188. The 300 dpi screen of the PW3 isn't all that superior to the 212 dpi of the PW2.

- *Physical property: existing 300-dpi screen, superior resolution*

189. You'd think that it would be, but I have them side by side, both showing the same page from Steven Erikson's Memories of Ice, and if anything the PW2 is easier to read due to the darker text and the warmer screen color.

- Ability to think the resolution is higher. (quality: existing)

- Ability to show book page. (quality: existing)

- Ability to read kindle [easier]. (quality: easily)

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- *Physical property: not darker text, not warmer screen color.*

190. SUMMARY.

191. If Kindle Paperwhite 3 Amazon had included the increases in RAM and in internal storage, but left the battery, the frontlight, and the darkness of the text as they were in the PW2, then the PW3 would have been a better ereader.

    - Ability to increase the ram and internal storage of kindle. (quality: existing)

    - Ability to upgrade battery, frontlight, darkness of the text. (quality: non-existing)

    - *Physical property: not better e-reader, increased RAM, increased internal storage, <u>unchanged</u> battery, <u>unchanged</u> frontlight, <u>unchanged</u> darkness of the text*

192. The Bookerly font and the increase in screen resolution are minor benefits that have been far over-hyped by other reviewers unknown to me.

    - Ability reviewers to far over-hype the bookerly font and increased resolution. (quality: far)

    - *Physical property: <u>existing</u> bookerly font, increased resolution*

193. Edit (29 July 2015): For reasons beyond my comprehension, the Kindle Paperwhite remains the eReader that seems most friendly to the hand.

    - *Physical property: hand-friendly kindle*

194. Slipped into one of the plainer black covers (my preference is Fintie classic folio), the PW does a better job at being forgotten in favor of whatever you're reading than any other device does.

    - Ability to slip into cover. (quality: existing)

    - Ability to forget <u>the existence of</u> kindle. (quality: existing)

    - *Physical property: plainer cover, black cover.*

195. It isn't just weight, either.

196. There are lighter eReaders, but the Paperwhite beats them all in handling ergonomics.

    - Ability to beat <u>other e-readers</u> [in handling ergonomics]. (quality: existing)

    - *Physical property: not lighter e-reader*

197. Then there's the text presentation.

    - Ability to present text. (quality: existing)

198. Even without the new Bookerly font, the layout of text on the Kindle is superior to what many other eReaders do.

    - *Physical property: superior layout of text, <u>non-existent</u> bookerly font, new bookerly font*

199. For example, the Kobo Aura bests the Kindle in a few categories (it has 1 GB RAM and a more even frontlight, but it doesn't display book pages with the finesse that the Paperwhite does.

    - Ability to beat kindle <u>market</u> [in a few categories]. (quality: existing)
      In fact, it is not the kindle that kobo beats. Instead, it is the market of kindle that kobo beats. Therefore, it is regarded as indirect affordance because "beat market" does not directly involve on kindle.

    - Ability to display book pages [with finesse]. (quality: existing)

200. For look-and-feel while in use, the Kindle Paperwhite has always been hard to beat.

    - Ability <u>e-readers</u> to beat kindle <u>market</u> [hardly]. (quality: hardly)

201. For these reasons, I'm going to give back the fourth star to my rating.

- Ability to give back the fourth star. (quality: existing)

202. I read the reviews of Voyage and early 300dpi PW until the occasional manufacturing issue seemed to subside...

   - Ability to read the reviews. (quality: existing)

   - Ability issue to subside. (quality: existing)

   - *Physical property: 300dpi resolution, occasional issue*

203. Then I purchased my PW 3 (I think it is 3rd gen), and it is everything I was hoping more.

   - Ability to purchase PW3. (quality: existing)

   - Ability to hope Kindle. (quality: existing)

204. I already had a PW 2 and loved it.

   - Ability to love kindle. (quality: existing)

205. However my wife's old Kindle DX needed replacement (battery life decreasing), so we decided to replace it with a PW 3.

   - Ability to replace old kindle DX. (quality: existing)

   - Ability life to decrease. (quality: existing)

   - Ability to decide to replace kindle dx with PW3. (quality: existing)

   - *Physical property: decreased battery life*

206. We did not need the tactile page turning or auto dim on the Voyage.

   - Ability to turn page [tactile]. (quality: non-tactile)

   - Ability to dim [automatically]. (quality: non-automatically)

   - *Physical property: tactile page turning, auto dim*

207. Orderin process was smooth, although it would be better if Amazon clearly said PW 3 instead of just 300 DPI (just to be clear on the order form).

   - *Physical property: smooth process*

208. The PW 3 package arrived intact, no damage in or out of the box.

   - Ability 3 to arrive [intact], [no damage in or out of the box]. (quality: existing)

   - *Physical property: intact package, not damaged <u>kindle</u>*

209. New product, not refurb.

   - *Physical property: new product, not refurb <u>product</u>*

210. Turned it on and the setup was straightforward, however we have several Kindles and are used to this.

   - Ability to turn on <u>kindle</u>. (quality: existing)

   - Ability to setup <u>kindle</u> [straightforwardly]. (quality: straightforwardly)

   - Ability to be used to <u>setup</u>. (quality: existing)

   - *Physical property: straightforward setup*

211. I was immediately able to download what I was reading and ... start reading.

   - Ability to download <u>books</u> [immediately]. (quality: immediately)

- Ability to read <u>kindle</u>. (quality: existing)

212. Next I deauthorized the old Kindle DX (will be gifted), and we still have the PW 2 to use, plus various Android Kindle apps still authorized.

- Ability to deauthorize kindle. (quality: existing)

- Ability to use kindle. (quality: existing)

- *Physical property: authorized apps*

213. This process was straightforward, but like I said, we are used to the Manage Kindle page on the main Amazon website.

- Ability to be used to manage kindle page on website. (quality: existing)

- *Physical property: straightforward process*

214. No comment on the need to re-download books.

- Ability to re-download books. (quality: need)

215. Yes that has to be done, however we tend to not keep all of our books on the Kindle at once.

- Ability to keep all of books [at once]. (quality: <u>no-need</u>)

216. When I started reading with the PW 3 I immediately compared it to the PW 2.

- Ability to read <u>books</u>. (quality: existing)

- Ability to compare PW3 [to the PW2] [immediately]. (quality: immediately)

- *Usage condition: when user started reading*

217. Here is what I found... First, the Bookery new font is awesome.

- *Physical property: awesome font, Bookery font, new font*

218. Now, some reviewers have complained that the contrast is less on PW 3 than PW 2.

- Ability to complain the contrast is less. (quality: existing)

- *physical property: less contrast*

219. I believe that is because they were looking at two different fonts.

- Ability to believe. (quality: existing)

- Ability to look [at two different fonts]. (quality: existing)

- *Physical property: different fonts*

220. The contrast on PW 3 is excellent, however the Bookery font is thinner slightly so it looks lighter.

- *Physical property: excellent contrast, slightly thinner font, Bookery font, lighter font <u>appearance</u>*

221. This is a plus a lot, but may be confusing when comparing side to side.

- Ability to read <u>kindle</u> [a lot]. (quality: a lot)

- Ability to feel [confused]. (quality: confused) (polarity: harmful)

- Ability to compare <u>kindles</u> [side by side]. (quality: existing)

- *Usage condition: when comparing side by side*

222. Next the adjustable light.

- Ability to adjust light. (quality: existing)

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- *Physical property: adjustable light*

223. It does seem slightly less strong than the PW 2, however still works great in strong sunlight (and I read in planes above clouds in strong sunlight a lot), no issue there.

    - Ability to work [greatly] [in strong sunlight]. (quality: greatly)

    - Ability to read kindle [in planes] [above clouds] [in strong sunlight] [a lot]. (quality: a lot)

    - *Physical property: slightly less strong light, great working state*

    - *Usage condition: in strong sunlight, in planes, above clouds*

224. Next the consistency of the background light.

    - *Physical property: consistent background light*

225. Some folks have complained about blotches and uneven light.

    - Ability to complain blotches and uneven light. (quality: existing)

    - *Physical property: blotches, uneven light*

226. In the PW 2 at low light levels (e.g. 7) in a dark room, it is possible to see slight unevenness.

    - Ability to see unevenness. (quality: existing)
    This is an affordance of PW2, not PW3

    - *Physical property: uneven light*
    This is a physical property of PW2, not PW3

    - *Usage condition: at low light levels, in a dark room*

227. With the PW 3, I don't even notice that.

    - Ability to notice unevenness. (quality: non-existing)

228. Very consistent.

    - *Physical property: consistent lighting*

229. Some folks have complained about the PW 3 having black kindle logo whereas PW 2 has that logo in silver.

    - Ability to complain the black kindle logo. (quality: existing)

    - *Physical property: black logo*

230. Personally I like the black because then there is absolutely nothing taking away from the immersion reading experience...

