SUSTAINABLE LIGHTING PRODUCT DEVELOPMENT UNDERPINNED BY ONLINE DATA MINING AND LIFE CYCLE ASSESSMENT

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A thesis submitted in partial fulfilment of the requirements of Nottingham Trent University for the degree of Doctor of Philosophy

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Copyright Statement

Abstract

The accurate acquisition of customer requirement information is an important part in product planning and positioning, it plays a decisive role in the success of products in the market. the rapid development of e-commerce makes increasing more consumers shopping online and a big volume of customer reviews are posted on different Websites. The online reviews contain valuable opinions of customers, enabling designers to understand their concerns. In this research, an integrated approach has been developed to mine customer requirements according to the online reviews collected from e-commerce sites to form product design specifications. The main research contents include the following aspects: (1) development of useful online review prediction and classification approach; (2) online review implicit product features and sentiment analysis based on the constructed feature and sentiment lexicon; (3) built a knowledge base containing customer requirements mined from online reviews; (4) conduct a dedicated environmental and social LCA on the proposed domestic lighting product by using a professional LCA software.

In this study, multiple models and technologies/methods have been successfully implemented: review helpfulness classification model has been constructed based on the training set and test set by tuning and optimizing; proposes a new approach to implicit feature and sentiment analysis, based on explicit formal feature-emotion sentences, implicit feature sentences and implicit sentiment sentences, combined with a feature lexicon, a 1V1/1Vn sentiment-feature rule base and the feature-emotion word pairs are extracted; based on the preliminary analysis results of feature extraction and sentiment analysis, combined with KANO model to establish user requirement mining rules, and consider satisfaction, propose the user demand priority to obtain the final list of user requirements; a real industrial context with lighting product manufacturer (ONA) in Spain has involved with the lighting product life cycle analysis and development for new product. The analytical results of these studies present an in-depth modelling and analysis on the sustainable lighting product lifecycle with the aid of real manufacturing data.

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Publication List

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Daizhong Su, You Wu and Zijian Chai, ‘Advanced Integrated Manufacture by Application of Sustainable Technology through Product Lifecycle: a Circular Economy Approach’. Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing, 17 – 19 October, 2019. Dublin, Ireland. ISBN: 978-1-4503-7202-2. Published by ACM New York. Article No. 29, pages 1-4, Doi 10.1145/3358331.3358360

Zijian Chai, Wenjie Peng and You Wu, Deliverable 3.3 ‘Development of the model for online mining consumer views for eco-products’, 28 December 2018. EU Horizon 2020 CIRC4Life project

Zijian Chai and You Wu, ‘Overview of the Co-Creation Approach by Using Data Mining Technologies’, in Deliverable 1.4 ‘Interaction in supply chain concerning consumers’, 24 April 2020. EU Horizon 2020 CIRC4Life project.

Zijian Chai, ‘Data Analysis for ALIA’s Survey dataset’, Technical Report, 10 March 2021. EU Horizon 2020 CIRC4Life project.

Zijian Chai, ‘Data analysis of ONA online reviews’, Technical Report, 15 May 2020. EU Horizon 2020 CIRC4Life project.

Table of Contents

List of Abbreviations

LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
EoL	End of Life
SIA	Social Impact Assessment
SLCA	Social life cycle assessment
CEMS	Certification in environmental management systems
SEIA	Socio-Economic Impact Assessment
SROI	Social Return on Investment
SEIA	Socio Economic Impact Assessment
PDS	Product Design Specification
ISO	International Standards Organization
SM	Sustainable Manufacturing
BoM	Bill of Materials
CAD	Computer Aid Design
LED	Light-Emitting Diode
DC	Design Concept
AHP	Analytical Hierarchy Process
IR	Information Retrieval
MAE	Mean Absolute Error
MAP	Mean Average Precision
MFS	Maximal Frequent Sequences
MLP	Multilayer Perceptron

API	Application Programming Interface
PMCC	Pearson product Moment Correlation Coefficient
POS	Part of Speech
RMSE	Root Mean Squared Error
SVM	Support Vector Machines
TF-IDF	Term Frequency - Inverse Document Frequency
UGC	User Generated Contents

Chapter 1: Introduction

1.1 Background

Sustainable development has become a significant research area these days (Zhen et al., 2015), of which sustainable product design places an important role because 80% of product's sustainability is determined at the design stage (EU Science Hub, 2022). It emphasizes the balance between human and the environment with consideration of environmental benefits, reflecting in all aspects of the design process. The core of sustainable design is "3R", namely Reduce, Recycle and Reuse. It aims to make maximum use of materials and energy, strive to reduce their consumption and waste, reduce the emission of harmful substances in the process of manufacturing or use, and design products in accordance with the principles of renewability or reusability.

The increasing demands of infrastructures in terms of energy consumption, raw material demand, greenhouse gas emissions, waste management, treatment of components after their lifetime period, and financial costs are nowadays a serious threat for sustainability. Governments of many countries, such as Indonesia, China, and India, are actively focusing on modernizing their infrastructure, thus pushing up the requirement for LED lighting. Additionally, governments of the U.A.E., India, Austria, China, Spain, and Singapore are making huge investments in smart city projects, which is also propelling the advance of the LED lighting market. From "LED Lighting Market Research Report - Global Industry Latest Trends and Growth Forecast to 2030", it states that the global LED lighting market 2020 size stood at $55,201.9 million, and it is expected to reach $152,442.3 million by 2030, demonstrating a CAGR of 10.7% from 2020 to 2030 (Research and Markets, 2021).

The accurate acquisition of customer requirement information is an important part in product planning and positioning, it plays a decisive role in the success of products in the market. Traditionally, customer requirements are obtained from questionnaires, call centres or customer services. After digesting all these data, designers conceive to improve their products. But it is usually time-consuming and labour-intensive to gain these data and conduct the analysis manually.

With the fast development of e-commerce makes more consumers prefer go online-shopping and a big volume of customer reviews about the products are posted in different websites. These online reviews enrich valuable customer requirements, which benefit designers in understandings consumers' concerns. Opinion mining is a field involving natural language process (NLP) to analyze people’s sentiments and opinions from the texts written in natural language. It is one of the most active research areas in NLP and is widely studied in information mining (Pang and Lee 2008). Customer reviews are the texts written in natural language. Nowadays, with the rapid development of Internet technology and e-commerce in the past decade, a mass of online customer reviews has emerged. These reviews provide relatively trustable, continuously updated and free customers’ responses which involve customers’ sincere emotions and opinions. Consumers always consult others’ opinions and experiences via online customer reviews (Lin et al. 2012). Figure 1.1 depicts an example of an online customer review for a table lamp. This consumer gives this lamp a 5-star rating, as evidenced by the graph. Many different aspects of lamps are mentioned, as well as positive feelings about various product features. "120 people found this helpful" after reading this review. This online review provides useful information about customer preferences and concerns, and it has the potential to assist table lamp designer improving their product


Perfect

Reviewed in the United Kingdom on 29 December 2019

My little boy LOVES this! He wanted a lamp for his desk which is only small so I bought him this one. It fits perfectly and is bright enough to 'work' by (he's 6). It's then little enough that he also takes it to bed and on the dimmer setting reads before he goes to sleep.
It is also slim and bendy and with a couple of loo-roll tubes can make a pretty convincing alien to scare your mum with when she's coming up the stairs. Just in case you wanted it for this purpose

Read more

120 people found this helpful

Figure 1.1 A sample of online customer review

This study strives to build up an E-commerce customer comment data classification/categorization framework integrated with LCA which rely on the customer requirement attributes and environmental impact assessment to cover the following perspectives:

1) In sustainable area of lighting design, the conversation is centered on power consumption and embracing LED technology as the way forward, but this conversation is not always inclusive of customer requirements considerations. However, lighting has a greater environmental impact than simply power consumption, including manufacturing processes, the lifespan of equipment, ability to perform maintenance and even the behaviour of individuals.
2) In customer-driven product design aera, the research mainly focusses on the methods of mining customer requirements to create customer-preferred design in a short time to improve the customer loyalty. However, the sustainability of the product is less considered, which it also plays a key role in product design.
3) This study proposes the idea of developing the customer-oriented and sustainable lighting product as a bundle, facilitating the links between product sustainability development and customer requirements with the consideration throughout the whole product life cycle.

This study is a part of CIRC4Life project (CIRC4Life, 2021) which is a large-scale collaborative project that aims to promote a novel circular economy approach to the life cycles of products and services and is supported by the European Commission's H2020 Circular Economy program. Ona Product SL is a Spanish SME manufacturer of lighting products that specializes in domestic and contract lighting for hotels, leisure-related premises, offices, and public places (https://ona.es/). As an industrial partner of the CIRC4Life project, Ona demonstrated eco-design, sustainable production and eco-shopping for domestic LED lighting products using the methods developed by the project. Ona lighting products are utilized in the research reported in this paper.

1.2 Research aim and objectives

The aim of this research is to develop and implement a novel intelligent system to mine customer requirements from online reviews and to facilitate sustainable product design which contributes to the understanding of how to design, manufacture lighting products that meet customer requirements and with low environmental impact.

In order to achieve the aim, the research had accomplished the following objectives: the first objective of this research is to build a collection of helpful online reviews. The key question here is which online review is helpful. Several aspects of online customer reviews that are regarded by product designers regarding as helpful will be investigated in this research. These aspects will be utilized to predict the helpfulness of online reviews in the viewpoint of product designers. Also, whether the helpfulness of online reviews, as a concept being perceived by product designers in one domain, is able to be transferred to other domains will be examined.

The second objective of this research is to recommend rating values on online reviews with consideration of designers' assessments. The reasons why some reviews receive a divergence in judging the helpfulness will be investigated in this research. These reasons, together with several aspects of customer reviews that are regarded by designers as helpful, will facilitate this research to build a method for recommending rating values on online reviews from different product designers.

The third objective of this research is to connect customer reviews with product engineering characteristics. The statistical information about various words in online reviews as well as their complex relationships with product design specifications will be examined. Accordingly, a linguistic approach for connecting online reviews with product engineering characteristics automatically will be derived for product designers to ease them from analyzing all user generated contents (UGC) sentence by sentence.

The fourth objective of this research is to prioritize product design specifications based on customer online reviews for improving the current product model. The customer sentiments of different product specifications as well as the overall customer satisfaction will be extracted from online reviews. Based on this, a method to prioritize product design specifications will be developed.

The Fifth objective of this research is to conduct a comprehensive LCA analysis to identify the root of the negative environmental performance through the lighting product in order to define the different life cycle scenarios for the designed lamp, as a comprehensive LCA requires to consider three scenarios: cradle-to-grave; cradle-to-gate; cradle-to-cradle. As the analysis of each scenario will highlight the negative components/materials in the specific stage, which will be helpful for the manufacturer to develop the targeted optimal solutions.

Overall, the objectives of this research are:

- to build a collection of helpful online reviews.
- to recommend rating values on online reviews by taking designers' personal assessments into consideration.
- to connect customer reviews with product design specifications.
- to prioritize product design specifications based on online customer reviews for improving the current product model.
- to conduct a comprehensive LCA analysis to identify the root of the negative environmental performance through the LED lighting produced.
- to use the proposed approach in the development of a novel sustainable lighting product.

- to conduct a detailed Social LCA for the LED lighting manufacturing company.

These objectives form a guideline for this research.

1.3 Structure of the thesis

This thesis is structured with eight chapters (Figure 1.3): 1) Introduction, 2) Literature review, 3) Research methodology, 4) Identify design-centered online reviews, 5) Design-centered knowledge base development, 6) Environmental life cycle assessment, 7) Social life cycle assessment, 8) Conclusions.

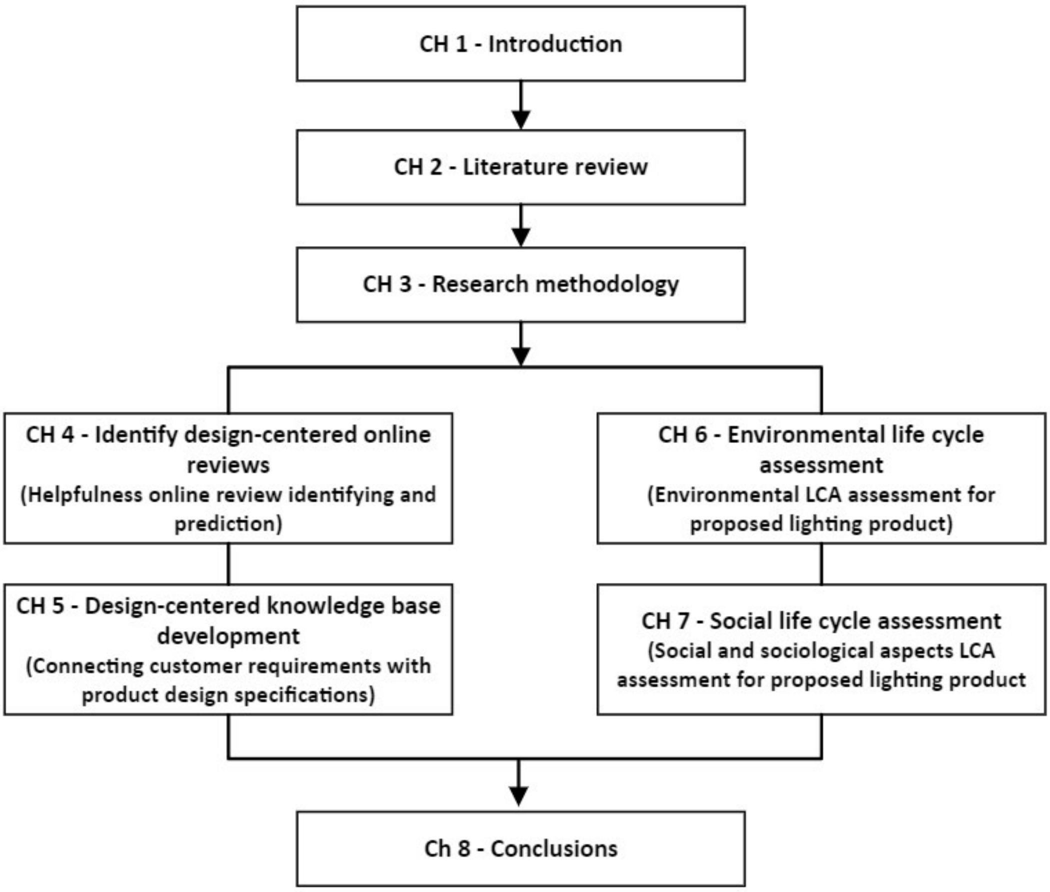


Figure 1.2 Structure of the thesis

In chapter 1, it mainly expounds the research background, research motivations, research purpose and research purpose of this paper. An overview of the structure of this paper has been presented.

In chapter 2, it introduces a large amount of literature, introduces the relationship between quality assessment, recommender systems, customer needs and design quality; conducts research on product design specifications and product life cycle evaluation. Opinion mining and QFD are the basis of this study. Recent developments in both fields are reviewed.

In Chapter 3, it expounds the research methodology and the framework of this thesis. This intelligent system focuses on the identification of online reviews of design preferences and the development of a design-oriented knowledge base from online reviews. Through the experiment, it is possible to understand from the point of view of the product designer how to test the online evaluation in the customer reviews.