    - Ability to like the black. (quality: existing)

    - Ability to take away something [from immersion reading experience]. (quality: non-existing)

    - *Physical property: black logo*

231. In short, we are thrilled with the PW 3 (and PW 2) and would purchase the PW 3 again because of the Bookery font, and the amazing 300 DPI resolution.

    - Ability to feel [thrilled]. (quality: thrilled) (polarity: harmful)

    - Ability to purchase PW3 [again]. (quality: again)

    - *Physical property: Bookery font, amazing resolution, 300 DPI resolution*

232. I can view diagrams and pictures much more clearly than with the PW 2, and consider the purchase to be an excellent decision.

    - Ability to view diagrams and pictures [much more clearly]. (quality: clearly)

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- Ability to consider the purchase [to be an excellent decision]. (quality: existing)

- Ability to purchase <u>kindle</u>. (quality: existing)

233. We hope this helps prospective buyers.

- Ability to help buyers. (quality: existing)

- I've read other reviewers talk about this but it's pretty shocking to see it to read other reviewers talk about <u>dust</u>. (quality: existing)

- Ability to feel [shocked] [to see it]. (quality: shocked)

- Ability to talk [about <u>dust</u>]. (quality: existing)

- Ability to see <u>dust</u>. (quality: existing)

- *Physical property: <u>dust</u>*

234. The 3rd Kindle has already been dropped off at UPS to be returned.

- Ability to drop off kindle [at UPS to return kindle]. (quality: existing)

- Ability to return <u>kindle</u>. (quality: existing)

235. Now Amazon's customer service is incredible and deserves a 5-star rating.

- Ability service deserve a 5-star rating. (quality: existing)

- *Physical property: incredible service*

236. But I am not sure this product is up to par.

237. Kindle is an incredible product and makes reading so much more enjoyable.

- Ability to <u>feel</u> [enjoy]. (quality: enjoy) (polarity: beneficial)

- *Physical property: incredible product*

238. But who wants to stare at the screen when all you can notice is dead pixels, or dark shadows, or unknown particles under the screen.

- Ability to stare [at the screen (quality: existing)

- Ability to notice dead pixels, or dark shadows, or unknown particles [under the screen]. (quality: existing)

- *Physical property: dead pixels, dark shadows, unknown particles*

239. I am not sure if Amazon was trying to make a deadline so this product was prematurely released.

- Ability to release kindle [prematurely]. (quality: prematurely)

240. I've never owned a Kindle so I can't compare it to previous models.

- Ability to compare <u>kindle</u> [to previous models]. (quality: existing)

241. I'd REALLY like to own a Kindle - but I am scared to order a fourth one that's defective again.

- Ability to like [to own a kindle] [really]. (quality: really)

- Ability to feel [scared]. (quality: scared)

- Ability to order a fourth <u>kindle</u>. (quality: existing)

- *Physical property: defective kindle*

242. As easy as Amazon makes the return process, it's still a huge inconvenience.

- Ability to return <u>kindle</u> [easily]. (quality: easily)

- *Physical property: huge inconvenience*

243. I am also losing confidence that a fourth one would have a proper screen brand new product.

- Ability to lose confidence. (quality: existing)

- *Physical property: proper screen, new <u>kindle</u>*

244. This has been incredibly disappointing.

- Ability to feel [disappointed]. (quality: disappointed)

245. The is not a worthy upgrade... Uneven, and even dimmer lighting, no noticeable difference in text clarity or sharpness!

- Ability to upgrade <u>kindle</u> [worthy]. (quality: worthy)

- Ability to notice <u>difference</u> [in text clarity or sharpness]. (quality: existing)

- *Physical property: not worthy upgrade, uneven lighting, dimmer lighting, text clarity, text sharpness.*

246. As a matter of fact, at full brightness, last years version looks brighter and crisper, where the new unit looks dull, with blotchy and uneven lighting!

- *Physical property: <u>old</u> version, new <u>version</u>, dull appearance, blotchy lighting, uneven lighting, not bright appearance, not crisper appearance.*

- *Usage condition: at full brightness*

247. I mean, it's an obvious yellow tint which takes away from the higher resolution.

- *Physical property: yellow tint, higher resolution*

248. This device should literally be called the Kindle Paperbeige or perhaps the Papersepia but definitely not a Paperwhite, because it's nowhere near having a white background.

- Ability to call kindle Paperbeige. (quality: non-existing)

- *Physical property: not white background*

249. The display also has blotches on the lower portion which still haven't been eliminated despite this being the 3rd generation PW.

- Ability to eliminate blotches. (quality: non-existing)

- *Physical property: blotches, display*

250. The text is grey, not black as in the previous PW2 due to the very low levels of contrast.

- *Physical property: grey text, not black text, low contrast*

251. So here we go, let's start off with a 5 star review and then decrease one star based upon abnormalities we find.

- Ability to decrease one star. (quality: existing)

- Ability to find abnormalities. (quality: existing)

252. * Dull beige looking display - Minus one-star

- Ability to minus on star. (quality: existing)

- *Physical property: dull display, beige display.*

253. * Blotches on lower portion of screen and shadows throughout (see pic) - Minus one star

- Ability to minus one star. (quality: existing)

254. * VERY low contrast with washed out grey fonts - Minus one star

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- Ability to minus one star. (quality: existing)

- *Physical property: low contrast, washed out fonts, grey fonts.*

255.* Battery life is less than previous PW2 version - Minus one star

- Ability to minus one star. (quality: existing)

- *Physical property: less battery life*

256.* The resolution is better over the previous version which you can barely notice due to the dull screen - Plus one star

- Ability to notice better resolution. (quality: existing)

- Ability to plus one star. (quality: existing)

- *Physical property: better resolution, dull screen*

257.Total equals 1 star our of a possible 5

258.This is how you properly grade a device.

- Ability to grade <u>kindle</u> [properly]. (quality: properly)

259.Even though I wanted to love this device because I love Amazon, I am not some ego invested fanatic that isn't honest and will simply rate this device 5 stars with all the obvious flaws just because I bought it.

- Ability to love <u>kindle</u>. (quality: existing)

- Ability to love amazon. (quality: existing)

- Ability to simply rate 5 stars. (quality: simply)

- Ability to buy <u>kindle</u>. (quality: existing)

260.I feel like I would be doing a disservice to others by not being completely honest.

- Ability to <u>feel</u> [dishonest]. (quality: dishonest) (polarity: harmful)

261.These are all facts without any bias involved.

- Ability to involve bias. (quality: non-existing)

262.Personally I like the black because then there is absolutely nothing taking away from the immersion reading experience...

- Ability to like the black. (quality: existing)

- Ability to take away something [from immersion reading experience]. (quality: non-existing)

- *Physical property: black <u>logo</u>*

263.In short, we are thrilled with the PW 3 (and PW 2) and would purchase the PW 3 again because of the Bookery font, and the amazing 300 DPI resolution.

- Ability to feel [thrilled]. (quality: thrilled) (polarity: harmful)

- Ability to purchase PW3 [again]. (quality: again)

- *Physical property: Bookery font, amazing resolution, 300 DPI resolution*

264.I can view diagrams and pictures much more clearly than with the PW 2, and consider the purchase to be an excellent decision.

- Ability to view diagrams and pictures [much more clearly]. (quality: clearly)

- Ability to consider the purchase [to be an excellent decision]. (quality: existing)

- Ability to purchase <u>kindle</u>. (quality: existing)

265. We hope this helps prospective buyers.

   - Ability to help buyers. (quality: existing)

   - I've read other reviewers talk about this but it's pretty shocking to see it to read other reviewers talk about <u>dust</u>. (quality: existing)

   - Ability to feel [shocked] [to see it]. (quality: shocked)

   - Ability to talk [about <u>dust</u>]. (quality: existing)

   - Ability to see <u>dust</u>. (quality: existing)

   - *Physical property: <u>dust</u>*

Appendix C: Annotation guidelines

The purpose of the annotation is to detect design-related information from online reviews. Sentences from customer reviews industrial products will be provided to annotator. The task of the annotator is to add metadata to single or multiword terms (i.e. chunks) in online reviews. Figure 1 shows an example of annotation.
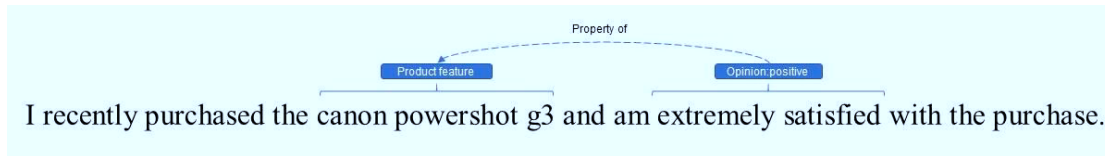
Figure 1 An example of annotation

Two kinds of metatags are used in the annotation:
- Independent tag, like *Product feature*, and
- Dependent tag, like *Opinion:positive*, whose head tag is *product feature*

The tags used in the annotation is shown in table 1. You can find detailed definition and example for each tag in section 1.

Table 1 Tags used in the annotation

	Independent tag	Dependent tag
1	$\langle product\ feature:|other\rangle$	
2	$\langle perceived\ configuration\rangle$	$\langle product\ architecture\rangle \xleftarrow{is\ property\ of} \langle perceived\ configuration\rangle$
3	$\langle action\ word\rangle$	
4	$\langle action\ source\rangle$	$\langle action\ word\rangle \xleftarrow{is\ property\ of} \langle action\ source\rangle$
5	$\langle action\ receiver\rangle$	$\langle action\ word\rangle \xleftarrow{is\ property\ of} \langle action\ receiver\rangle$
6	$\langle perceived\ quality\rangle$	$\langle action\ word\rangle \xleftarrow{is\ property\ of} \langle perceived\ quality\rangle$
7	$\langle usage\ condition\rangle$	$\langle action\ word\rangle \xleftarrow{is\ property\ of} \langle usage\ condition\rangle$
8	$\langle emotional\ word\rangle$	$\langle emotional\ word\rangle \xleftarrow{is\ property\ of} \langle emotion:pos|neg\rangle$
9	$\langle personal\ information\rangle$	

1. Detailed definition and example

1.1 <product feature: |other>

This tag is used to label the name of the product, the component, the attribute or the configuration of the product in the online reviews. Two sub-tags are:
- <product feature>: chunks concerning the product that customer bought, and
- <product feature:other>: chunks concerning the competitive products

Example:

                                                (1)
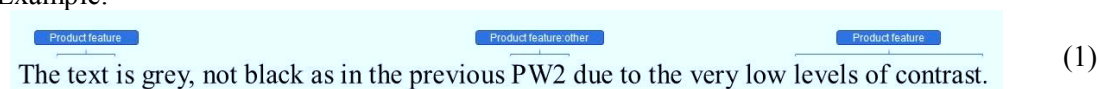
To clarify the meaning the product, component, attribute and configuration, Figure 2 shows the relation between these terms. Component refers to the sub part of the product (e.g. screen of the cell phone). Attribute refers to the characteristic of the component (e.g. resolution of the screen). Configuration refers to the quantitative metric of the attribute (e.g. 300dpi resolution). Component can have hierarchical decomposition. For example, the cell phone in a whole is the starting point of the decomposition, screen is a part of the cell phone, background light is a part of the screen, and so on.
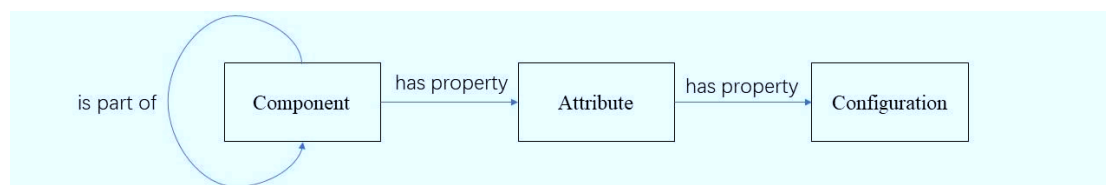
Figure 2 Three level hierarchical model of product feature

Notes:

- The things produced by the product, or the things physically attached to the product where they can be used together are considered as component. For example, "I like the case of Kindle", "the picture printed by this printer is nice", in these sentences, "the case", "the picture" are considered as component of the product.

- The terms further describe the dimension of the attribute are considered as attribute. For example, the words "difference" in the expression "difference of clarity of the screen" and the words "variation" in "variation of the color of the screen". (Example 2)

(2)
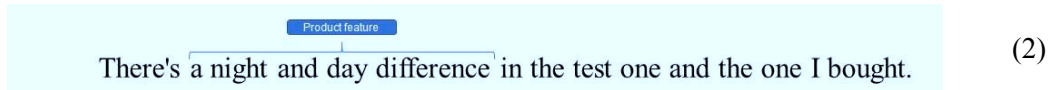
- Not all the product features are described with noun or noun phrases. Linking verbs, like "looks", "feels" in the sentences "The cell phone looks great", "It feels soft", are also labelled with this tag. (Example 3)

(3)
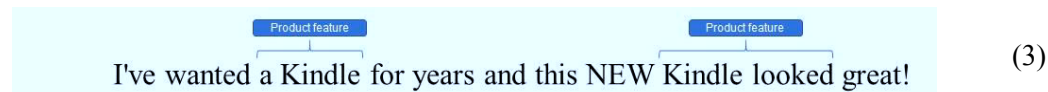
- If two terms should be labelled with <product feature> and they are connected by the preposition "of", then they are labelled within one tag. For example, "screen" and "resolution" in the sentence "The resolution of the screen is high" are labelled together, which is "resolution of the screen".

1.2 <perceived configuration>

This tag is used to label reviewers' perception on the product feature and attached to <product feature>. For example, the word "small" in "small screen".

Notes:

- This tag must be attached to a chunk labelled with <product feature> in the same sentence.

- The perceived configurations are mostly described in adjectives, the adverbs which modify the adjective in the same tag. For example, "extremely high" in the sentence "The resolution of the screen is extremely high".

- Upon last note, not all adjectives are perceived configuration. For example, "internal" in "internal storage" is not labelled with <perceived configuration>. Instead, "internal storage" will be labelled by <product feature> together.

- In case that the reviewers use negation word to describe the perceived configuration, a functional tag <neg> is used to label the negation word. (Example 4)

(4)
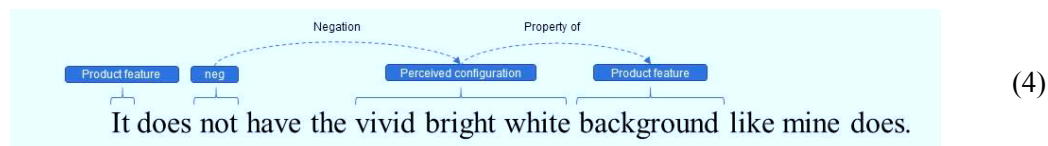
- Upon last note, in case that the reviewer describes that a component does not exist, the negation word is labelled with <perceived configuration>. For example, in the sentence "There is no 3G model", the word "no" is labelled with <perceived configuration>, not <neg>
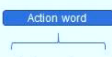
1.3 <action word>

This tag is used to label the action between two systems, where one of the two systems must be the product in discussion. For example, in this sentence, "I read books with Kindle", "read" is labelled with <action word>.

Notes:
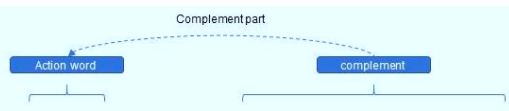
- Not all the action words are verbs. Nouns and adjectives derived from verbs are also labelled with

<action word>. Especially for the adjective with suffix -able or -ible. For example, in these sentences, "transportation of the cell phone", "the yellow tone screen is noticeable", "transportation", "noticeable" are labelled with <action word>. (Example 5)

(5)

- One of the two systems in the action should be the product. For example, in the sentence, "I contact the after sales person", "contact" is not labelled with <action word>, because it does not involve the product.