In Chapter 4, it focuses on the development of mining useful online reviews. Two questions were investigated. First, four features are extracted from the evaluation articles to evaluate the viewpoints of product designers. Secondly, from the perspective of overall evaluation and individual evaluation, the scoring standard of online review scoring is proposed. A classification method that combines two different perspectives. Finally, the effects of the two proposals are verified.

In Chapter 5, it aims to build a design-oriented knowledge base from online reviews. First, a linguistic method for combining customer evaluations with product design specifications is presented. Two language patterns are derived from this: Unigram pattern and Bigram pattern. Additionally, we propose a pairing-based approach that enables it to better improve existing product patterns. Finally, this paper presents an integer nonlinear programming optimization model based on sorting and ranking and the performance of the algorithm has been tests.

In Chapter 6, a detailed environmental LCA for the designed LED table lamp has been conducted. The LCA methodology and the scope of the study, the inventory data used and the assumptions, the LCIA results of the proposed LED lighting product by ONA company, and conclusions and recommendation are reported.

In Chapter 7, a comprehensive social life cycle assessment for the ONA lighting company in Spain is studied, using existing and new innovative methods of social impact analysis. These results represent a reference scenario for the future assessment of innovation solutions.

In Chapter 8, the achievements and contribution to knowledge of this research are provided. Finally, the conclusion and some prospects for future work are suggested.

Chapter 2: Literature Review

2.1 Introduction

The first chapter is the four main themes of this paper. This chapter reviews the relevant literature and knowledge.

This chapter is structured like this. Section 2.2 focuses on opinion discovery and quality issues. It also studies how to apply online reviews to product design. From Section 2.3 onwards, we present several related but differentiated studies, including: evaluation of written document quality, development of recommender systems, relationship between customer needs and design specifications, and engineering features of products. Finally, the article makes a summary in Section 2.9 to differentiate it from previous studies.

2.2 Opinion mining and quality function deployment

2.2.1 Opinion mining

There are three main types of opinion mining by scholars in the past: emotion recognition, emotion extraction, and opinion extraction.

2.2.1.1 Sentiment analysis

Technically, emotion recognition consists of various seed tasks, such as determining subjective and objective opinions, positive, negative, neutral, and emotional intensity. Generally, such literary works can be divided into word level, feature level, sentence level and document level.

- **Word level**

The purpose of word-level emotion recognition is to determine the emotional polarity of words. The goal is to use the similarity of vocabulary and dictionary augmentation in a dictionary or corpus. In this strategy, part-of-speech tags, synonyms and antonyms are used in WordNet (see Figure 2.1).

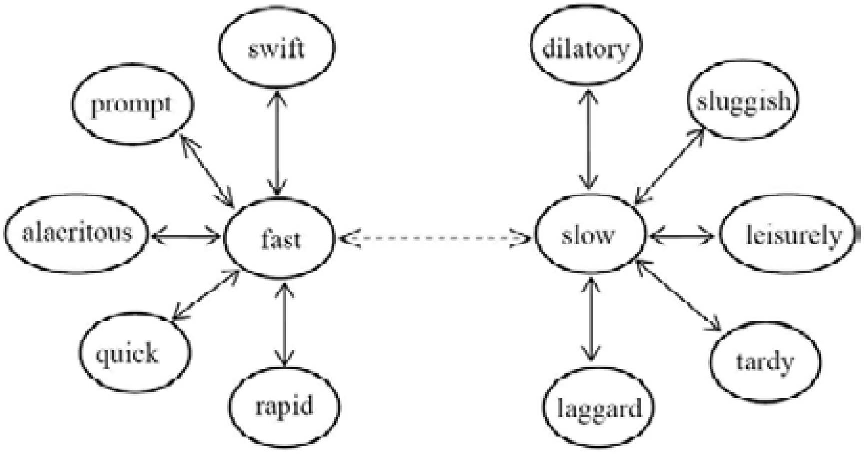


Figure 2.1 WordNet's bipolar adjective structure (Minqing and Bing, 2004)

Fundamental concepts are adjectives that identify nouns and their closest assumptions are opinion-only. In a follow-up study, other protocols were compared using the same technique. Figure 2.2 is a graphical comparison of the two product views (Bing et al., 2005).

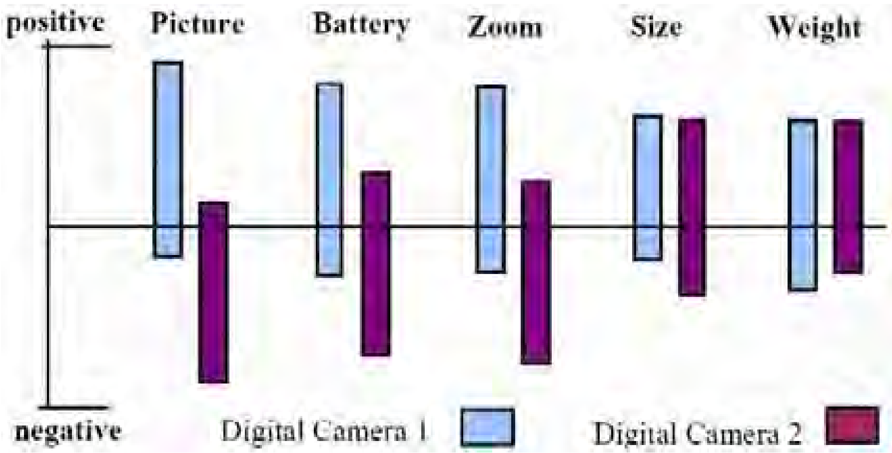


Figure 2.2 A visual comparison of opinions on two products (Bing et al., 2005)

Similarly, the random walk method (Ahmed and Dragomir, 2010) and the shortest path method (Jaap et al., 2004) were used to judge the similarity of terms in WordNet. In these techniques, the sentiment of opinion words is determined by their similarity to the trained words. These training terms have artificially assigned emotions. Ding them. (Xiaowen et al., 2008) propose a comprehensive dictionary-based approach that uses extrinsic evidence and linguistic norms to examine people's attitudes. This approach is further studied in their entity discovery and entity distribution (Xiaowen et al., 2009).

Compared to dictionary techniques, alternative corpora also have applications in emotion recognition. It has been found that web documents contain interactions between words and phrases (Peter, 2002), as well as domain-specific sentiment dictionaries (Weifu et al., 2010). This paper also introduces a vocabulary learning framework based on Hidden Markov Patterns (Wei and Hung, 2009).

- **Sentence level**

At present, many different emotion recognition techniques have been proposed, such as corpus-based, dictionary-based, and combination.

Pang uses SVM, naive Bayes, maximum entropy method (Pang et al. 2002) and other methods to classify emotions. The classification methods (Unigram, Bigram) for different text attributes are compared. At the sentence level, sentiment classification is also seen as a sequential labeling challenge (Jun et al. 2008). Using the original set of markers and additional hidden markers, a conditional random field (CRF) model was applied to construct the hierarchy. This method evaluates the emotional connection between the two sentences before and after.

In contrast to corpus-based methods, unsupervised sentiment classification employs a dictionary-based approach (Taraz, John, 2008). By detecting the sentiment of sentences and expanding the sentiment dictionary, an iterative training method is proposed to improve the classification accuracy.

This paper proposes a dictionary-based and corpus-based two-stage hybrid learning strategy (Likun et al., 2009). In the beginning, annotations were categorized by sentiment dictionaries. The second step is to build a supervised classifier using a large amount of training data. These training materials contain initial classification and annotations for classification using corpus-based techniques. In addition, a method for combining lexical information with domain corpora of expertise is published.

Additionally, the model is built using data from WordNet and a labelled corpus (Tao et al, 2009).

All classification methods classify the sentiment of a sentence or word as positive, negative or neutral.

- **Document level**

The sentiment analysis at document level of text can be evaluated from two aspects: the role of a phrase and an individual topic.

Pang et al. (2004) employed a graph-based technique to exclude objective clauses. Secondly, this paper uses subjective phrases to analyze the emotional polarity of the article. McDonald proposed a structural pattern that can recognize emotions at different levels, including sentence, paragraph, and document levels (Ryan et al., 2007). Emotion recognition is a sequence classification problem with certain reasoning ability. Finally, the problem is solved using the finite Viterbi algorithm.

Lin three people. (2009) proposed that document-level sentiment is topic or domain dependent (Lin et al., 2009). This paper presents a probabilistic model (LDA) based on the possible Dirichlet assignment method. At the document level, topics and emotional relationships are identified to determine sentiment. At the same time, the HMM-based model can judge the sentiment of the article from the perspective of the research object (Qiaozhu et al., 2007).

Other emotion recognition methods include cross-language and cross-domain emotion classification.

- **Cross-lingual sentiment categorization**

At present, some scholars believe that, to a certain extent, the lack of emotion corpus has become an obstacle restricting the development of emotion classification research. However, the existence of English corpus allows researchers to use sentiment classification between different languages to conduct research in this area.

A Chinese researcher first classifier was trained with English annotations. The second classification method is to train English annotations through web translation providers and Chinese translations.(Wan, 2009) Finally, combined with training techniques, the parameters of the two classification methods are learned. Finally, a single classification system is built by combining the results obtained from the two sentiment classification methods. Initially, unmarked Chinese annotations were converted into English during the exam. Finally, we will use the final sentiment classification system to judge whether these reviews are good or bad.

- **Cross-domain sentiment classification**

Sentiment classifiers trained in one domain cannot be used in others due to terminology mismatch. Therefore, to overcome regional dependence, cross-domain sentiment classification is required. At present, the classification of cross-domain sentiment is mainly carried out from two aspects: case and feature.

Initially, in this technique, a collection of pivot characteristics that exist in both domains was selected. The relationships between pivot features and other characteristics were subsequently taught using unlabeled data from both domains. Employing domain-independent terms to align domain-specific words (Sinno et al., 2010) and using common subjects with distinct words in various domains as the bridge to connect the domain-specific features were also applied in the cross-domain sentiment classification from the feature perspective (Kang and Jun, 2009).

2.2.1.2 Sentiment identification

Customer reviews tend to focus on product features. In customer evaluations, words and phrases are commonly used.

Hu and Liu used association mining techniques to generate some common nouns and noun phrases (Hu, Liu, 2004). These words or noun phrases are considered potential product characteristics. Next, nouns and noun phrases with impossible properties are removed using a clipping algorithm. Once again, we can observe some heuristic language rules to identify words or phrases that conform to the form of the rules, as features of the product (Bing et al., 2005). A direction was developed that utilizes slack markers to identify product characteristics and lexical meanings (Ana-Maris and Oren, 2005). In addition, this paper also uses the relationship between emotional words and product characteristics to iteratively extract emotional words and product characteristics (Guang et al. 2009). In addition, product feature extraction was performed using semi-supervised techniques (Jingbo et al., 2009) and supervised methods (Fang et al., 2010).

There are also limited studies that can help gather opinions.

2.2.1.3 Opinion extraction

Opinion search is a process of finding documents containing opinions about an inquiry (Wei et al., 2008).

This model can solve the problems of topic relevance score, sentiment word query irrelevant expansion, sentiment word query dependent expansion and so on. Representation word-based models fail to capture the connection between an opinion and its related targets (Binyang et al., 2010). This paper presents a unified graphical model for sentence-based opinion retrieval.
The fourth chapter uses text-level sentiment detection algorithms to extract online comments. These features are used to predict the validity of online reviews and give their ratings.

Quality function deployment (QFD)

One of the purposes of this paper is to analyze design preferences from the designer's point of view, and to build a knowledge base of users' needs through network evaluation. Therefore, the literature review described in this paper covers only the first few stages. This section will introduce several major research reports to determine the needs of customers and their weight. The work being done so far can help generate product design specifications and weights, and illustrate how customer needs relate to product design specifications.

It is easiest to rank customer needs with a numerical scale (Abbie and John, 1993). However, this procedure requires a lot of human interpretation. This paper proposes a method to compare and calculate the relative weights of customer needs using combinatorial analysis techniques (Anders and N, 1994). Meanwhile, we also propose a linear-based local classification strategy to evaluate customer quality (Chang et al. 2004).

In order to adapt to the rapidly changing consumer needs, grey theory and QFD must be organically combined (Wu et al. 2005). The Markov chain model is also used in QFD to timely update technical measures to adapt to rapidly changing customer needs (Hsin and Jiunn, 2006). To better understand consumer behavior, Chen and Ip say that many factors have been overlooked in past research that can influence purchasing power and value (Chan and Ip, 2011). Develop a decision support system to predict customer shopping behavior and estimate customer net worth.

In addition, the AHP method is used to rank customer requirements. AHP was originally designed for resource allocation and planning (Thomas, 1980).

In terms of product design, this paper proposes a design idea based on multiple components. Customer needs are often derived from survey data, expressed in simple language, and included in a large number of components according to the relevance of these data. On this basis, the AHP method is used to sort different types of user needs and apply them to the design of new products.

Feng them. Use QFD, AHP, Fuzzy, Fuzzy, Fung et al., 1998) to classify inaccurate customer needs. Chuang combined AHP with QFD and carried out on-site planning under certain circumstances (Chuang, 2001). According to the candidate sites, the best site selection scheme is given. In addition, it is believed that a QFD framework focusing on customer needs will enhance the design and production process of industrial dwellings (Robert et al, 1994).

The Kano model in Figure 2.3 is designed to understand customer needs and their role in customer happiness (Kurt and Hans, 1998).

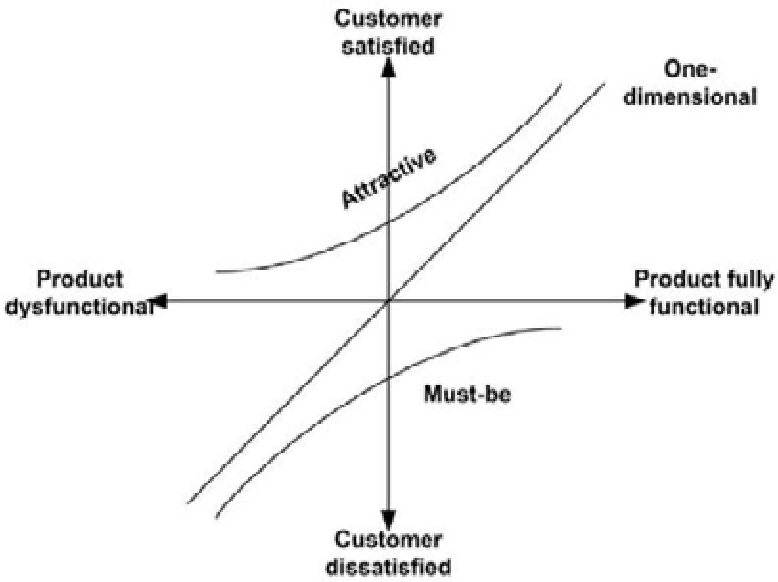


Figure 2.3 The Kano's Model diagram

Combining sentiment analysis with Kano patterns, including associating sentiment data with the four Kano pattern categories. Different user needs can be obtained through the relationship between the four needs and emotional values in the Kano model. slaughter them. Comprehensive text mining technology extracts subjective sentences from reviews, develops domain ontology, and realizes attribute-sentiment word pair retrieval with the help of grammatical analysis (Tu et al. 2015). Yang, and some others. According to the granularity of reviews and the position of reviewers in the community, an indexing method for user analysis is established (Yang et al. 2018). Using the K-means clustering method, four clusters were obtained using the K-means clustering method, and the relationship between the four clusters and Kano was obtained through the Kano model and the Kano model. The results show that when the two index values are high, it is the basic requirement , when the values of the two indicators are very low, there is no difference requirement; when the values of the two indicators are very low, there will be two expected requirements. However, previous studies did not take the sentiment analysis results into consideration when mining user needs in the KAMO mode. gold them. Through the analysis of online reviews, it is combined with conjoint analysis to obtain the classification and prioritization of users' needs (Jin et al. 2016). However, they ignored suggestive traits and suggestive emotional phrases.

Online reviews for product design

Although internet evaluations are widely acknowledged as a significant tool for gauging customer mood, experts in the design field are only beginning to take notice. Various text mining tools are used to extract useful information from online product reviews for the purpose of product design.

Analysing the subject structure of online reviews using an automated summarising method was observed (Jiaming et al., 2009). This method was used to identify and compile significant themes from internet reviews. Figure 2.4 illustrates an example of a review summary.

Cluster 1 (4 reviews)

Sound - excellent polyphonic ringing tones are very nice (check cons) it also doubles as a radio, which is a nice feature when you are bored.

Cons: ring tones only come with crazy songs and annoying rings, there is only one ring that sounds close to a regular ring.

...

Cluster 2 (3 reviews)

Nice and small and excellent when it comes to downloading games, graphics and ringtones from www.crazycellphone.com I thought this was the ultimate phone when it comes to basic features, but I was disappointed when I saw that it was only a gsm comaptible phone.

...

Cluster 3 (17 reviews)

I've had an assortment of cell phones over the years (motorola, sony ericsson, nokia etc.) and in my opinion, nokia has the best menus and promps hands down.

No other color phone has the combination of features that the 6610 offers.

From the speakerphone that can be used up to 15 feet away with clarity, to the downloadable poly-graphic megatones that adds a personal touch to this nifty phone.

...

Figure2.4 An example of review summarization (Jiaming et al., 2009)

Initially, the customer reviews were pre-processed and parsed into phrase sequences, each of which related to a specific notion. The clustering of these pre-processed phrases into first ideas followed. The largest clique defining the relevant logical set of concepts was then identified via a graph-based technique. Based on the collection of concepts, an ontology induction was created in the conclusion. In addition, a graphical model was used to determine the link between competing items based on user feedback (Kaiquan et al., 2011).

Also seen were research initiatives contributing to the examination of how online customer evaluations affect the economic income of a product. Using rough set theory, inductive rule learning, and multiple information retrieval (IR) techniques, a system was created to investigate the link between customer reviews and review ratings (Wingyan and Tzu, 2012). Archak et al. dissected internet evaluations into distinct product characteristics (Archak et al., 2007). Then, they assessed the weights of product features, the customer ratings of product characteristics, and the impact of these ratings on revenue. Also explored were the impact of unfavourable reviews on customer sentiment (Jumin et al., 2008). Through categories of hypotheses and tests, it was determined that the influence of negative reviews depends on the quantity, quality, and kind of customer interaction. With a greater number and higher quality of negative online customer evaluations, the proportion of highly involved consumers who prefer to conform to reviewers' ideas is seen to grow. It has been observed that consumers with little engagement care little about the quality of negative evaluations.

According to these research papers, internet evaluations are rarely examined, analysed, and immediately integrated into the product creation process. Nonetheless, the goals of this study are to compile a database of useful online reviews, to recommend rating values for online reviews based on designers' personal assessments, to connect customer reviews with product engineering characteristics, and to prioritise product engineering characteristics based on online customer reviews in order to enhance the current product model. Considering this, the following four parts will introduce some pertinent research papers that match to the aims of this study.

2.3 Evaluation of text documents

The primary purpose of this study is to compile a database of useful web reviews. In order to distinguish this research, this part will describe how the usefulness of online reviews is defined and assessed in this study. In addition, some contributions to the evaluation of the quality of requirements papers in software engineering are presented. Although not directly related to the evaluation of the quality of text documents, feature selection will be used in this study to determine which components of online evaluations product designers find most useful. Consequently, certain fundamental principles of feature selection are also discussed.

2.3.1 Evaluation and analysis of the helpfulness of online reviews

In a limited number of studies, the helpfulness of online reviews is often determined by the proportion of online helpful votes or based on a predefined criterion.

2.3.1.1 The review helpfulness evaluation based on the online helpful votes

As indicated in Figure 1.1, online helpful votes typically refer to the number of votes, e.g., "120 people found the review helpful." In certain academic papers, the proportion of online helpful votes was also considered the gold standard for determining the usefulness of product reviews. The prediction of usefulness was posed as a binary classification (Michael et al., 2009; Richong and Thomas, 2010), multiple classification, or regression (Cristian et al., 2009, Miao et al., 2009, Yu et al., 2010).

The research from Mahony considers the most valuable are those that are rated more than 75% (Michael et al., 2009). A binary classification method is used to recommend hotel reviews with features such as reputation, content, sociality, and emotion. Zhang classified helpful comments as: more than 60% positive help (Richong and Thomas, 2010). Use information collection technology to predict network evaluation.

Liu and several others. Three main observations were reviewed: reviewer expertise, writing style, and time of publication. As can be seen in Figure 2.5

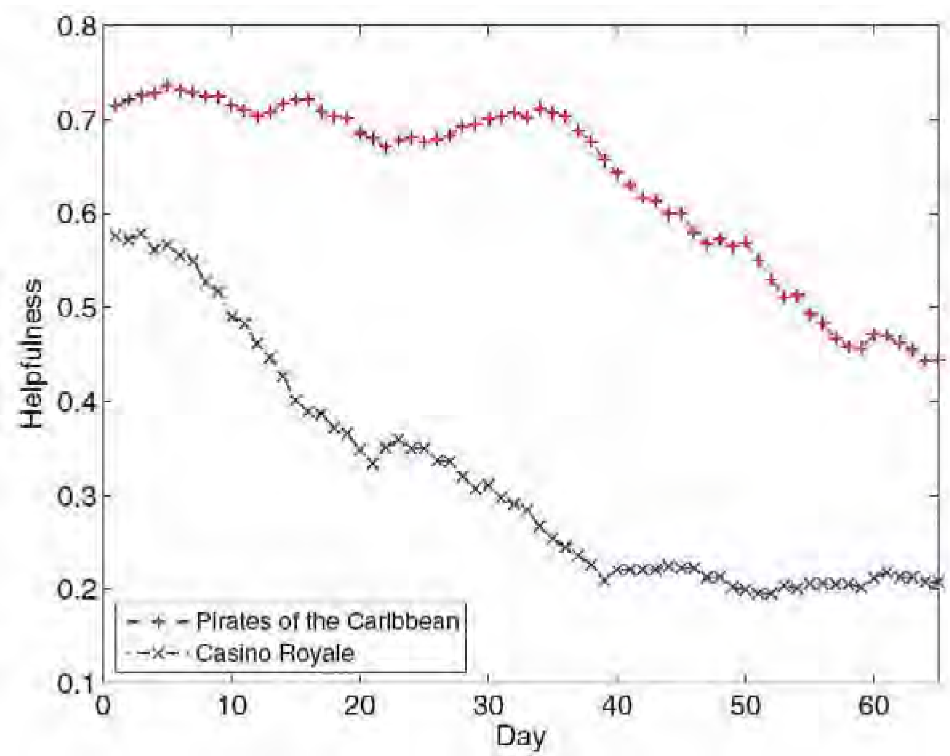


Figure 2.5 an example of review usefulness vs review duration (Liu et al., 2008)

Miao et al. find the rate of online assisted voting has also been used to rate the usefulness of online reviews (Miao et al., 2009). To recover the sentiment information of online reviews, a linear combination of this model's anticipated helpfulness and the relevance model was built.

2.3.1.2 Predefined standard to define review helpfulness

It is different from the evaluation method based on the online help voting ratio (Liu et al. 2007). As can be seen from Figure 2.6, more than half of all comments have more than 0.9 valid votes. Figure 2.7 shows how the offset of the winner's circle is interpreted. This shows that "both the first two reviews have an average of 250+ and 140+ votes, while the share of those that rank lower is exponential."

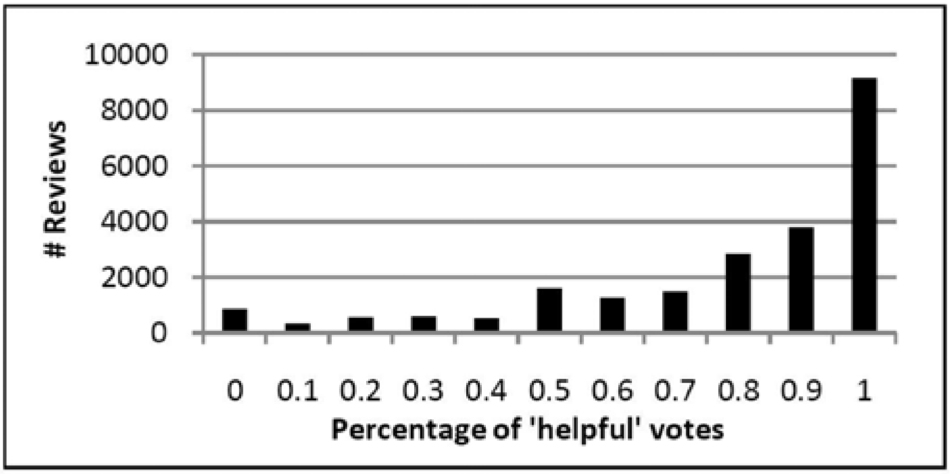


Figure 2.6 Imbalance vote bias (Liu et al. 2007)

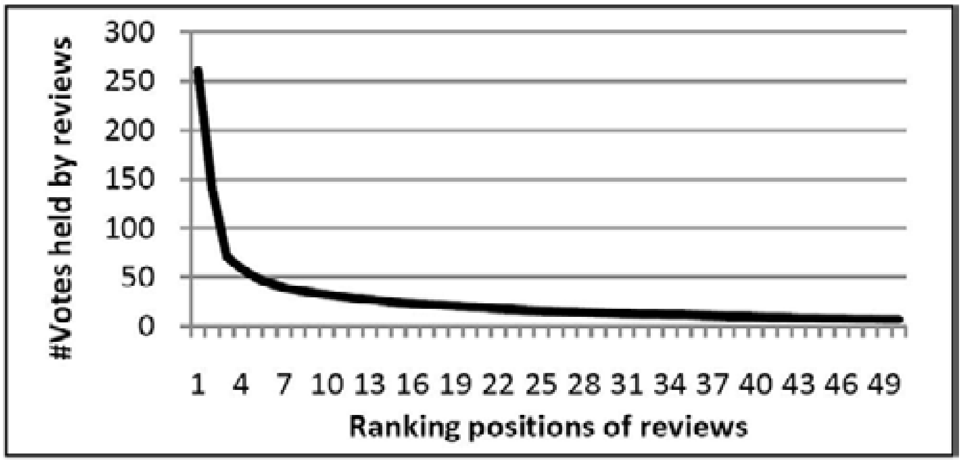


Figure 2.7 Winner circle bias (Liu et al. 2007)

Figure 2.8 depicts the early bird bias, "The sooner you post a comment, the more votes you get." In fact, a similar pattern can be seen in Figures 2.8 and 2.5. The exploratory case study on review effectiveness presented in Chapter 3 will further support this conclusion.

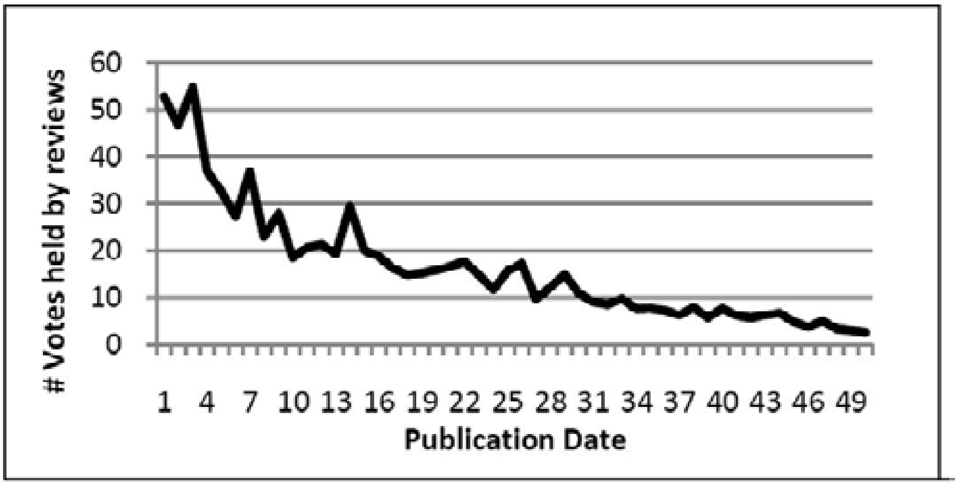


Figure 2.8 Early bird bias (Liu et al. 2007)

Four artificial annotators were subsequently used for evaluation as described by Liu et al. 2007. The study found a significant difference in the rates of critics and online assisted voting. They use kappa statistics to assert and give usability criteria to align registrants' ratings of usability. Finally, help predictions are expressed using multiple classifications. Use multi-class features and SVM to make predictions on the data.

The preceding research (Liu et al., 2007) inspired the development of a quality evaluation methodology for online reviews (Chien and You-De, 2010). In contrast to prior attempts, in which evaluations were solely rated as useful or not helpful, reviews were categorised as "high-quality," "medium-quality," "low-quality," "duplicate," and "spam." In addition, many feature groups and SVM were used to estimate the quality of product reviews. Similarly, Li et al. stated that it is impossible to annotate a corpus for each topic of interest (Yijun et al., 2011). To understand the sentiment of online reviews, this paper proposes a segment-based unsupervised learning method. This method can be used to distinguish whether comments on the Internet are approved or not. However, there are only assessments that both registrants agree with. A probability distribution model can also be seen to evaluate the value of online reviews (Richong and Thomas, 2010). Using expectation maximization techniques, an efficient probability assignment is made to a particular training corpus. The vocabulary bag pattern is used to express and predict the availability of web reviews. It is said that this method achieves an appropriate correlation between people's assessments and expected useful values.

While there are many algorithms that can predict the validity of an online review, its integrity is judged by humans.

Assist clients in understanding requirements documentation for software engineering. Some researchers have attempted to assess quality. Figure 2.9 shows an example that uses QFD for requirements analysis. This strategy is used to address different stakeholder perceptions and perceptions of competition during software requirements identification (Joao et al., 2005).