- Upon last note, verbs like "be", "have" etc., which describe a state, are not labelled by <action word>.

- Upon last note, emotional verbs, like "hope", "want", "feel" etc. are not labelled with this tag.

- In the case that the action word is a verb and has complement part, the complement part is labelled with <complement>. For example, "The vacuum cleaner keeps the room clean", in this sentence, "clean" is labelled as the complement part of action word "keep".

- Upon last note, the <complement> tag is used only when the meaning of the verb changes without the complement part. For example, in this sentence, "I read Kindle to gain knowledge", "to gain knowledge" is not labelled with <complement part>. (Example 6)

(6)

- In the case that the action word is an intransitive verb, and it has an object through a preposition, the intransitive verb and the preposition is labelled with <action word> together. For example, in the sentence, "look at the Kindle", "look at" is labelled with <action word> together.

- In the case that the action word is described with negation, for example, "I do not hear the voice", a functional tag <neg> is used to label the negation, and attach it to the tag <action word> tag.

- Upon last note, in the case that the action word is described with negation like modal verb, like "cannot", "do not need", "must not" etc., the modal verb is labelled with <perceived quality>, the negation is labelled with <neg> and point it to the tag <perceived quality> (see 3.6).

1.4 <action source>

This tag is used to label the source of the action and attached to <action word>.

Notes:

- Usually, the action source is the subject of the action word.

- If the subject is not traceable from the clause, the antecedent of the clause should be considered. For example, in the sentence, "the man who sell the Kindle", "man" is labelled by <action source> and attached to "sell".

- If the action word is in passive mode, the subject of the action word is labelled by <action receiver>. The word after the preposition "by" is highly probable to be the source of the action. For example, in this sentence, "This Kindle is sold by the seller", "seller" is labelled by <action source>.

1.5 <action receiver>

This tag is used to label the receiver of the action and attached to <action word>.

Notes:

- Usually, the action receiver is the object of the action word.

- If the object is not traceable from the clause, the antecedent of the clause should be considered. For example, in the sentence, "the Kindle that I buy", "Kindle" is labelled by <action receiver> and attached to "buy"

- If the action word is in passive mode, the subject of the action word is labelled by this tag.

1.6 <perceived quality>

This tag is used to label reviewers' perception to the action word and attached to <action word>. For example, "quickly" in the sentence "The Kindle is delivered quickly".

Notes:

- If the action word is a verb or an adjective, the adverb of the action word is labelled by this tag.

- If the action word is a noun, the adjective of the action word with this tag. For example, in this sentence, "I threw the ball high", we label "high" with this tag.

- The adverb describes the perceived quality is labelled together with the perceptual word. For example, the word "very" in Example 7.

(7)
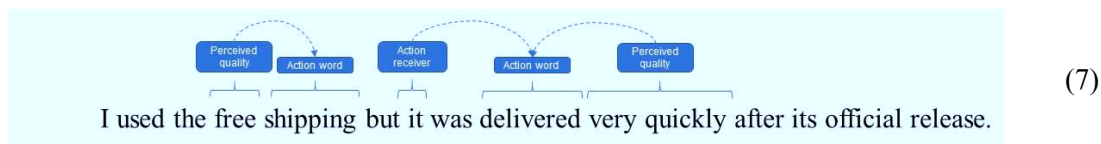
- A tag <neg> is used to label the negation of the perceived quality, including the negation of the modal verb. For example, in this sentence, "I cannot hear the voice", "hear" as labelled by <action word>, and "cannot" is labelled by <perceived quality>. (Example 8 and 9)

- Modal verbs are labelled by this tag, like "need", "have to", etc. For example, "I need to wear my eye glasses because the font is so small", in this sentence, the word "need" is labelled with this tag.

(8)

(9)
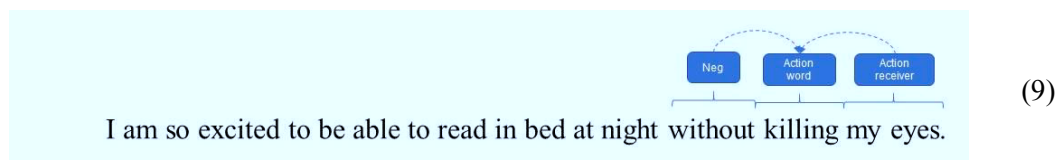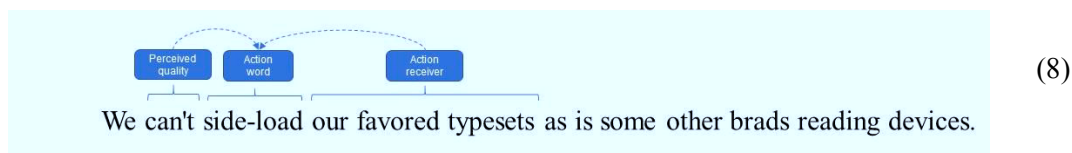
- When the sentence is an interrogative sentence, or describes an assumption, or in subjunctive tone, the perceptual terms are not labelled.

1.7 <usage condition>

This tag is used to label the environment of the in which the action take place. This tag is attached to <action word>. The environment includes physical surroundings and time perspective. For example, duration of the usage, frequency of the usage, weather, location, sound. More specific examples are "in dark at night", "on plane", "three times a day", "when it rains", etc.

Notes:

- Only consider the absolute time. For example, "in the dark", "at night", "on plane". Do not label the relative time. For example, "as soon as I receive it", "when the work is done".

1.8 <emotional word>

This tag is used to label the emotional words in the online reviews. Figure 2 shows a classification of emotions.

Notes:

- Emotion describes the emotional state of the reviewer, not a property of the product. For example, in this sentence, "this nice product makes me happy", the word "nice" is labelled with the tag <perceived configuration>, while the word "happy" is labelled with the tag <emotional word>.

- The wheel of emotions proposed by Plutchik (1994) is used to target the emotional word.
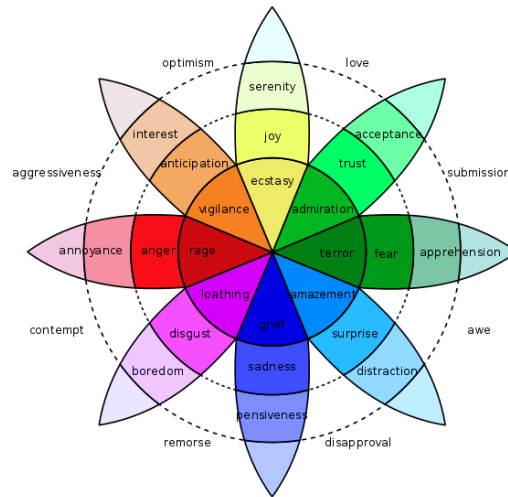
Figure 2 Wheel of emotions (Plutchik, 1994)

1.9 <emotion:pos|neg>

This tag is used to label the polarity of the emotional word in each review sentence. It reflects whether the emotion is beneficial or harmful for customer.

This tag has three sub-tags:
- <emotion|pos> means the positive emotion, and
- <emotion|neg> means the negative emotion.

Notes:

- The polarity of emotion is different from that of perception and satisfaction. Positive emotions are beneficial to the customer, such as desire, love, etc., while negative emotions are harmful to the customer, such as disappointment, sadness, etc. While the polarity is of the perception means whether the quality of the product is good or bad for general users. For example, large battery is generally considered as good quality for a cellphone, small space is generally considered as bad quality for a cellphone. The polarity of the satisfaction means whether the quality of the product fulfills customer's need. For example, small space refrigerator may also be satisfactory for a particular user.

- The categorization of emotions proposed by HUMAIN Emotion Annotation an Representation Language is used to determine the polarity of the emotion[1].

1.10 <users' personal information>

This tag is used to label the words or expressions which infers users' demographic information, such as profession, family situation, etc. For example, "my husband", "informatic profession", etc.

Notes:

- Do not consider users' habit or preference.

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[1] http://emotion-research.net/projects/humaine/earl

Online review analysis: how to get useful information for product improvement and innovation

2. During annotation

The annotation can be done separately in several times or continuously in one time. We suggest doing the annotation of one review continuously without stop.

The annotation can be done using 5 Excel table: product feature, affordance, emotional word, emotion polarity and users' personal information. In the tables, each column stands for a tag. For each sentence, annotators put the relevant words into the corresponding column. Each row stands for an independent tag and its dependent tags.

Keep the following notes in mind:

- the article like "a", "the" is not considered in the annotation if it is in the beginning of the chunk

- the pronouns like "it", "them" are resolved and annotated if it is relevant to an entity. (Example 11)

Product feature

I used the free shipping but it was delivered very quickly after its official release.   (11)

- Do not forget the 2 functional tags <neg> and <complement>

- Do not make deduction. For example, although "I bought the Kindle yesterday" infers that the customer "turn on the computer", "surf the internet", "make payment online", etc. Do not consider these steps if they are not explicitly described in the online reviews.

- The annotation is at the sentence level. Each sentence should be read carefully.

- Product feature of other products are labelled with <product feauture:other>

- Once a product feature is labelled, we look for if there are perceived configurations

- Perceived configurations are mostly adjectives

- The action word describes a behavior between two systems, where one of the systems must be the product.

- The action word describes a physical action, not a state or an emotional action

- Once an action word is labelled, we look for if there are action source, action receiver, perceived quality and usage condition.

- The perceived quality is the adjective modifier or adverb modifier of the action word.

- Whether the <neg> is linked to action word or the perceived quality depends on the modal verb.

- Emotional word describes reviewers' subjective feeling state.

- Emotional word is different from perception and satisfaction. Emotional word describes personal feeling of the reviewer. Perception describes the judgement of the characteristics of the product. While satisfaction describes the preference of the customer.

3. Q&A

Frequent asked questions and answers are listed here.

Q: I do not have any background knowledge of the design engineering. Can I take part in the annotation?

A: No, the annotators should at least understand the general design process to read the annotation guidelines, to understand the meaning of each metatags. The annotators are encouraged to read the reference in the Table 1 to get more familiar with the concepts in design.

Q: Can I stop in the middle of the annotation?

A: Yes, you can stop at anywhere you like. However, we suggest to annotator continuously for one review.

Q: The word "aesthetics" seems refer to the process of seeing the product. Should I consider it as an action word?

A: No, you only consider the literal meaning of the words. The word "aesthetics" describes an attribute of the appearance of the product. Therefore, you only label it with <product feature>

Q: There are many pronouns and coreferences in the sentence. Should I label them?

A: Yes, you need to understand the meaning of the pronouns and coreferences. If they are relevant to the scope of a tag, then label them with this tag.

Q: Some adjectives are used to refer in particular to a component, like the word "internal" in "internal storage". Should I label it with perceived configuration?

A: No, the perceived configurations are adjectives does not mean that all the adjectives are perceived configurations. In the "internal storage" case, the reviewer does not express a perception on the product. While in other case, like "new Kindle", it does means that in reviewer's perception, the model of the Kindle is new. You should label "new" with <perceived configuration>

Q: Are all action words verbs?

A: No, we do not advise annotators to annotate the online reviews based on the language features like part of speech. Action words can also be nouns and adjectives. For example, "transportation", "noticeable", etc.

Q: Are all verbs action words?

A: No, action words describe an action, not a state. Therefore, verbs like "be", "have", etc. are not considered as action words. Besides, emotional verbs like "love", "want", "prefer" are not considered as action words. They are considered as emotional words. Also, the product should be involved in the action. For example, "I call the after sales service", in this sentence, "call the after sales service" does not involve the product "Kindle".

Q: Neither the action source nor action receiver of the verb involves the product, should I consider it as action word?

A: It depends. The product should be involved in the action does not mean that the product should play a role as action source or action receiver. It may also be the supporter of the action. For example, "I read books a lot with Kindle", in this sentence, the action "read books" requires the presence of the Kindle. While " I call the after sales service ", in this sentence, " call the after sales service " does not require the presence of the Kindle.

Q: How to point the functional tag <neg>?

A: It depends on the modal verb. For "does not", the tag <neg> point to the action word. For "cannot" or "do not need", etc., the tag <neg> point to the perceived quality.

Q: For the use's personal information, should I label the product that the user used before?

A: No, the other products are considered in the label of <product feature:other>

Appendix D: Affordances that appeared more than 10 time in the online reviews of Kindle Paperwhite

read book	7504	own kindle	246	get kindle	138
get one	3053	put -PRON-	243	sell -PRON-	135
use -PRON-	2625	leave -PRON-	242	run app	134
make difference	1630	light screen	238	improve experience	133
do job	1551	build device	237	borrow book	132
work kindle	1500	buy kindle	234	sleep husband	132
buy one	1465	show book	229	stick -PRON-	129
find book	1296	navigate paperwhite	226	talk -PRON-	128
see screen	945	appear website	225	respond time	127
know word	940	move book	222	write review	124
turn page	925	ask -PRON-	218	fail -PRON-	121
say that	902	use kindle	216	get paperwhite	120
try kindle	836	buy this	215	cover screen	119
take -PRON-	779	offer discount	210	access book	118
purchase kindle	743	learn word	202	listen both	117
download book	721	arrive replacement	192	get -PRON-	114
charge -PRON-	718	lose place	192	get this	113
give star	567	notice difference	188	hurt eye	111
recommend this	509	switch page	186	suggest paperwhite	109
decide paperwhite	505	tap screen	183	drop -PRON-	108
tell -PRON-	495	update software	178	click button	107
change page	480	sit paperwhite	176	support content	106
return -PRON-	466	understand problem	173	sync book	106
upgrade kindle	422	save money	172	recharge battery	104
pay extra	368	transfer -PRON-	169	delete book	103
call support	336	freeze device	166	remember name	103
compare -PRON-	333	fix problem	163	finish book	102
expect everything	327	highlight word	163	strain eye	102
order one	326	believe -PRON-	162	advertise reader	101
replace kindle	322	buy paperwhite	162	close cover	99
send -PRON-	300	choose paperwhite	160	imagine life	99
help -PRON-	295	remove ad	160	force -PRON-	98
connect -PRON-	288	flip page	159	bring -PRON-	97
add book	273	bother -PRON-	156	operate kindle	97
carry book	268	consider voyage	156	begin tutorial	96
refurbish -PRON-	263	fall reading	156	display ad	96
travel lot	260	load book	155	jump page	96
touch screen	259	play game	155	buy -PRON-	95
adjust size	257	buy book	151	store book	95
miss button	256	search -PRON-	151	check email	94
open book	252	swipe screen	146	press button	93
receive paperwhite	248	register device	143	restart kindle	93
die kindle	247	break kindle	138	increase size	92

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cause problem	91	advance page	59	mind ad	43
handle document	91	convert book	59	charge kindle	42
hit button	91	flash image	59	enlarge font	42
use paperwhite	91	purchase book	59	read kindle	42
provide -PRON-	90	view book	59	crash issue	41
deliver book	87	drain battery	58	price book	41
forget book	87	limit -PRON-	58	read more	41
get book	86	drive -PRON-	57	receive kindle	41
manage content	86	opt opportunity	56	receive this	41
figure update	84	promise -PRON-	56	claim -PRON-	40
create collection	83	stand device	56	exchange paperwhite	40
print label	83	enter password	54	get case	40
read lot	83	purchase one	54	refer -PRON-	40
list book	82	shop store	54	order book	39
follow instruction	81	buy device	53	perform search	39
contact amazon	80	use reader	53	reduce size	39
read -PRON-	80	admit -PRON-	52	troubleshoot kindle	39
reset device	80	develop problem	52	buy reader	38
solve problem	79	disappear model	52	explore device	38
skip page	78	link -PRON-	52	place book	38
trade one	78	plan trip	52	put book	38
use this	77	use app	52	refresh page	38
browse library	76	damage -PRON-	51	relax -PRON-	38
purchase paperwhite	76	debate most	50	report problem	38
refuse few	72	sound gentleman	50	return paperwhite	38
discover feature	71	invest money	49	shin paper	38
explain problem	69	take time	49	slip -PRON-	38
push button	69	buy case	48	test -PRON-	38
select book	68	release product	48	attach light	37
ship -PRON-	67	answer question	47	email -PRON-	37
experience strain	66	watch tv	47	glare screen	37
complain people	65	control brightness	46	recommend kindle	37
waste money	65	justify cost	46	use light	37
meet expectation	63	lay thing	46	address issue	36
note -PRON-	63	post review	46	blink format	36
organize book	63	reboot -PRON-	46	buy product	36
plug kindle	62	type letter	46	change size	36
purchase this	62	avoid light	45	recommend product	36
read review	62	function sensor	45	scratch -PRON-	36
agree exchange	61	protect screen	45	send replacement	36
design kindle	61	sort book	45	treat -PRON-	36
review word	61	attempt step	44	wake -PRON-	36
use device	61	describe issue	44	accept game	35
hear book	60	enable -PRON-	44	activate kindle	35
resolve issue	60	pull trigger	44	encounter problem	35
scroll page	60	age eye	43	illuminate screen	35