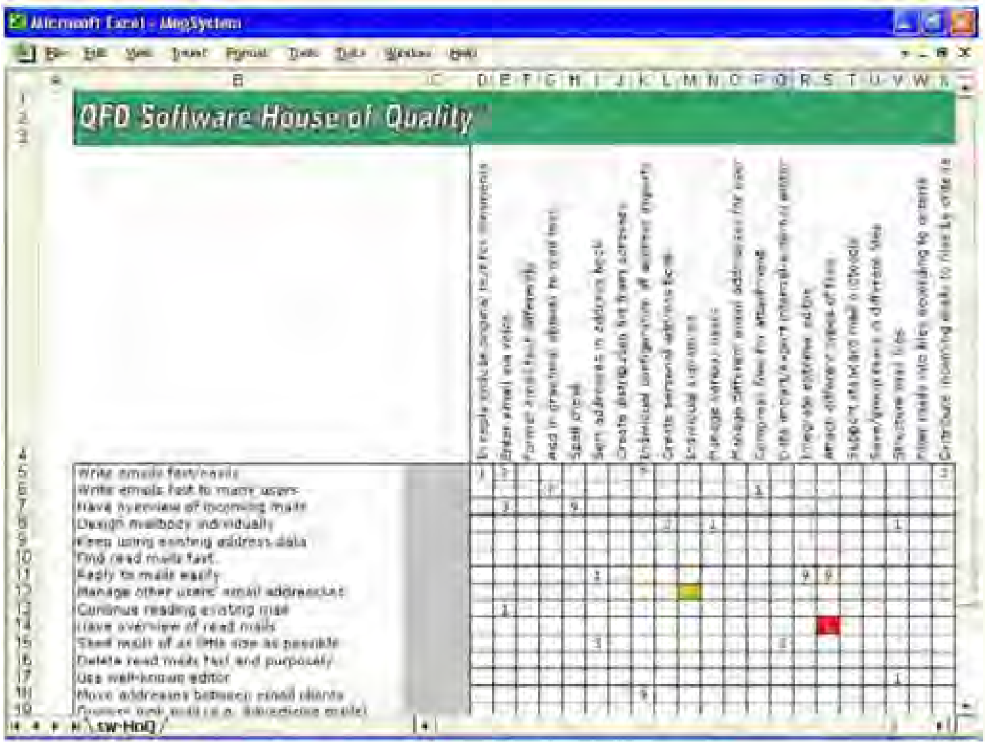


Figure 2.9 *QFD in software analysis (Joao et al., 2005)*

Quantification (Ron, 1996), natural language patterns (Fabbrini et al., 2000) have been found in several studies evaluating the quality of demanding articles. The quality of demanding articles is mainly measured by language statistics and manual labor. The automatic evaluation algorithm proposed in this paper (Yunhe et al., 2009). Using ten language principles, functional requirements are extracted from the software requirements specification. Figure 2.10 illustrates a language for expressing required specifications (Carlos and David, 2006).

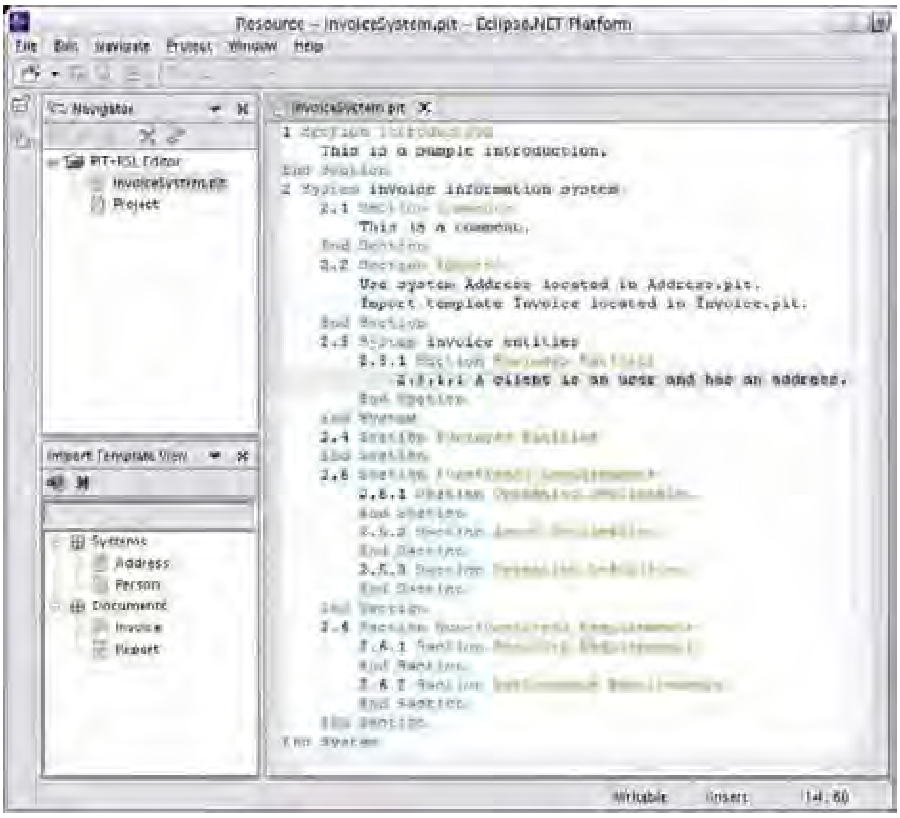


Figure 2.10 A language to describe the requirement specifications (Carlos and David, 2006)

The language is built from one of the most common language models in natural English used in required articles. To ensure text coherence, they are evaluated using analytical tools and checked against grammatical and semantic criteria.

In addition, machine learning techniques are used to determine whether requirements specifications are confusing. At the discourse and phrase level, we employ decision trees for binary classification (fuzzy or clear) (Ishlar et al, 2007). Additionally, we designed two classification methods to distinguish similar phrases to exclude ambiguity when needed (Jantima and Aditya, 2008).

Although such efforts also help people better understand customers, they are completely different from online reviews. First, in software engineering, the quality evaluation of requirements documentation mainly depends on the effective collection of specific design requirements, usually including tables, diagrams and questionnaires. In sharp contrast, most of the online comments are unorganized text, which is mostly user-generated, which is also an important feature of online comments. They are achieved through designer-emphasized reviews, which, for example, make the designer aware of customer needs, but the designer does not understand these qualities. Second, online reviews are not the same as the articles required by software engineering, which contain many words expressing strong and non-strong emotions. Designers will pay more attention to this feeling when combined with existing or expected product characteristics. These visceral reports contain valuable feedback from customers and often help designers come up with new solutions or enhance existing ones. Third, designers tend to be overwhelmed by the sheer volume of comments online, not to mention other technical obstacles, than the few requirements documents in software engineering.

2.3.3 Feature selection

Feature selection is the process of selecting a subset of characteristics, which assists individuals in acquiring key features, comprehending their relationship, and enhancing the efficiency of learning algorithms. The four fundamental phases of a typical feature selection procedure are subset creation, subset assessment, stopping criterion, and outcome validation (Figure 2.11).

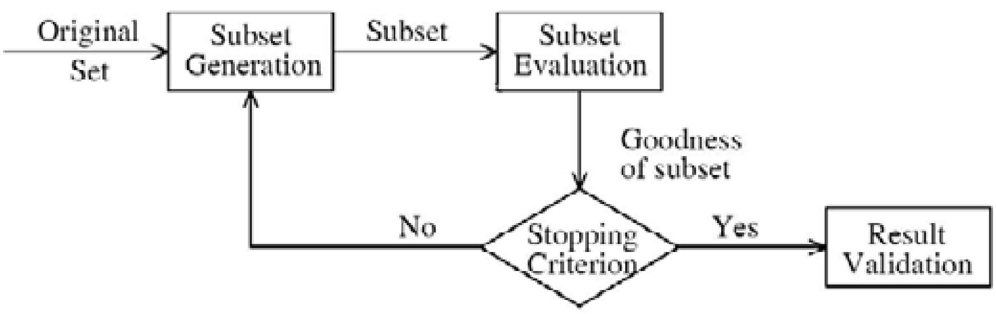


Figure 2.11 Four key steps of feature selection

In several fields of data mining, including classification, regression, clustering, and association rules, feature selection is applied. The high dimensionality of the data may result in inaccuracy and a significant computational cost. Consequently, feature selection becomes an essential stage in several data mining applications.

Principal Component Analysis (PCA) is a well-known data pre-processing technique that is frequently employed for feature selection. Capturing the linear relationships between characteristics and identifying the most representative features. The feature space is then reduced by these representative features while losing as little original data information as feasible.

The three variables of PCA are: covariance matrix, correlation matrix and eigenmatrix (Andreas et al., 2008). The original mean deviation method was used in this study, making each feature an average of 0. Then the performance of the above three variables is compared. On this basis, the eigenmatrix are used respectively. The attributes are sorted by the correlation coefficient of the first principal component, and the attribute with the largest value is the priority.

The various feature selection methods are divided into three categories (Isabelle and Andre, 2003), namely filter models, wrapper models and mixture models.

The first one is filter mode (Duja and Marko, 1999). The basic principle of this similarity-based feature selection method is that when a feature has the highest similarity with the target, it will be regarded as an important feature. On this basis, the feature selection is carried out by similarity, and the similarity analysis of each feature is carried out. These properties are arranged in order of their similarity. Yang, and some others. Various filtering techniques were compared and analyzed (Yiming and Jan, 1997). The results show that in text classification, information gain and chi-square are the two most effective methods.

The second is the encapsulation mode. Feature subsets are generally evaluated using predetermined mining methods (Ron and George, 1997, Huan and Let, 2005). Each feature subset is evaluated based on the best mining process. Different mining strategy functions can produce different packing algorithms. In the process of selecting feature subsets, the mining technology is used to control the feature subsets, so that the feature subsets can be selected effectively. However, the amount of computation is generally larger than that of the filtering model.

The third is the hybrid design (Sanmay, 2001). The method adopts the above two modes, and adopts different evaluation criteria in different search stages. The features are analyzed using independent measures and data mining techniques. The purpose of independent measurement is to find a specific cardinality. At each base, the best subset is obtained. If the optimal subset of the base is good, the algorithm will continue to find the optimal subset in the next base.

2.4 Recommendation system

The second task addressed by this research is how to propose rating values for online reviews while taking designers' opinions into account. This question will be investigated in light of the existing literature on recommendation systems.

With the rapid growth of the information technology, recommendation systems have become a leading research issue for sifting through the abundance of data. Recommendation systems leverage the historical ratings of users to anticipate their possible future interests. According to the personal evaluation, a number of specific goods are suggested to their consumers.

Recommendation systems aid users in discovering fascinating and useful information about books, music, movies, etc. Tapestry, one of the first recommendation systems, was announced in 1992. (David et al., 1992). This recommendation system employed the term "collaborative filtering." This phrase has been extensively accepted whether or not recommendation systems work overtly with receivers and whether or not they propose products.

There are typically three types of recommendation systems: content-based suggestions, collaborative recommendations, and hybrid methods.

In a content-based algorithm, recommendations are generated using project content data. The content of the item is often used for analogy. It also includes some people reviewing things. Therefore, the recommendation should be to find the right one among the products that the target customer has previously loved.
Content-based algorithms are mainly for the recommendation of textual materials such as web pages and news. This paper proposes a method based on cosine similarity for text mining. In addition, this paper also conducts text mining on content-based algorithms. For example, the Rocchio method is used to calculate the average content of objects (Ken, 1995, Marko and Yoav, 1997).

Generally, in the TF-IDF method, the document is represented by a vector that contains the weights of different words. Next, a classifier weight vector is used to evaluate whether a project is recommended (Michael and Daniel, 1997, Raymond et al., 1998).

In collaborative recommendations, recommendations are previously evaluated by other users. So, the reviews from a large number of previous users are very critical. In cooperative recommendation, the data of many other users with similar preferences are first collected. Then recommend other content with similar preferences to the target user.

Currently, the two most common approaches are storage-based and model-based.

In the memory-based collaborative screening algorithm, the recommended objects can be other objects that are similar to the target user's evaluation, or can be compared with other objects.

Assessments for a particular user or object are generally obtained from other similar people or products. The sum can be an average or a weighted sum. Weights can be measures such as similarity, relatedness, and the like. The stronger the similarity between users, the greater their share of the predictions. However, different users can choose different scoring methods. Therefore, the improved method has been widely used. Do not use absolute ratings, but use averages that deviate or deviate from users or projects.

Also, there are several extensions that enhance the recommendation. Since similarity depends on the degree of intersection of items, memory-based techniques are unsatisfactory when there are fewer evaluations (John et al., 1998). For missing ratings, the precision of the suggestion can be increased. Compared with several methods that exploit user similarity, both association-based and cosine-based methods employ inter-item similarity (Badrul et al, 2001). In addition, the strategy of exploiting similarity of things extends to the most popular products (Mukund and George, 2004).

The results show that the engineering-based similarity method is more computationally efficient than the user-based model.

In model-based collaborative screening algorithms, items are realized by learning how to recognize patterns in input data. Statistical and machine learning techniques are used to recommend the item.

Some studies view suggested roles as a classification. In the recommender system, Bayesian belief network is used for classification (Xiaoyan and Taghi, 2006). This method assumes that the scores of different users are independent of each other. Using this classification method, the probability of scoring a particular item is calculated. Divide the most likely grades into predicted grades. However, Bayesian belief networks do not maximize classification accuracy (Russell et al., 2005). This paper proposes a method based on extended logistic regression to achieve better classification accuracy.

Some researchers also see advice as a returning task. On this basis, a probability-based factor analysis model is established. The method is to add the average scores of other products to objects that have not been rated by users. Finally, a regression model is proposed as an initialized expectation maximization (EM) method. This paper also proposes a regression-based numerical ranking method (Slobodan and Zoran, 2005). In this strategy, item similarity is adopted.

This paper proposes a content-based collaborative recommendation algorithm and combines it with other collaborative algorithms. For example, a hybrid algorithm can be generated from different collaborative recommendations, collaborative recommendations based on content recommendations, or collaborative recommendations with other recommender systems. Likewise, the results of content-based recommendations and collaborative proposals are subject to majority voting (Michael, 1999). Additionally, a content-based approach is recommended to populate unrated content (Prem et al., 2002). Then, according to the weighted Pearson correlation, the items are submitted to specific users. Burke evaluated some of the proposed mechanisms (Robin, 2002). On this basis, a weight-based hybrid system is proposed and combined with multiple recommendation algorithms.

This paper introduces a hybrid method based on the combination of memory and model for reference. On this basis, using the generated method, the scores of other users are uniformly sampled, and Gaussian noise is added to generate the user's personal data.

Next, estimate the user's personality like everyone else, and how likely they are to like the new product. In addition, a probabilistic technique that combines the mnemonic approach with the model approach is reported (Kai et al. 2004). In this technique, we use the posterior distribution of user data to build a hybrid model.

2.5 Connecting customer requirements with product design specifications

The final topic of this study is the integration of customer requirement with the product design specifications. As mentioned before, a major aspect of QFD technology is an in-depth discussion of customer requirements and product design specifications. Therefore, this section begins to discuss how to translate customer requirements into QFD. In addition, some computer scientists are working to automatically determine the meaning of words in a special environment through a method called "word sense disambiguation". The third question is consistent with the purpose of the World Health Organization. Modern WSD methods are also explored.

2.5.1 Translating customer requirements into QFD

Overall, the research had to deal with ambiguity in human language and the subjectivity of customer speech (Kwang et al., 2000). The problem is usually a combination of fuzzy sets and QFD. On this basis, a marketing-oriented design system based on fuzzy logic is proposed to meet customer expectations and make information sharing between designers simple (Harding et al. 2001). On this basis, the requirements for converting marketing messages into products. In addition, this paper introduces a fuzzy linear regression-based method to estimate the uncertainty of customer requirements and product engineering characteristics in product design; this is an important link in QFD-based new product design (Richard, 1999). year 2006). This paper also proposes a fuzzy expert system to identify the engineering properties of basic products (Kwong et al., 2007). In this paper, the fuzzy correlation analysis of customer demand and product engineering characteristics in QFD is carried out and analyzed. Also, in QFD, linguistic variables and fuzzy integers can better describe the input (Yizeng et al). This strategy differs from previous attempts, because previously people viewed the input data as exact and only as numbers (Yoji, 1990, Anders and N, 1994). The Kano model is said to be used in QFD to measure user needs in unpredictable and ambiguous situations (Lifeng et al, 2008). On this basis, the fuzzy multi-objective model is used to balance customer satisfaction and development cost.

2.5.2 Word sense disambiguation

Word sense disambiguation (WSD) is a major research direction in computational linguistics that can identify the meaning of words in specific contexts. According to the source of knowledge, WSD is mainly classified into knowledge type, supervised type and supervised type (Roberto, 2009).

2.5.2.1 Knowledge-based methods

Due to the lack of corpus support, a learning method mainly rely on dictionaries and dictionaries. These knowledge resources contain the meaning of vocabulary, which plays a positive role in improving learning strategies.

This paper introduces a method that exploits word sense relations to increase the number of overlapping words in WordNet (Satanjeev and Ted, 2002). This set of repeated words is used in WSD. In some studies, the definition of the word was also used in the dictionary (Ryu et al., 2008). The definition-based similarity is augmented with the similarity method. Finally, the target word and neighboring words in WSD were compared using the nearest neighbor method (Ryu et al., 2008).

In addition, WSD uses a chart-based approach. For example, semantic relations are used to construct lexical chains in WordNet (Michel and Kathleen, 2003). Individual links are weighted according to their respective semantic relationships. Then, this paper proposes a disambiguation algorithm for WSD. Using random walks associated with encoded markers, a graph structure is built for sequence data markers. These graphic elements were then incorporated into the unguided WSD diagram (Rada, 2005).

2.5.2.2 Supervised methods

In a supervised setting, the semantics of words are predicted using annotated corpora in machine learning and different classification algorithms. Various algorithms for monitoring learning in WSD employ labeled words (Rada and Timothy, 2003, Eduard et al, 2006).

Some useful monitoring techniques for WSD in specific areas are described. Different comparative analysis results show that in the same learning and testing, the extraction of dominant semantics from mixed-domain corpora is better; dominant semantic extraction has better expressive effect (Rob et al., 2005). By using a domain corpus as input, hand-annotated data can be adapted to those regions that are not frequently available (Diana et al. 2007).

While the WSD method of monitoring is a very effective method of WSD, it has a fundamental disadvantage that it cannot be used very often. To build a training corpus, some possible semantic contexts need to be examined. This paper examines a number of data properties, supervised algorithms, and factors that may affect the performance of WSD methods (David and Radu, 2002). Similarities, differences, advantages and disadvantages of different algorithms are also described (David and Radu, 2002).

2.5.2.3 Unsupervised methods

In a tag-based approach, the words appearing in different instances are grouped together. For example, a contextual clustering algorithm was reported (Hinrich, 1998). The system can infer semantics from a corpus without the need for annotated training instances or external knowledge resources. Words, settings, and meanings are categorized by their semantic similarity. On this basis, the data are classified and tested. The meaning of indeterminate phrases can be viewed as a set of comparison situations.

2.6. Product design specification

PDS is a standard process for manufacturing and manufacturing products. They specify the characteristics of the product, including:

- Size, specifications, and materials
- Environmental performance
- Cost
- Lifespan
- Performance
- Maintenance
- Packaging and shipping
- Safety

Using a typical PDS template (Pugh, 1991), the plan aims to combine sustainable design with the concept of a circular economy.

However, since agriculture is a non-industrial ecosystem, this strategy is difficult to apply to basic agricultural products. At the same time, JS and ALIA "created" agricultural products by using PDS templates, with the right adjustments to the technology.

This technology allows ecological constraints to be incorporated into the design process, producing a product with minimal environmental and social impact. For example, ONA LED Services requires LED desk lamps:

- low energy consumption
- Reparable and modularly constructed
- Designed using minimal impact materials
- Have a minimum lifetime of 10 years
- 100% recyclable at the end of its life

2.7. Online data mining for PDS

Online reviews are opinions expressed by users while shopping online to help other customers make new purchases. Customers' emotional inclinations, desires and other product-related preferences can be obtained through online reviews.

Online reviews can make decisions for customers and provide an important basis for manufacturers to formulate product development and improvement strategies. These comments provide product manufacturers with valuable insight into customer needs. A product design specification is a set of detailed instructions that summarizes product design requirements. This can include physical properties such as size, weight, color, etc., but can also include functions such as the product must perform or be fulfilled (Zijian et al., 2018).

Validating specifications is a critical start in the product development process. Product manufacturers, in addition to their own experience, often apply market research, surveys, mechanical understanding; have knowledge of production and ergonomics, and be able to write PDS documents. The whole process is time-consuming and labor-intensive. These results also need to be tested in the market and manually improved based on user input. However, through network data mining techniques, user preferences can be greatly simplified. This saves a lot of labor and generally gives more reliable results. This article improves the PDS presentation with an algorithm based on mining user needs from online reviews.

2.8 Life cycle assessment

The new focus on planning for a sustainable world has revived interest in natural materials. However, it is timely to consider whether the claimed benefits of these materials can be justified quantitatively. Life Cycle Assessment (LCA) is an environmental assessment method which, according to ISO 14040:2006(E), "considers the entire life cycle of a product from raw material extraction and acquisition, through energy and material production and manufacturing, to use and end-of-life treatment and final disposal" (Chai and Wu, 2020). A LCA study has four stages shown in Figure below:

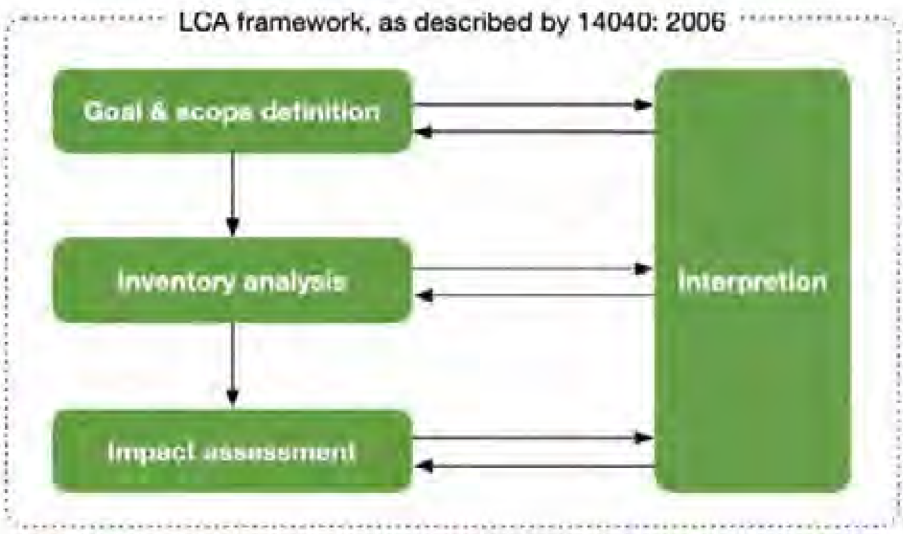


Figure 2.12 LCA framework

There are two types of approaches to assess the environmental burden at micro and meso level (e.g., from products and companies):

- Resource based approaches: Approaches focusing on resources (inputs) taken from nature based on resource indicators. (Table 2.1)
  Examples: Material Input per Service Unit, Water Footprint
- Emission based approaches / models: Approaches focusing on outputs to nature, allowing the assessment of one or multiple specific emissions (outputs) with help of extended assessment models.
  Examples: Carbon footprint, USEtox, ReCiPe

Table 2.1 Resource-oriented approaches and models for environmental indicators

Methods	**Description**
Cumulated energy use	All primary energy required for production, use and disposal of a product.
Ecological Footprint	Considers all biologically productive land and sea area necessary to produce all consumed products and absorb generated waste. Covers directly or indirectly all resource categories.
Material Footprint	Measures all material resources from nature over the whole value chain (including all resources induced by energy generation). The approach gives a rough estimation of the overall environmental burden and allows to measure resource efficiency.
Material Input Per Service Unit (MIPS)	Measures quantity of resources used for one unit of service and identifies input-oriented environmental impact of a product. Covers directly or indirectly all resource categories.
Total Material Requirement (TMR)	Measures all material flows of an economic system. Also applicable at micro level similar to Material Footprint.
Water Footprint	Gives information about the direct and indirect amount of used fresh water for producing a product, measured over the entire supply chain. Covers only the category water.

A summary of relevant emission-oriented approaches and models is provided in Table 2.2 below:

Table 2.2 emission-oriented approaches and models

Methods	Description
CML 2002	CML 2002 uses nine baseline impact categories and twelve study-specific impact categories, which can be excluded if appropriate. It considers only midpoint impacts.
Eco-indicator 99	Follow-up of Eco-indicator 95, covering all emission categories and parts of the resource categories. Considers only endpoint impacts.
Ecological Scarcity Method (Ecopoints 2006)	Weights environmental impacts with eco-factors, which are derived from political targets or environmental laws (critical flows).
EDIP 2003	Model is a follow-up of the EDIP 97 methodology and covers only emission categories and considers midpoint impacts.
Environmental Footprint	Multi-criteria measure of the environmental performance of goods or services throughout its life cycle, considering different models linking to midpoint impacts. Covers all categories except of biotic resources.
IMPACT 2002+	Is mainly based on Eco-indicator 99 & CML 2002 linking 14 midpoint categories to four damage categories.
ReCiPe	Model is a follow up of Eco-indicator 99 and CML 2002 methods, which integrates and harmonizes midpoint and endpoint approaches.
SM 2011 (Okala)	Evaluates ten midpoint impacts, which lead to four endpoint impacts and one final Okala score.
Climate Change IPCC 2007	Method to assess the impact that a product or process has on the climate change impact category.

Product Carbon Footprint	Measures GHG-emissions of goods or services throughout their whole life cycle.
USEtox model	Scientific consensus model for comparative assessment of toxics of goods and services.

ISO 14040 (2006) suggests that the goal of an LCA should state:

- The intended application
- The reasons for carrying out the study
- The intended audience
- Whether the results are intended to be disclosed to the public

Its scope should be clear so as to be consistent and adequate in breadth, depth and detail with the objectives identified. LCA is a method that requires adjustment of each area in order to achieve the original research purpose when obtaining data and data. The authority of the LCA shall include:

- The product system to be studied - determining the framework for the LCA to be carried out
- The functions of the product system (or systems for comparative studies) – behaviour and the process of the production system
- The functional unit – the key element of LCA which has to be clearly defined. The functional unit is a measure of the function of the studied system and it provides a reference to which the inputs and outputs can be related. This enables comparison of two essential different systems.
- The system boundary – determines which unit processes are included/not included in the LCA. Defining system boundaries is partly based on a subjective choice, made during the scope phase when the boundaries are initially set.
- Allocation procedures – which attribute shares of the total environmental impact to the different products of a system.

- Impact categories selected and methodology of impact assessment, and subsequent interpretation to be used
- Initial data/data requirements - Reliability of the results of LCA study depends on the extent to which data quality requirements are met which includes precision, completeness, representativeness, consistency and reproducibility.
- Assumptions – which include engineering estimates or decisions based on values and are clearly and comprehensively explained in conclusions drawn from the data.
- Limitations which are incompleteness due to cut offs and lack of process specificity
- Type of critical review, if any which can be a simple peer review of the final report, or integrated quality assurance involving typically three review steps (after the scope definition, after the data collection, and after the conclusion)
- Type and format of report required for the study - in which the results, data, methods, assumptions and limitations are clearly, fairly, and accurately reported in sufficient detail to allow the intended audience to comprehend the complexities and trade-offs inherent in the study.

2.9 Summary

As one of the most significant forms of user-generated content, online reviews are intensively studied by numerous researchers. However, most of them are computer scientists. Their online review research focuses primarily on several tasks of opinion mining, including sentiment identification, sentiment extraction, and opinion retrieval. They disregard how to facilitate the implementation of their results to product design.

Online reviews are a valuable source of information for product designers regarding customer preferences and needs. It is expected that customer needs will be extracted automatically. As an example, consumer survey results contribute to the discovery of client demands in the design domain. This information is fundamentally distinct from internet reviews. Therefore, most of contemporary design methods are not suitable to internet evaluations.

This research has four objectives: to collect useful online reviews, to recommend rating values for online reviews based on designers' personal assessments, to connect customer reviews with product engineering characteristics, and to prioritise product engineering characteristics based on online customer reviews in order to enhance the current product model. To distinguish this research from previous efforts, this chapter reviews a large number of significant publications in four relevant areas. Reportedly, significant progress has been made in several areas. However, there remains a vacuum in visual research between the computer science and design fields. Although the usefulness of online reviews is generally acknowledged by both customers and product designers, they are not understood, reviewed, analysed, or exploited by product designers. Moreover, the sustainability of the product, which plays a crucial part in product design, is given less consideration.

LCAs can give up-to-date information on items, processes, and products, according to a study of LCA and its latest research. Modern civilization depends on a broad and complicated economic system, which makes the collecting of trustworthy data even more crucial and challenging. In the sustainable domain of lighting design, the discourse centres on power consumption and the adoption of LED technology as the way ahead, but consumer preferences are not always considered. However, lighting has a larger environmental influence than just electricity consumption, encompassing manufacturing processes, equipment longevity, maintenance capability, and even individual behaviour.

This study proposes the idea of developing the customer-oriented and sustainable lighting product as a package, so enabling the linkages between product sustainability development and customer requirements over the product's whole life cycle.

The framework of the intelligent system to assess online review evaluations for product design will be presented in the next chapter. Additionally, two case studies will be undertaken to determine how online reviews might be incorporated into product design

Chapter 3: Research Methodology

3.1 Introduction

Chapter 2 provides an overview of a variety of pertinent studies. Although the significance of online reviews is widely acknowledged, little efforts have been made to mine information from online reviews from the perspective of product design.

This chapter describes how this study will be done in order to meet the objectives outlined in Chapter 1. Methods and procedures employed and followed to achieve the results of this study are also described. Proposed is the framework for an intelligent system. From the standpoint of product design, this intelligent system will be applied to extract vital information about customer requirements from online reviews. In addition, this intelligent system will enable product manufacturer/designer to link online reviews with product design specifications and will recommend how to prioritise product design specifications based on online reviews.