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lag way	35	replace -PRON-	31	hide fingerprint	27
pass book	35	see difference	31	make sense	27
recommend paperwhite	35	struggle student	31	order kindle	27
repair unit	35	surf web	31	own paperwhite	27
adjust brightness	34	try paperwhite	31	purchase device	27
assure -PRON-	34	use screen	31	ruin experience	27
buy version	34	complete book	30	slide finger	27
inform -PRON-	34	consume book	30	study book	27
rat -PRON-	34	do reading	30	take care	27
read page	34	frustrate -PRON-	30	warn -PRON-	27
refund money	34	instal battery	30	beware offers	26
research reader	34	order this	30	buy another	26
rest thumb	34	pick one	30	discount book	26
suffer -PRON-	34	purchase reader	30	fade page	26
walk -PRON-	34	read ebook	30	get cover	26
chat time	33	read paperwhite	30	pop fire	26
locate book	33	return item	30	purchase version	26
lock screen	33	send one	30	react way	26
log -PRON-	33	steal kindle	30	recommend device	26
replace one	33	thrill -PRON-	30	rent book	26
wear glass	33	advise -PRON-	29	send kindle	26
apply update	32	darken text	29	take advantage	26
beat book	32	disable function	29	transfer book	26
collect book	32	fly upgrade	29	use feature	26
determine pattern	32	format book	29	use fire	26
dim light	32	pay more	29	adjust light	25
find -PRON-	32	read light	29	archive book	25
get device	32	read time	29	carry -PRON-	25
get replacement	32	recommend -PRON-	29	color light	25
give try	32	return kindle	29	draw eye	25
indicate study	32	throw -PRON-	29	interfere deal	25
order paperwhite	32	express doubt	28	read all	25
read this	32	find way	28	read hour	25
repeat process	32	get reader	28	read novel	25
space all	32	get use	28	read screen	25
unlock device	32	get version	28	retire -PRON-	25
use product	32	give -PRON-	28	return this	25
act case	31	interrupt reading	28	spoil -PRON-	25
charge battery	31	pay 20	28	take hour	25
crack screen	31	read one	28	take kindle	25
make purchase	31	request -PRON-	28	take this	25
pack book	31	surprise -PRON-	28	use nook	25
read much	31	trust -PRON-	28	change -PRON-	24
regard book	31	adapt font	27	disconnect -PRON-	24
render resolution	31	convince -PRON-	27	drop kindle	24
replace paperwhite	31	hand kindle	27	get model	24

give rating	24	appeal	21	register kindle	19
hat fire	24	buy thing	21	rock infant	19
install update	24	charge device	21	solve issue	19
purchase product	24	communicate issue	21	take charge	19
read device	24	fix issue	21	try one	19
read text	24	make switch	21	call service	18
remind -PRON-	24	reflect light	21	fix -PRON-	18
see ad	24	return one	21	get voyage	18
subscribe user	24	send book	21	give shot	18
accomplish that	23	turn device	21	give this	18
blow -PRON-	23	update kindle	21	lose kindle	18
drag -PRON-	23	use hand	21	make kindle	18
immerse -PRON-	23	use version	21	miss keyboard	18
malfunction	23	addict	20	open box	18
maneuver	23	bother husband	20	own one	18
open cover	23	buy model	20	purchase item	18
oppose keyboard	23	change setting	20	read instruction	18
prompt -PRON-	23	contact service	20	receive device	18
receive one	23	defect	20	replace fire	18
send device	23	do reset	20	say -PRON-	18
settle one	23	gift -PRON-	20	send this	18
splurge much	23	give headache	20	turn -PRON-	18
take book	23	give option	20	bring book	17
take minute	23	miss kindle	20	call amazon	17
take second	23	open kindle	20	charge paperwhite	17
buy cover	22	own generation	20	contact support	17
change font	22	purchase -PRON-	20	download app	17
doubt idea	22	read that	20	get message	17
fight -PRON-	22	replace keyboard	20	open -PRON-	17
fix this	22	take plunge	20	own device	17
give chance	22	try -PRON-	20	put kindle	17
give discount	22	turn light	20	read anything	17
give one	22	use backlight	20	read manual	17
give paperwhite	22	bring kindle	19	read paper	17
lug book	22	carry library	19	read something	17
prepare illustration	22	do research	19	remove book	17
produce product	22	find one	19	replace device	17
purchase case	22	get email	19	take chance	17
return device	22	get screen	19	take while	17
swear people	22	lose -PRON-	19	tell difference	17
tempt -PRON-	22	own kindles	19	touch page	17
use book	22	pay attention	19	update review	17
use case	22	read pdf	19	charge life	16
use keyboard	22	read print	19	download one	16
use that	22	receive -PRON-	19	get help	16
zoom page	22	recommend case	19	get tablet	16

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get time	16	get offer	14
give definition	16	give kindle	14
own reader	16	lose one	14
read ebooks	16	make note	14
read material	16	pay price	14
receive replacement	16	recommend one	14
recommend reader	16	return unit	14
register -PRON-	16	use battery	14
say thing	16	use some	14
see book	16	add feature	13
touch word	16	buy voyage	13
use kindles	16	get money	13
bother eye	15	get product	13
buy tablet	15	make product	13
choose one	15	open paperwhite	13
download all	15	receive unit	13
download game	15	remove offer	13
find time	15	restart device	13
get headache	15	return book	13
leave home	15	send email	13
make decision	15	turn button	13
make improvement	15	waste time	13
meet need	15	carry paperwhite	12
offer -PRON-	15	get refund	12
own book	15	highlight passage	12
pay money	15	read everything	12
purchase cover	15	replace model	12
replace amazon	15	send paperwhite	12
replace touch	15	try_out paperwhite	12
see cover	15	use calibre	12
see page	15	use dictionary	12
see -PRON-	15	get all	11
send unit	15	open case	11
show -PRON-	15	read_on book	11
support game	15	say all	11
take note	15	touch side	11
use cover	15	find_out problem	10
use font	15	go_out	10
buy ebook	14	make change	10
buy kindles	14	put case	10
change life	14	read_off kindle	10
contact -PRON-	14	send log	10
find place	14	take try	10
get access	14		
get deal	14		
get definition	14		

Appendix E: Affordances that appeared more than 10 times in the online reviews of Kindle Paperwhite 2

read book	9816	tap screen	234	use app	133
go page	2860	adjust size	225	recharge battery	130
get one	2582	bother -PRON-	219	strain eye	129
use -PRON-	2307	buy -PRON-	216	finish book	126
work kindle	1839	replace kindle	215	use this	124
make purchase	1656	get kindle	214	suppose this	123
do job	1482	receive paperwhite	209	purchase book	120
turn page	1339	come_out kindle	208	save money	120
find book	1271	order book	206	register kindle	119
say that	1205	get -PRON-	205	recommend this	114
know word	1039	notice thing	201	set_up kindle	113
try kindle	988	miss button	200	hurt eye	111
see -PRON-	870	use paperwhite	197	drop -PRON-	109
buy kindle	861	get book	194	sell -PRON-	109
download book	665	believe -PRON-	192	transfer book	104
charge -PRON-	584	turn_off light	186	read more	103
upgrade kindle	526	break kindle	184	use reader	103
purchase paperwhite	521	read lot	183	change size	102
tell -PRON-	491	put -PRON-	180	check email	102
take -PRON-	482	send one	180	use device	101
light screen	446	read -PRON-	179	use light	101
recommend paperwhite	441	choose paperwhite	178	purchase one	98
give star	437	flip page	178	give_up book	97
help -PRON-	396	turn_on light	178	increase size	97
use kindle	390	get this	173	close cover	95
buy one	383	stick -PRON-	173	follow instruction	94
compare -PRON-	380	figure_out -PRON-	170	display book	92
change page	366	borrow book	165	purchase this	92
buy paperwhite	360	show -PRON-	164	support book	91
buy this	354	load book	162	take time	91
connect -PRON-	313	fix problem	160	press button	90
pay extra	294	play game	159	read kindle	89
touch screen	293	swipe screen	157	organize book	88
buy book	285	highlight word	153	get version	86
add book	269	write review	153	store book	86
travel lot	267	jump page	151	recommend product	85
own kindle	259	look_up word	147	skip page	85
return -PRON-	249	offer -PRON-	146	solve problem	85
leave -PRON-	246	open cover	146	ship -PRON-	84
get paperwhite	239	lose place	144	browse web	83
move page	238	update review	138	force -PRON-	82
ask -PRON-	236	read review	137	give try	82
carry book	235	purchase kindle	134	read what	82

buy cover	80	purchase -PRON-	56	take advantage	44
order paperwhite	79	read paperwhite	56	turn_off -PRON-	44
buy product	77	remind -PRON-	56	charge battery	43
drive -PRON-	77	contact amazon	55	get case	43
restart kindle	77	experience problem	55	get fire	43
order one	76	recommend -PRON-	55	make sense	43
put book	76	take_up space	55	pay 20	43
adjust brightness	75	do research	54	read screen	43
meet expectation	75	select word	54	read that	43
read this	75	charge kindle	53	convince -PRON-	42
return paperwhite	75	get replacement	53	enable -PRON-	42
access book	74	replace keyboard	52	get use	42
advance page	74	turn light	52	give one	42
bring -PRON-	74	create collection	51	give -PRON-	42
pick_up -PRON-	74	make -PRON-	51	read ebook	42
use feature	74	read much	51	read page	42
hit button	73	read time	51	take plunge	42
buy reader	72	take paperwhite	51	give rating	41
view book	71	read pdf	50	purchase device	41
receive -PRON-	70	read text	50	turn_down light	41
recommend kindle	70	resolve issue	50	use book	41
send -PRON-	70	try paperwhite	50	buy another	40
buy device	69	waste money	50	carry kindle	40
adjust light	68	watch movie	50	lose kindle	40
find -PRON-	68	blow -PRON-	49	purchase reader	40
get reader	68	carry -PRON-	48	read one	40
receive kindle	67	open book	48	receive one	40
remove ad	67	turn button	48	buy model	39
frustrate -PRON-	66	bother husband	47	miss keyboard	39
reboot kindle	66	check_out book	46	read anything	39
buy version	65	return this	46	return one	39
find way	65	upload book	46	tell difference	39
sort book	65	use product	46	own one	38
push button	64	take book	45	post review	38
use screen	62	take kindle	45	purchase version	38
buy case	61	try -PRON-	45	read novel	38
delete book	61	use button	45	see screen	38
own -PRON-	61	use hand	45	surprise -PRON-	38
place order	61	change font	44	assure -PRON-	37
use keyboard	60	do reading	44	get device	37
crack screen	59	get what	44	get message	37
return kindle	59	give this	44	put_down -PRON-	37
order kindle	58	make difference	44	read device	37
read hour	58	order -PRON-	44	recommend case	37
reset device	58	own paperwhite	44	see paperwhite	37
drain battery	56	recommend device	44	take second	37

touch word	37	turn -PRON-	32	encourage -PRON-	28
charge paperwhite	36	use browser	32	find light	28
get cover	36	browse internet	31	find one	28
make note	36	carry paperwhite	31	get model	28
own kindles	36	change -PRON-	31	get that	28
purchase case	36	fix issue	31	hit screen	28
purchase cover	36	get deal	31	leave page	28
use case	36	get headache	31	make paperwhite	28
give option	35	get screen	31	meet need	28
open box	35	highlight passage	31	own keyboard	28
pay attention	35	lose -PRON-	31	purchase item	28
put paperwhite	35	offer discount	31	purchase that	28
replace amazon	35	open kindle	31	put kindle	28
see book	35	spoil -PRON-	31	read fiction	28
send kindle	35	use cover	31	read paper	28
take care	35	use version	31	receive this	28
take this	35	adjust font	30	return item	28
choose one	34	bring book	30	say thing	28
drop kindle	34	buy what	30	take day	28
open -PRON-	34	carry library	30	use generation	28
order this	34	make product	30	waste time	28
pay more	34	own ipad	30	buy thing	27
read light	34	pay money	30	contact service	27
read print	34	read article	30	do search	27
return book	34	replace device	30	find page	27
send replacement	34	return device	30	find place	27
take note	34	say this	30	get light	27
tempt -PRON-	34	take minute	30	get star	27
turn_off kindle	34	answer question	29	give headache	27
bother eye	33	contact support	29	inform -PRON-	27
bother wife	33	give paperwhite	29	introduce -PRON-	27
change setting	33	make decision	29	leave house	27
give kindle	33	make mistake	29	make kindle	27
look_up definition	33	miss kindle	29	pick_up one	27
see word	33	read magazine	29	show book	27
take while	33	read minute	29	treat -PRON-	27
turn_off wifi	33	read something	29	try this	27
turn_on -PRON-	33	replace one	29	update software	27
use that	33	see ad	29	use option	27
add feature	32	see difference	29	watch video	27
fix this	32	see one	29	buy item	26
lose page	32	surf web	29	charge life	26
make read	32	use battery	29	charge this	26
make switch	32	use function	29	fix -PRON-	26
purchase product	32	charge device	28	get something	26
take hour	32	compare paperwhite	28	make choice	26

notice difference	26	replace book	24	read file	22
read manual	26	reset kindle	24	restart device	22
read material	26	say least	24	say enough	22
read title	26	swipe page	24	see cover	22
receive email	26	take tap	24	see page	22
replace fire	26	turn_off fi	24	see what	22
replace generation	26	use computer	24	try everything	22
resolve problem	26	watch tv	24	turn_off screen	22
return product	26	buy generation	23	use calibre	22
return unit	26	buy nook	23	use kindles	22
turn mode	26	buy something	23	use nook	22
turn paperwhite	26	get life	23	use software	22
use setting	26	get product	23	find kindle	21
use thing	26	give chance	23	get refund	21
use touch	26	give review	23	miss color	21
adjust backlight	25	lose one	23	own touch	21
buy lot	25	make device	23	replace reader	21
buy unit	25	make money	23	see that	21
contact -PRON-	25	miss text	23	sell paperwhite	21
find something	25	own fire	23	send book	21
leave kindle	25	purchase model	23	touch page	21
leave review	25	read couple	23	turn screen	21
make change	25	receive message	23	turn_on kindle	21
own device	25	recommend reader	23	use power	21
own reader	25	remove book	23	add weight	20
purchase another	25	save book	23	change life	20
replace paperwhite	25	see text	23	change mind	20
take one	25	set_up -PRON-	23	close case	20
try one	25	solve issue	23	download ebook	20
turn kindle	25	turn device	23	find that	20
use font	25	use amazon	23	find time	20
use hd	25	use glass	23	get g	20
use wifi	25	adjust lighting	22	get page	20
bother other	24	buy two	22	get time	20
buy warranty	24	buy white	22	miss feature	20
find thing	24	change thing	22	order cover	20
get definition	24	download app	22	read newspaper	20
get hang	24	find device	22	read thing	20
get help	24	find spot	22	receive product	20
read all	24	finish chapter	22	replace battery	20
read chapter	24	get hour	22	sell book	20
read document	24	make collection	22	sell one	20
read glass	24	move book	22	support format	20
read pleasure	24	open case	22	take bit	20
read word	24	order what	22	take chance	20
register device	24	pay price	22	use charger	20

use stylus	20
buy copy	19
change rating	19
make book	19
take device	19
choose book	18
make screen	18
own book	18
pick_up book	18
read day	17
make adjustment	16
buy paper	15
make thing	15
read way	15
download collection	14
get all	13
miss thing	13
try time	13
say all	11
work way	11
say everything	10
use something	10