Moreover, for the purpose of gaining a better knowledge of how internet reviews might be incorporated into product design, this chapter presents two case studies.

3.2 Research design and outcomes

1) Development of an integrated sustainable lighting product design approach

The first step was to develop an integrated approach to be used as a reference to guide the development of sustainable lighting product with combination of customer requirement mining from online reviews and low environmental impacts. In order to create the approach, the relevant literature is reviewed and analyzed. The literature review consists of the research status of online review usefulness, the research status of feature extraction (including implicit feature extraction and explicit feature extraction), the research status of sentiment analysis, the research status of user needs, and the research status of product sustainability analysis.

The selection of the relevant issues from these areas, to be used to develop the approach, is based on the review and discussion by other researchers and design practitioners in published material (papers and books) of these topics, and on the judgement of the author based on trials with these methods and tools during the study also on previous professional experience in design practice.

2) Build a thesaurus for helpful online review collection

The second step was built of thesaurus for helpful online review identification and collection. The construction of the thesaurus includes the construction of the product feature thesaurus and the sentiment thesaurus. The product feature thesaurus is constructed based on the product parameters, and then filter the nouns in the reviews as candidate words, build a Word2vec word similarity analysis model, and analyze the similarity between the candidate words and the feature words in the initial feature thesaurus template to expand the initial feature thesaurus to form the final product feature thesaurus. The construction of the sentiment feature thesaurus is to use the adjectives in the comments as candidate sentiment words and use the similarity analysis to expand the existing emotional dictionary to form the sentiment thesaurus.

3) Online review helpfulness classification

To obtaining customer requirements from online reviews, the helpfulness of online reviews is classified from the perspective of products. Determine the influencing factors of the helpfulness of online reviews based on literature research and the perspective of designers. On the premise of comprehensively comparing the effects of the classification algorithms, determine the text classification algorithm, and optimize the parameters based on the training set and test set to build a text classification model with good performance.

4) Customer requirements mining and classification

Next is to apply text mining technology to extract product feature words and sentiment words, conduct sentiment analysis and quantification, and then combine SMV and K-mean model for customer requirement mining and classification. Using feature thesaurus, dependency syntax analysis, 1V1/1Vn feature-sentiment rule base, and sentence similarity analysis, the feature-sentiment word pairs of explicit feature sentiment sentences, implicit feature sentences and implicit sentiment sentences are extracted and analyzed. The sentiment analysis is carried out based on the sentiment thesaurus, and the sentiment analysis results are weighted and adjusted in combination with degree adverbs. On this basis, the SMV model is combined to construct customer requirement mining and classification rules to mine and classify customer requirement and calculate the priority of customer requirement.

5) Sustainable lighting product design

After the customer requirements extracted from online reviews, Ona company has proposed the concept design for a new lighting product with low environmental impact. The design process of the new product has focused on the online customer requirements and how to reduce the environmental impact.

6)Evaluation from the environmental LCA perspective

The environmental LCA will be carried out to assess, compare and evaluate the developed lighting product which comprises the following four phases:

Goal and scope definition: this research aims to evaluate the life cycle environmental performance of luminaire Medusa featured with sustainable concepts, in order to achieve optimum design solutions, with particular attention in the materials selection. The results obtained will also be used to develop the production and consumption strategy towards more sustainable domestic luminaires.

Inventory analysis: compiling a complete record of the important materials and energy flows throughout the lifecycle, in additional to releases of pollutants and other environmental aspects being studied.

Impact assessment: online LCA Platform http://h2020.circ4life.net/ is used for the LCA modelling. It links the reference flows with the life cycle inventory (LCI) database, and then utilizes the LCI flows with relevant characterization factors. The ReCiPe single score method is applied in this study, and the total environmental impact is expressed as a single score.

Interpretation: identifying the meaning of the results of the inventory and impact assessment relative to the goal of the study.

7) Evaluation from the social LCA perspective

The LCA framework was selected to creation a social assessment method for a new domestic lighting product model. The different phases of the LCA architecture can effectively cover the above important parts. Early in this phase, the relevant social impacts must be identified and listed. Identifying all types of interests, stakeholders and influences relevant to all functions is critical. Talking to product designers and asking for their input can help you achieve this. The next step is segmentation, which is to determine the causal relationship between the list of functions and revenue. In the description process, these advantages are translated into understandable symbols.

3.2 Proposed system framework

Figure 3.1 shows the structure of the architecture, which consists of three closely related components.

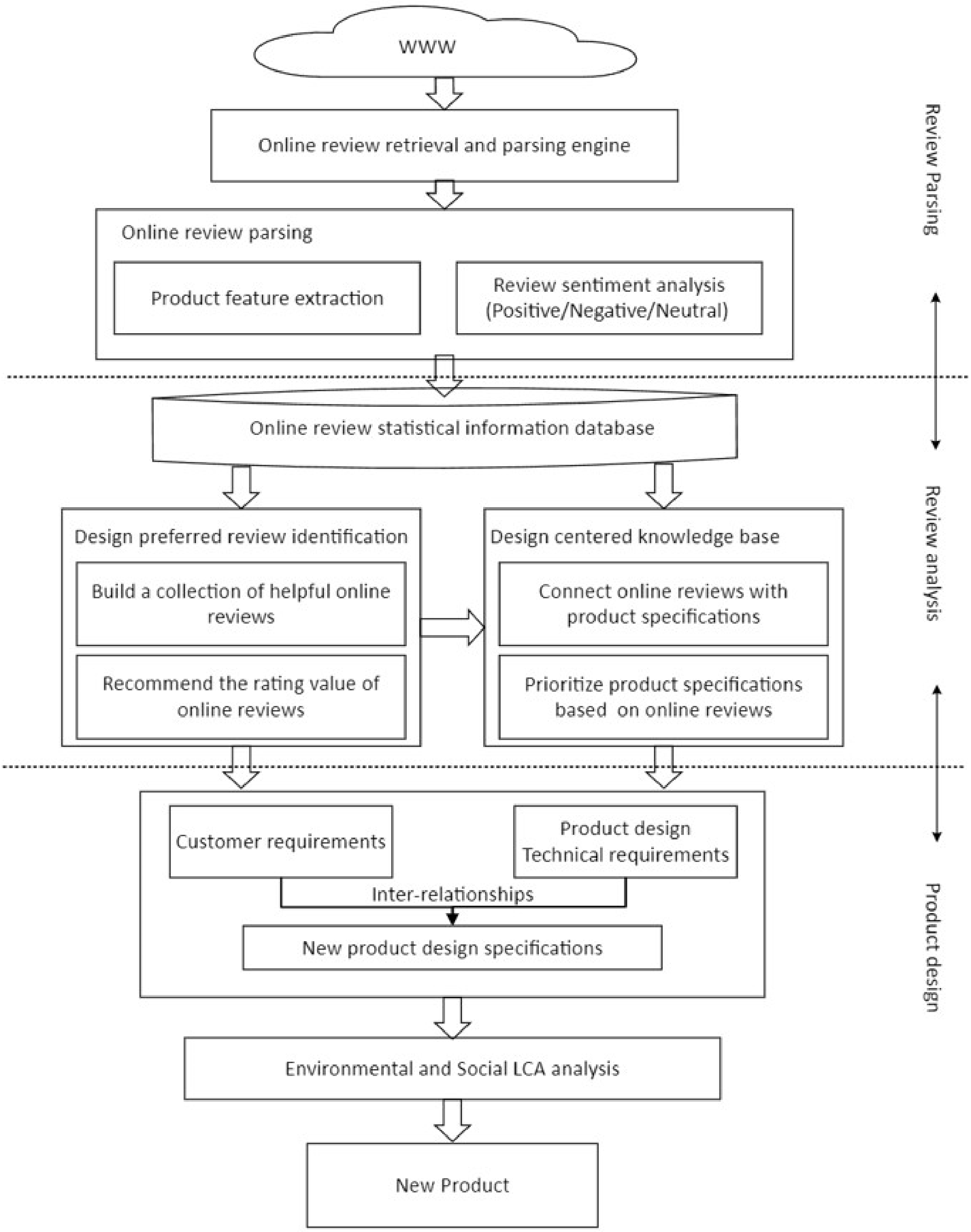


Figure 3.1 The framework of the proposed system

The first step is to collect a big number of online customer reviews and extract statistical information from their parsing, such as product specifications and consumer requirements. In this part, at first, online customer reviews are collected by an information retrieval and parsing engine. These online reviews are utilized as the source to analyse customer requirement. State-of-the-art technologies in data mining, machine learning and natural language processing are then applied on these online reviews to extract some statistical information. For example, some methods of natural language processing are used to obtain the POS tag for each word in online reviews. These POS tags are helpful for the analysis of online reviews. Also, some opinion mining algorithms, which are introduced in Chapter 2, can be utilized to extract product features and analyses the corresponding sentiments implied in online reviews.

Online reviews, as well as the statistical information, which is extracted in the first part, are stored in a database. With all these data, online reviews will be analysed for product manufacturers, which is the major task in the second part of the proposed system. Two problems are concerned, that is, Problem One: how to identify design-preferred online reviews from the perspective of product manufacturers, and Problem Two: how to build a design-cantered knowledge base from online reviews. As a matter of fact, these two problems are the focus of this research.

In Problem One, the identification of design-preferred reviews will be explained. Two research questions are included: (1) how to build a collection of helpful online reviews from the perspective of product manufacturers, and (2) how to recommend rating values on online reviews by taking product design specifications assessments into consideration.

The first question in Problem One is to help product manufacturers to find helpful online reviews from a large number of user-inputs, rather than taking all reviews as the input for customer analysis. The second question in Problem One is to facilitate a specific product design specification to focus on those reviews which are relevant to the specific product design requirements. These two research questions are different. The former stresses how to filter out online reviews in a generic viewpoint for product manufacturer, while the latter targets at taking product design specification assessment into considerations.

In this research, the two questions in Problem One will be analyzed and some innovated models will be elaborated for these two questions. With these models, design-preferred reviews are obtained from a large number of online customer reviews. These design-preferred online reviews still need to be further analyzed in order to facilitate product design directly. Hence, the next goal is how to translate this valuable customer reviews into product design.

For Problem Two, the objective is to build a design-centered knowledge base from online reviews. Two research questions are: (1) how to connect online reviews with product design specifications, and (2) how to prioritize product design specifications based on online reviews to improve current product model.

The first question in Problem Two points to the association between customer requirements and product design specifications. The second question in Problem Two is to generate the weights of product design characteristics in product design specifications. As explained in Chapter 1, both questions are important in QFD, and they are highly correlated. The output of the first question is to suggest how online reviews can be connected to product design specifications. This connection will be then utilized as the input of the second question. Together with the customer satisfaction information, which is reflected in online reviews, the weights of product design characteristics will be suggested in the second question.

Taking the findings of both Problem One and Problem Two as the input, the last process is to combine these results seamlessly for product design which meet both customer requirement and product design technical requirements, then the LCA analysis will be carried out to assess the environmental and social impact of the new product. This contributes to the future work of this research.

The emphasis in this research is how to make online reviews to be utilized from the perspective of product designer specifications. For a better understanding of customer requirements for product design, two case studies of review analysis in the customer-driven product design paradigm are conducted.

3.3 Method of select helpful reviews

Learning about product designers' perceptions of useful reviews through a wealth of real-life online reviews. helpfulness can be measured by pre-set criteria, or it can be defined by the generosity of online voting. From a designer's point of view, the usability of evaluations is very different conceptually and cognitively. However, product designers need to analyze reviews, understand customer needs, and incorporate those needs into new models. The online evaluation is tested from the perspective of a product designer.

In Figure 1.1, 120 people found this opinion useful. It is debatable whether the utility of customer reviews should be defined as helpful online polls, so this review has a usefulness rating of 120. The goal of this case was not to determine the accuracy of the assessment, but to determine whether a product designer's assist score was significantly related to the rate of online assist votes. Its goal is to evaluate whether the design of the product is beneficial to it through online reviews. Six full-time college students manually rated the validity of online reviews by reading online reviews related to review topics, product brands, and models.

On Amazon.co.uk, 1,000 reviews of desk lamps from different brands were randomly selected from the latest 500 reviews, and the best review (500) of the 10 desk lamps on Amazon. These annotations are all downloaded manually.

Among these 1,000 reviews, each user's review has an average of 298.4 words and 15.4 sentences. But their distribution is not uniform. Although each comment has a maximum of 3,421 words, most of the comments are short, such as "I just love this lamp," "Nothing to say" and "Excellent." Again, each annotation contains an uneven number of phrases.

In this case, each classmate will read the 1,000 comments. Unlike other studies, there were no pre-set guidelines to aid in the evaluation. The only question of evaluation is whether it helps the product being reviewed. Take "-2", "-1", "0", "1", "2" as evaluation indicators. "2" means "most helpful" and "-2" means "least useful". Each annotation should be assigned a most appropriate help tag.

Finally, the designer evaluates his online reviews based on his own knowledge, training and experience.

3.3.1 Evaluation metrics

In this survey, the average evaluation of the three designers is considered an absolute fact useful to a thousand reviews on the web. This evaluation is mainly to compare two random variables, namely the relationship between the rate of online assisted voting and the average score.

Mean absolute error (MAE) and RMSE (RMSE) were used to determine distance. Typically, both methods are used to measure the difference between the value derived from the model and the actual value observed from the item represented. In addition, the network-assisted voting rate and actual student value were analyzed using the Pearson Product Moment Correlation Coefficient (PPMCC).

- Mean absolute error

Statistically, mean absolute error (MAE) is used to measure the agreement between predictions and true results. MAE is the mean of absolute errors given by

$$MAE(real, predict) = \frac{1}{n}\sum_{i=1}^{n} | real_i - predict_i | \qquad (3.3.1)$$

$real_i$ is the true value for the sample i and $predict_i$ is the prediction value.

- Root mean squared error

RMSE is also a common measure in statistics to measure the difference between the values provided by the model and the real data of the simulated object. The square root of the mean error is the RMSE value between the estimated value and the estimated parameter. The formula is as follows:

$$RMSE(real, predict) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(real_i - predict_i)^2} \tag{3.3.2}$$

- Pearson product moment correlation coefficient

PPMCC is a measurement tool that measures the relationship (linear relationship) between numerical values from -1 to 1. This is a commonly used measure to measure the linear relationship between two variables.

$$PMCC\ (real, predict)$$

$$= \frac{\sum_{i=1}^{n} real_i \cdot predict_i - n \cdot \overline{real} \cdot \overline{predict}}{n \cdot S_{real} \cdot S_{predict}}$$

$$= \frac{n \cdot \sum_{i=1}^{n} real_i \cdot predict_i - \sum_{i=1}^{n} real_i \cdot \sum_{i=1}^{n} predict_i}{\sqrt{n \cdot \sum_{i=1}^{n} real_i^2 - \left(\sum_{i=1}^{n} real_i\right)^2} \cdot \sqrt{n \cdot \sum_{i=1}^{n} predict_i^2 - \left(\sum_{i=1}^{n} predict_i\right)^2}} \tag{3.3.3}$$

3.3.2 Preliminary Results

In Figure 3.2, the statistics show how many people got no votes, one time, etc. votes. Confirmed the fact that only a few reviews ended up getting enough support from users. Therefore, the proportion of effective votes used on the Internet, which is directly used as an indicator for evaluating the validity of comments, is basically questionable.

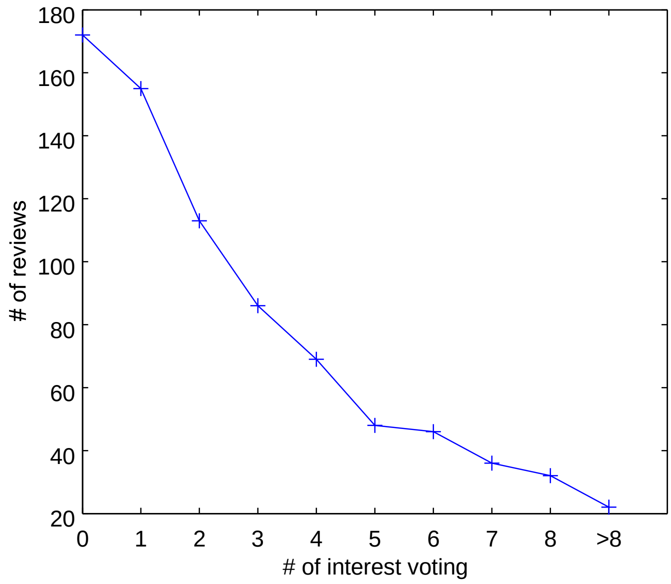


Figure 3.2 Helpfulness rating profile from student designers

The designer can rate it from two to two. So, online help polls and designers score the same on all three evaluations. Table 3.1 gives the values for 1000 annotations.

Table 3.1 online votes vs. designer votes

MAE	*RMSE*	*PMCC*
1.201	1.399	0.398

As shown in Table 3.1, there is a weak median relationship between the average designer score and the proportion of the network assisted in voting. MAE and RMSE were 29.5% and 35.3%, respectively. This phenomenon further confirms the previous hypothesis: the assistance score of designers is not closely related to the proportion of online assistance voting. There are some unacceptable mistakes between them.

- Designer’s Rating

Compare the percentage of online assisted votes with the student designer's score. Similarly, Figure 3.3 shows the percentage of 1,000 valid online votes.

The proportion of "online assisted voting" mentioned above is not necessarily the same as the designer's score, see Figure 3.3. Even in the minimum MAE and RMSE (1), the proportions of these two evaluation indicators within the scale range are still 28.0% and 37.3%. In the PPMCC, there are 5 designers with only over 0.25 points, indicating that they have little relationship with the proportion of online assistance.

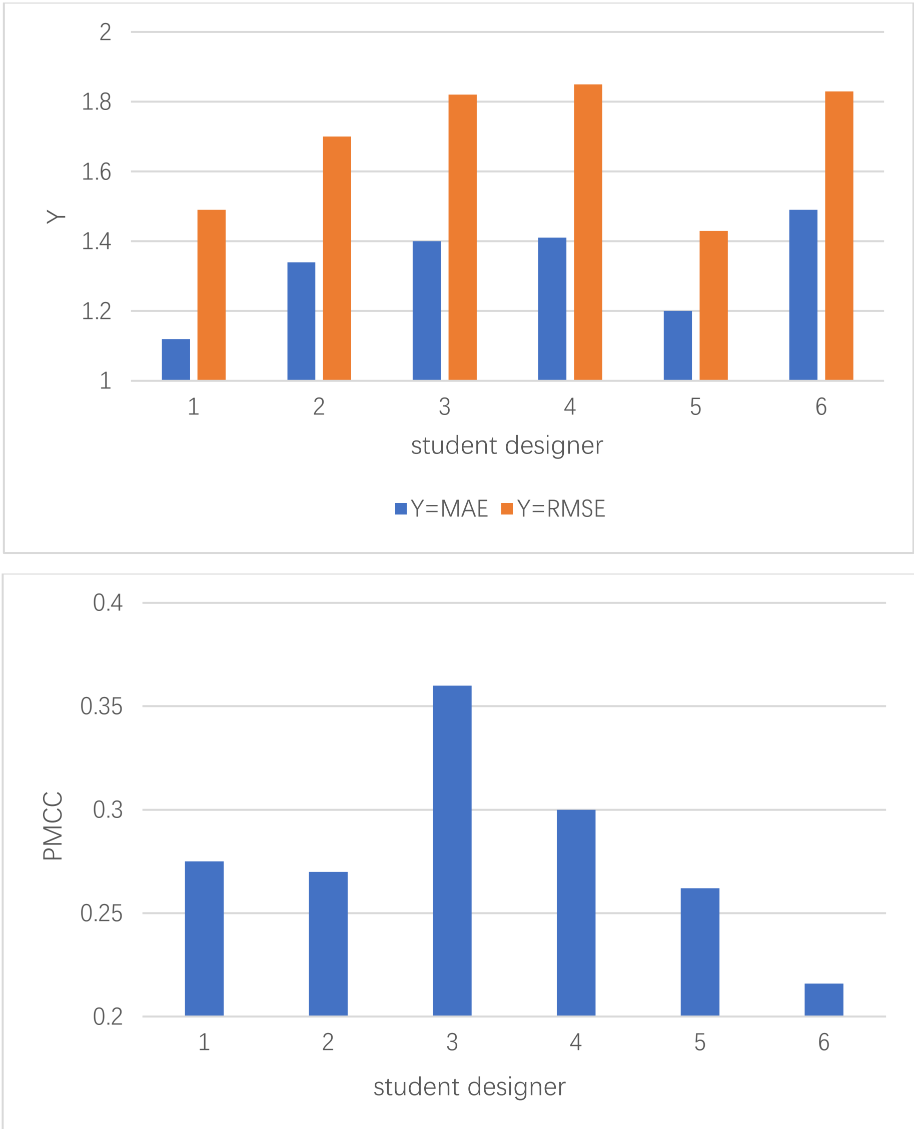


Figure 3.3 Student designers' ratings vs. online votes

Another interesting study found that different designers evaluate usability differently. Out of 1,000 comments, only 12 (just over 1%) received unanimous praise from the designers. On the other hand, the helpful evaluation criteria in many reviews deviate significantly. For example, use "2" for a comment, "-2" for one, and "1" for one. Annotators gave three different evaluations. There is also a case where a comment is marked with two "2"s, while another comment is marked with a "-2" by another designer. As can be seen from the survey results, some opinions differ significantly.

The above interesting research results show that different product designers will have different evaluation criteria for evaluating the usefulness of evaluation. This explains why adjusting the validity of reviews from the designer's perspective does little to help other designers.

3.3.3 Helpful definition

Obviously, the first objective is to figure out why certain evaluations earn a unanimous rating of helpfulness. Specifically, why did the designers provide the same polarity helpfulness label (i.e., assigning all "–2" labels or "2" labels to some reviews) without providing evaluation instructions? In this case study, an interview with these designers was conducted to determine the reasons for this. According to the interview, some of the reasons reviews receive all "2" ratings are as follows: "a long review covers one's tastes," "mentions many various characteristics," "highlights the product's pros and cons," etc. While the grounds for those obtaining all " 2" ratings include "did not express anything positive or negative regarding features" and "no performance information," etc.

Second, it is also interesting as to what happened to the reviews whose labels diverged significantly. Therefore, a second inquiry was posed to analyse the designers' motives and viewpoints. Due to the fact that each designer's labelling is unique in this instance, all three designers were questioned separately. Consider the prior review that received a "2," a "–2," and a "1." The designer who gave rating "2" for "most useful" said that this review "stated that the light did not function correctly because the switch was somewhat jammed." This review also highlighted that "the light flashes intermittently after prolonged usage (needs switching off and waiting a short period for the device to cool)" The designer found it useful because a number of issues were identified along with probable causes. Other designer, offering "least helpful" with label "–2", highlighted that this review "just focuses on the switch problem" and "the problem described should not be tied to the lamp." Another intriguing example is a review with two "2" ratings and one "–2" rating. The designer who gave a score of "–2" noted that "customers discuss the lamp's helpful much more than its negative aspects." These explanations for why online evaluations were assessed as such help this study's ability to comprehend the product designers' perspective.

3.3.4 Discussions

This section aims to understand how designers interpret annotations as a concept. In subsequent interviews, the three designers gave some important critiques to explain why some critiques are useful. This allows this article to explore the web evaluation of design preferences from the perspective of a product designer.

From a product designer's point of view, it is inappropriate to use online voting ratios or pre-set evaluation criteria to predict whether online reviews are useful. People overlook how product designers interpret, define and evaluate online reviews.

The first exciting problem from the standpoint of product designers, is how to get relevant input about client desires from the huge amount of online reviews. These elements make it easier to find relevant online reviews. Furthermore, it has been revealed that some causes are not clearly limited to a specific domain area. A number of explanations, in particular, are domain-independent, such as "a long assessment addresses one's preferences" and "discusses numerous topics," and so on. As a result, it is vital to determine if the utility of assessments conducted by product designers in one domain can be transferred to other ones.

Second, the problem to be solved is to rate the network while taking your own opinion into account. In the interviews, some cases showed that product designers have their own criteria for evaluating the effectiveness of feedback. an evaluation system based on network evaluation is required, and the designers' own viewpoints are comprehensively considered. Online reviews and personal information of designers are important because they can help you develop this recommender system.

3.4 Review analysis for consumer preference

The goal of this case study is to learn how product manufacturers/designers may use customer online reviews to analyse customer needs. As seen in Chapter 2, customer survey results are used to analyse customer demands in current research initiatives. However, it is commonly agreed that internet reviews offer essential consumer information. However, they are not presently being analysed and used in consumer requirements analysis. Traditional survey data are mostly derived through customer investigations, in which customers are asked specific questions. Consumers submit replies in response to these questions. The solutions are often drawn from a predefined answer list, however there are some open questions with evident meaning. However, internet reviews vary from the survey results. Online reviews are essentially free writings. They are created at random by customers and are not guided by any queries. Online reviews are often considered as a great research tool for analysing client attitudes. However, it has not been completely investigated how online reviews may be used directly in product design.

In this case study, six products on https://onaemotion.com/en/ were selected, they are "Dottie", "Cobalt", "Marble", "Embolic", "Panau" and "Ele".

Table 3.2 reviews number

Lamp	Dottie	Cobalt	Marble	Embolic	Panau	Ele
Number of reviews	370	306	318	304	210	287

In the beginning, a recommend listing the keywords in the product design specification, they are all based on the PDS project documentation and are not very precise; however, as more reviews are analyzed, this conclusion will be more accurate. See Table 3.3.

Table 3.3 Keywords of product design specifications items

Keywords of PDS items –training data			
light	Switch	Cold light	intelligent
design	Function	Bulb	Easy to use
Bright	Warm light	LED	Assemble
package	recycle	material	delivery
price	frame	base	stand
color	repair	cover	shade

The next step is to label the online opinions collected. Read all the notes and identify the key words in each note. A "keyword" here means a word or a phrase. Sometimes, a single word is used to express the design specifications of a product, and other times, a single phrase is used. If a sentence contains these keywords, it will tie the keywords to the design description of the product.

Connectivity is the customer's view of product design specifications. Take "0", "1" as the unit, "-1" as the unit. The least satisfied is "-1" and the most satisfied is "1". Figure 3.4 shows an annotation marker.

No.	sentence	keywords	cons(1) / pros(-1)
1	Really gorgeous table lamps. Even better in real life than I expected.	-	
2	The bottom of the support could be improved to increase the stability when the lamp is placed on the table	support	1
3	Easy to assemble	assemble	1
4	good lamp but the down side is the delivery, it takes too long to receive it.	delivery	-1
5	A nice looking lamp for my bed room.	-	
6	It seems a bit expensive for such a simple lamp. Not worth the price	price	-1
7	It package was a large box and all parts came with their own little boxes, which is unnecessary.	package	-1
8	After two months use, the shade is broke,	shade	-1
10	I'm so pleased with this lamp ... Very good quality... Very well packaged and delivered without a scratch	quality	1
11	I'm so pleased with this lamp ... Very good quality... Very well packaged and delivered without a scratch	package	1
12	I'm so pleased with this lamp ... Very good quality... Very well packaged and delivered without a scratch	delivery	1
13	Good idea but light not nearly strong enough	light	-1

Figure 3.4 Review labeling

In this example, the opening line is: "Very beautiful lamp. Much better than I imagined." There are no keywords related to the product design description, so it is indicated by "-". Line 10: "I like this lamp a lot, it is of good quality, well packaged and delivered without scratches", there are many keywords on it, so after writing the keyword "quality", put it Paste to the next two lines, lines 11 and 12, with "package" and "delivery" as keywords.

Finally, to prevent misidentification in such time-consuming and laborious work, all annotations were re-examined.

3.4.1 Preliminary results

- Words connected with different product design specifications

After careful check, it can find from the dataset's debates about keywords and product design descriptions in online reviews. Specifically, some specific keywords only contain a product design description. However, some keywords also indicate the design specifications of the product.

Take the word “bright” as an example. One is “...It obviously bright enough for me in the needs of...” and the other is “...Very bright color and well packed in the box when I...” In the first sentence, the word “bright” is utilized to refer to “brightness of the light”, while the other sentence is referring to “appearance”.

Table 3.4 lists the word counts associated with different product design specifications. As shown in Table 3.4, there are many keywords related to the engineering characteristics of different products.

Table 3.4 words connected with product design specifications

Lamp	Dottie	Cobalt	Marble	Embolic	Panau	Ele
Number of reviews	33	29	24	36	22	34

The same keyword is associated with different product design parameters, that is, the user's concerns cannot be dealt with in a single word. Intuitively, a word similar to a keyword or a context word can be used to describe a topic relevant to the user. These exciting phenomena led this study to explore an approach that combines online reviews with product design criteria.

- The frequency of product design specifications

Once online reviews are linked to product design specifications, evaluating new product design specifications is a critical step.

User reviews online often refer to a product's design specifications, depending on its importance. In other words, we can recommend more weights for those product design specifications that customers often talk about. Five commonly used keywords are listed in Table 3.5.

Table 3.5 Top five frequent keywords

Dottie		Cobalt		Marble	
Keywords	Frequency	Keywords	Frequency	Keywords	Frequency
easy to assemble	30%	Material	31%	Design	29%
Small	21%	Quality	22%	Material	26%
Design	20%	Recycle	19%	Easy to assemble	21%
package	17%	Design	15%	Recycle	16%
delivery	12%	Price	13%	Price	8%

Embolic		Panau		Ele	
Keywords	Frequency	Keywords	Frequency	Keywords	Frequency
design	28%	Design	29%	easy to assembly	33%
Value	25%	structure	23%	Design	28%
material	21%	Recycle	22%	Delivery	17%
Recycle	17%	Delivery	15%	Price	12%
package	9%	Package	11%	Recycle	10%

As seen from the table, for table lamps “Dottie”,” Marble” and ”Ele”, there were nearly 50% consumers prefer talking about “easy to assemble”, “design” and “delivery”. It is easy to understand. For a table lamp, the easy to use and the design may always be the first concern for consumers. However, whether they should be assigned with a higher priority is unknown. This hypothesis will be examined in Chapter 5.