Appendix F: The results of similar affordance clustering

Cluster name	Affordance
read book	read book see book see screen see page read lot read kindle read paperwhite read one sit paperwhite fall reading read device read more read page read screen read text read print read much do reading read ebook read novel read pdf read ebooks read material read all read paper see text read chapter
receive paperwhite	receive paperwhite get kindle get version get model get paperwhite get voyage receive kindle replace paperwhite send kindle own kindles send paperwhite arrive replacement send replacement receive replacement receive product send unit get device receive unit send device receive device get reader get product get tablet
give star	give star give rating get star
download book	download book add book open book show book move book load book borrow book access book sync book delete book finish book store book deliver book forget book create collection list book browse library select book organize book convert book view book sort book place book put book pass book locate book beat book collect book pack book regard book complete book format book transfer book archive book lug book remove book download ebook access library load pdf send book return book find book
purchase kindle	purchase kindle buy kindles buy kindle buy paperwhite choose paperwhite consider voyage purchase paperwhite buy version order paperwhite order kindle purchase version buy model buy voyage give discount buy reader purchase reader buy ereader buy tablet buy device buy product purchase device purchase product purchase item make purchase
take charge	take charge charge kindle charge device charge paperwhite plug kindle recharge battery drain battery charge battery charge day recharge battery use battery
make difference	make difference make improvement upgrade kindle replace kindle replace fire replace model notice difference see difference tell difference replace device improve experience get replacement make switch make change replace amazon replace generation
do job	do job work kindle die kindle operate kindle use kindle use paperwhite use fire use nook use version use kindles explore device use device use product use reader handle kindle
turn page	turn page change page switch page flip page jump page skip page scroll page advance page refresh page fade page navigate paperwhite find page
know word	know word learn word review word use dictionary study book
hurt eye	hurt eye strain eye age eye bother eye get headache kill eye experience strain experience strain give headache
touch screen	touch screen touch page touch word tap screen swipe screen use touch use touchscreen swipe page slide finger
carry book	carry book take book use book carry library borrow book carry kindle carry paperwhite bring kindle put kindle bring device take kindle bring book
sleep husband	sleep husband sleep wife bother husband bother wife
recommend reader	recommend reader recommend kindle recommend paperwhite recommend device chat time suggest paperwhite recommend case
adjust size	adjust size increase size reduce size change size
light screen	light screen glare screen use screen light screen illuminate screen
click button	click button press button hit button push button turn button hit button own keyboard oppose keyboard type letter touch side tap side
pay extra	pay extra offer discount remove ad justify cost pay 20 pay money pay price remove offer save money waste money invest money beware offers get deal pay more get offer charge 20 display ad save 20
understand problem	understand problem fix problem cause problem solve problem explain problem resolve issue develop problem describe issue crash issue report problem address issue encounter problem doubt idea communicate issue fix issue solve issue troubleshoot kindle find way find problem resolve problem make mistake develop problem ruin experience
avoid light	avoid light attach light dim light adjust light color light reflect light use light use backlight turn light adjust lighting adjust backlight change brightness change light control brightness adjust brightness render resolution change setting
take hour	take hour take minute take time get time find time read time read hour take second take while
price book	price book discount book get book buy book purchase book order book buy ebook splurge much purchase ebook consume book shop store rent book
enlarge font	enlarge font adapt font change font use font adjust font choose font enlarge text zoom page darken text
buy case	buy case get case get cover buy cover purchase case purchase cover
leave home	leave home travel lot plan trip take trip
call support	call support contact amazon contact service call service call amazon contact support get help
try kindle	try kindle try paperwhite take try give shot give try
own paperwhite	own paperwhite own generation own kindle own device own reader own model

return paperwhite	return paperwhite return kindle return unit return item return device exchange paperwhite
use hand	use hand hurt hand rest thumb
miss button	miss button miss keyboard miss kindle
use app	use app download app run app
close cover	close cover open cover see cover open case put case use case use cover
read review	read review write review answer question post review update review
begin tutorial	begin tutorial follow instruction prepare illustration indicate study read instruction read manual
crack screen	crack screen break kindle protect screen protect screen cover screen
figure update	figure update agree exchange apply update fly upgrade install update do update update software update kindle
connect kindle	connect kindle connect paperwhite use wifi
open paperwhite	open paperwhite turn device open kindle
see ad	see ad display ad mind ad
play game	play game download game accept game support game support content
repair unit	repair unit replace battery replace screen replace touch replace keyboard
build device	build device design kindle produce product make product release product advertise reader add feature
register device	register device activate kindle subscribe user register kindle register paperwhite
highlight word	highlight word highlight passage highlight text make highlight
lock screen	lock screen freeze device unlock device enter password
appear website	appear website perform search surf web find information surf internet research reader do research
reset device	reset device restart device restart kindle do reset
drop kindle	drop kindle drop device
get email	get email get message send email send log receive email check email check email
change life	change life meet need
complain people	complain people swear people express doubt
make note	make note take note
steal kindle	steal kindle lose kindle lose paperwhite
hear book	hear book
take care	take care pay attention draw eye
manage content	manage content handle document
refund money	refund money get money get refund
download all	download all download collection
give paperwhite	give paperwhite give kindle
function sensor	function sensor wear glass
rock infant	rock infant
sell book	sell book
watch tv	watch tv
waste time	waste time
open box	open box
hide fingerprint	hide fingerprint
interrupt reading	interrupt reading
proof water	proof water

Titre : L'analyse des commentaires de client : Comment obtenir les informations utiles pour l'innovation et l'amélioration de produit

Mots clés : commentaire de client ; innovation ; ingénierie de conception ; traitement du langage naturel

Résumé : Avec le développement du commerce électronique, les clients ont publié de nombreux commentaires de produit sur Internet. Ces données sont précieuses pour les concepteurs de produit, car les informations concernant les besoins de client sont identifiables. L'objectif de cette étude est de développer une approche d'analyse automatique des commentaires utilisateurs permettant d'obtenir des informations utiles au concepteur pour guider l'amélioration et l'innovation des produits. L'approche proposée contient deux étapes : structuration des données et analyse des données.

Dans la structuration des données, l'auteur propose d'abord une ontologie pour organiser les mots et les expressions concernant les besoins de client décrient dans les commentaires. Ensuite, une méthode de traitement du langage naturelle basée des règles linguistiques est proposé pour structurer automatiquement les textes de commentaires dans l'ontologie proposée.

Dans l'analyse des données, deux méthodes sont proposées pour obtenir des idées d'innovation et des visions sur le changement de préférence d'utilisateur avec le temps. Dans ces deux méthodes, les modèles et les méthodes traditionnelles comme affordance-base design, l'analyse conjointe, et le Kano model sont étudié et appliqué d'une façon innovante.

Pour évaluer la praticabilité de l'approche proposée dans la réalité, les commentaires de client de liseuse numérique Kindle sont analysés. Des pistes d'innovation et des stratégies pour améliorer le produit sont identifiés et construites.

Title: Online review analysis: How to get useful information for innovating and improving products?

Keywords: online reviews, innovation, design engineering, natural language processing

Abstract: With the development of e-commerce, consumers have posted large number of online reviews on the internet. These user-generated data are valuable for product designers, as information concerning user requirements and preference can be identified.

The objective of this study is to develop an approach to guide product design by analyzing automatically online reviews. The proposed approach consists of two steps: data structuration and data analytics.

In data structuration, the author firstly proposes an ontological model to organize the words and expressions concerning user requirements in review text. Then, a rule-based natural language processing method is proposed to automatically structure review text into the propose ontology.

In data analytics, two methods are proposed based on the structured review data to provide designers ideas on innovation and to draw insights on the changes of user preference over time. In these two methods, traditional affordance-based design, conjoint analysis, the Kano model are studied and innovatively applied in the context of big data.

To evaluate the practicability of the proposed approach, the online reviews of Kindle e-readers are downloaded and analyzed, based on which the innovation path and the strategies for product improvement are identified and constructed.