3.4.2 Discussions

This paper aims to understand how to use online reviews to analyze customer needs from the perspective of product designers. In this case, we found some interesting phenomena, and can get useful manual annotation data.

First, you need to combine online reviews with product design instructions. After knowing all the information, you can come up with the design priorities for the new product. However, now both tasks are done manually. This takes time and effort. This report aims to explore how to build a design-oriented knowledge base through online reviews.

The first thing that piqued interest was how to automatically link online reviews to product design specifications. Many keywords in online reviews refer to different product design standards. A single sentence cannot accurately determine the relevant product design standards. I hope to learn about the relationship between customer requirements and product design specifications from online comments. The purpose of this language approach is to combine online reviews with product design specifications, while also helping designers avoid reading online reviews verbatim for analysis.

The second interesting question is where should place it in user-oriented product design. The issue of weights in product design specifications has always been a concern. The current research in this field only focuses on the survey data of customers, while ignoring the important customer information in the online evaluation. It is expected that there will be a way to put the product's design specifications on an online review. In a customer's evaluation of a product, the customer's emotions, the customer's overall satisfaction and dissatisfaction can be conveyed to the customer.

3.5 Summary

In this chapter, the framework of proposed system was explained. This system focuses on online evaluation of design preferences from the designer's point of view and builds a knowledge base with design as the core through online comments.

There are two problems in the question, namely how to construct a set of useful online reviews and incorporate them into the evaluation of online reviews. To understand designers' perceptions of reviews, we conducted a case study using a large number of actual online reviews.

The second question is the relationship between customer evaluations and product design specifications, and how to make customer evaluations an emphasis on existing product models. To better understand how product designers use online reviews to analyze customer needs, we did another exploration.

Through two exploratory case studies have obtained some valuable information and interesting observations. All of this is the basis of this research and helps it to build a well-developed model and algorithm to unearth useful information from online reviews for product design. The next job is to figure out the answers to the four questions.

In the next chapter, some new techniques will be introduced to simulate the first problem of determining design preferences of online review from the perspective of a product designer.

Chapter 4: Helpful Online Reviews Identification

4.1 Introduction

Chapter 3 introduces the architecture of the system. Currently, there are two problems: one is how to find online reviews suitable for design, and the other is how to build a design-oriented knowledge base through online reviews. In addition, we also made two case studies to discuss how to use online reviews in product design. Through the empirical analysis of two instances, it is found that the designer's answers and data are very useful and can help us ensure the normal operation of the model and algorithm.

This chapter focuses on identifying design-related reviews on the web. The first question answers two questions: one is to write a practical online review list from the designer's point of view, and the other is how to determine the rating of online reviews based on the designer's subjective judgment. In the first exploratory case study, product designer evaluation utility was weakly correlated with the proportion of positive online evaluations. Product designers provide many important evaluation elements to explain why some evaluations can help with the two follow-up investigations of the initial exploratory case. These guidelines allow us to replicate both cases in our study. This chapter will discuss specific technical issues.

4.2 Define online reviews helpfulness

4.2.1 Approach Overview

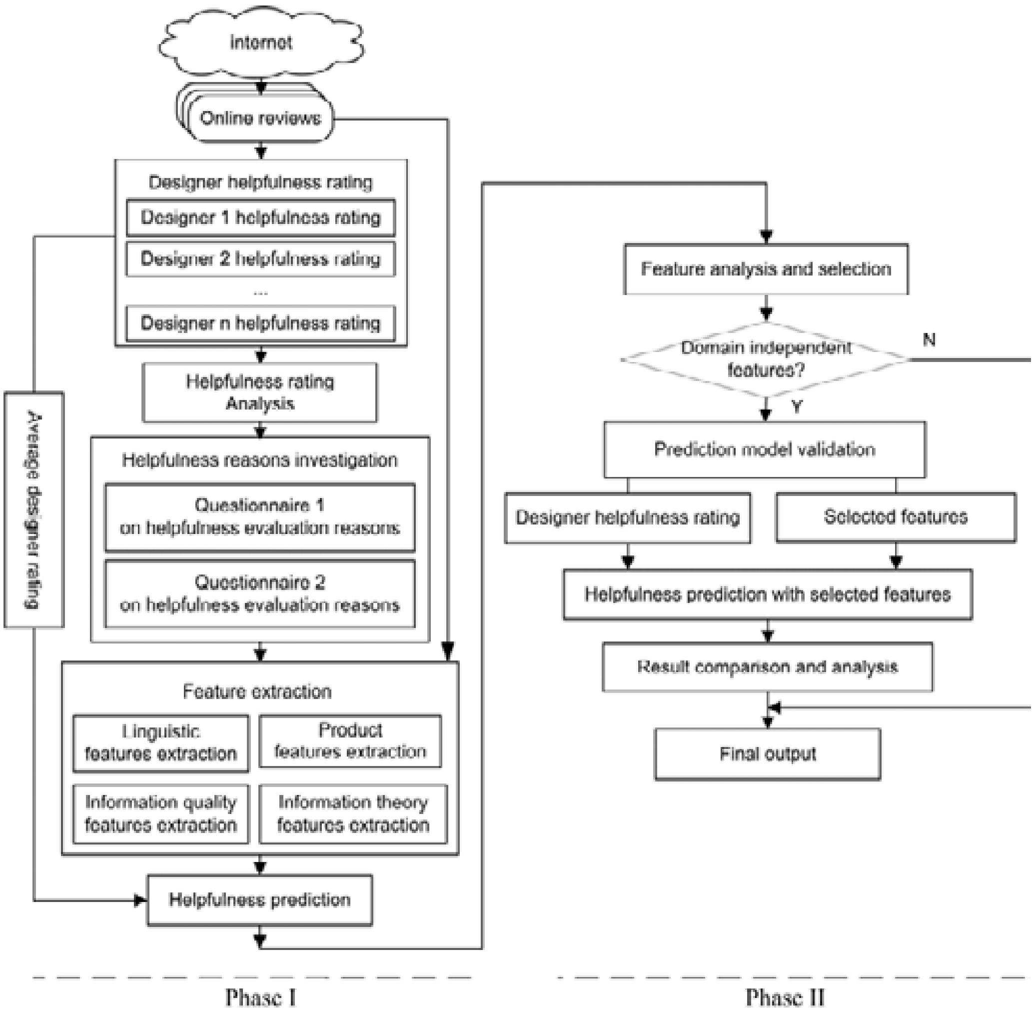


Figure 4.1 The approach overview

The first stage is to build a model to predict the effectiveness of network evaluations using the designer's gold standard of usability evaluation. Based on the designer's perception of usability, this paper proposes four basic characteristics: language, product, information quality, information quality, and information-theoretic information retrieval. Identifying and extracting these features is independent of the designer's hierarchy and other external knowledge sources. Since these four features are directly extracted from the content of the reviews, we call them "internal features". These features are used as input and the designer's average availability, and a regression model is constructed to find a suitable learning strategy. The first phase of the investigation has come to an end.

The information of features is gathered only from the content of the reviews themselves. The purpose of this research is to investigate whether the domain features, which are one of the four types of features, have a significant link with the helpfulness evaluation. During the second phase, feature selection and feature analysis are carried out with the goal of determining whether the categories of domain-dependent features would have a significant impact on the accuracy of the helpfulness prediction. The regression model that was developed from one particular product during Phase I is then applied to forecast the usefulness of unrated reviews, either with or without the domain attributes, on different products in other domains. The question that needs to be answered is if the properties of the domain have a strong association with the helpfulness that is being perceived. In other words, the modelling of helpfulness cannot be confidently migrated to another domain because, without domain features, if there will be a significant loss suffered in terms of the correlation between the predicted helpfulness and the designer ratings, then the modelling of helpfulness cannot be migrated. In Phase two, these will function as the primary components of the research material.

In step 2, will focus on assisting with problem identification. Since the number of review reviews in a given area is limited, the question is whether a useful model can be built from review text alone, and whether this model is general enough to be used in other fields that may not be able to use manual Scoring notes.

4.2.2 Four categories of features

Empirical analysis results show that designers are concerned with the usability of online reviews. Some designers believe that a large number of words and phrases, measured by a large number of words and phrases, can provide more useful information. In addition, some customers provide feedback to customers about their likes and dislikes about the product. It is useful for product designers to understand the reasons for such feelings, as they are often expressed through adjectives and adverbs. Meanwhile, three designers who were invited to participate in the survey rated online reviews, saying they lost interest in reading and understanding online reviews if there were a lot of grammatical errors, spelling mistakes. All of the above can be thought of as a feature that mimics the useful properties of online reviews.

During this time, some product designers have also been concerned about whether the main features of these products have been clarified. For example, designers may list their own product features. When designing new models, these product features are seen as an important carrier of information, as each list contains the most important product elements that customers are talking about. If a product's characteristics are considered to be a particular product, then it affects its usefulness. Therefore, this paper takes product characteristics as the main type of model construction.

In designer reviews, some designers said: "There's a lot of character in this review, but other designers say, "A lot of these reviews are about what critics love and hate. "In fact, at a higher, more abstract level, designers integrate these arguments into different qualities of information. For example, first because of the breadth of the information, and second because of the accuracy of the information. All of these reasons , so that this paper explores the possibility of collecting characteristics from different levels.

In case studies, some designers classified the least important evaluation as "information without (specific) product user experience". Obviously, from the designer's point of view, when evaluating, the presentation of information will be different. For example, the designer's perception can be significantly influenced by the functional emotions of the product, and the different or opposing causes of these emotions often bring additional information. Also, both positive and negative discussions about the product are generally seen as favorable. In their analysis, both designers highlighted an important aspect, the positive and negative evaluations of many aspects of the product.

This phenomenon is sometimes referred to as "attitude differences," and this pattern is a manifestation of it. Plus, the review is even more valuable when it makes a strong, in-depth point of view on a specific product, and it's well-argued. Therefore, we recommend using information theory to understand these results.

4.2.3 Modeling of helpfulness

Whether all the information gained from online reviews can be used to build a pragmatic rationale for online reviews by product designers. This feature does not need to exploit specific area information. These features come only from network evaluations and are used to build useful models. In the following sections, we define four properties derived from exploratory cases.

4.2.3.1 Linguistic features extraction

Following Section 4.2.2, linguistic features are used to predict the validity of online reviews. Table 4.1 contains the characteristics of the language.

Table 4.1 Linguistic features

Feature Alias	Description
L-NW	number of words
L-NS	number of sentences
L- ANWS	avg. number of words per sentence
L- NADJ	number of adjectives
L- NADV	number of adverbs

This step uses several natural language processing (NLP) methods such as word attribute (POS) tags. Part-of-speech tagging refers to tagging words in a discourse according to certain parts of speech, such as nouns, verbs, pronouns, etc., prepositions, adverbs, adjectives, or other signs of parts of speech according to the definition and context of parts of speech. The association of adjacent words in a phrase, sentence or paragraph with related words. In addition, the English and grammar checking software "LanguageTool" is an open source that can count grammar errors.

4.2.3.2 Product features extraction

Commonly, POS tagging was also utilised to determine product parameters. After POS tagging is complete, candidate features are created using linguistic criteria. For example, in the review "The package is recyclable," "N> [feature] good" is a rule, where "package" precedes "good," and "good" is a rule that matches the segment "package good" to identify feature candidates.

On the basis of a document profile (DP) model, this process creates a list of desirable attributes for a given product (Soon et al., 2009). Figure 4.2 shows the process flow of a DP model.

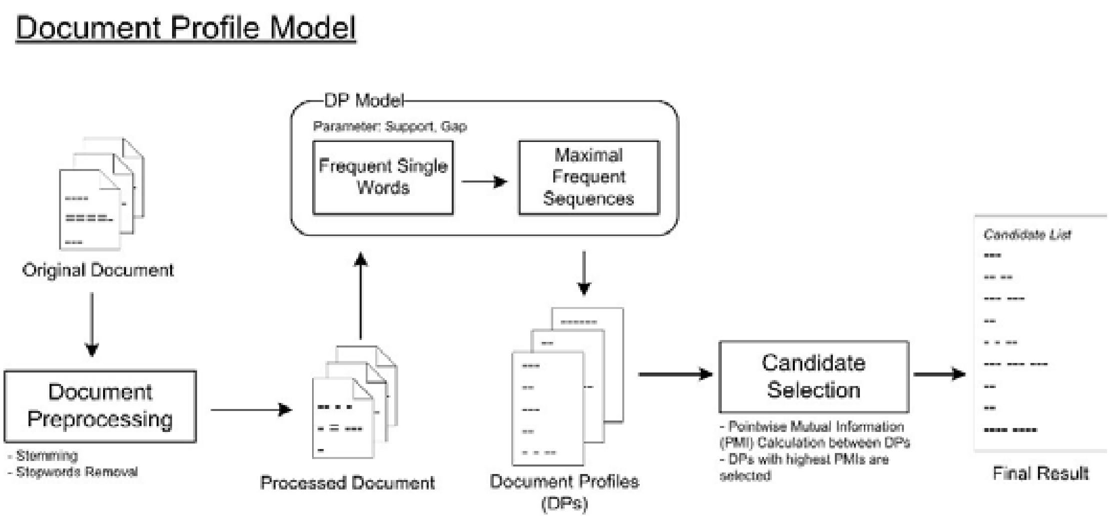


Figure 4.2 The process flow of a DP generation (Soon et al., 2009)

The result of the DP mode is a word and their associated frequency, denoted by wi, where wi is the word, and vi is the occurrence of that word. When describing text, DP mode mainly studies how to capture words or strings of words that often have semantic meaning at the word level. The method uses point-wise mutual information to quantify word-based maximum frequency sequences (MFS). Point-by-point average mutual information is a basic statistic to quantify the series of attributes.

The vocabulary list is generated by DP mode, and the most frequent vocabulary is found. Note: Product features are usually denoted or represented by nouns or noun phrases. In this study, the most frequently used nouns and noun phrases were considered as possible product attributes.

Unsurprisingly, if all candidates are considered to be a product feature, it would be "light", "ona", etc. Designers use their expertise to remove words from many predefined contexts. In DP mode, low frequency items that are not product attributes are also included. Those low-frequency terms that would cause the results to vary were excluded.

4.2.3.3 Features extraction based on information quality

Several studies have attempted to identify different information quality (IQ) characteristics that can be used to quantify information quality. This paper proposes a variety of criteria for evaluating the quality of information. This article is based on five indicators of information correctness, timeliness and comparability; information coverage and information relevance. Table 4.2 lists the features captured by information quality.

Table 4.2 Features

IQ Aspects	Feature Alias	Description
information accuracy	IQ-NSS	number of subjective sentences
	IQ-NOS	number of objective sentences
information timeliness	IQ-TIM	number of total elapsed days
information comparability	IQ-NRP	number of referred products
information coverage	IQ-NPF	number of product features

information relevance	IQ-NSPF	number of sentences referred product features
	IQ-RPFR	number of product features / number of sentences referred product
	IQ-RPFS	number of product features / number of sentences
	IQ-RRS	number of sentences referred product features / number of sentences

- Identification of sentence sentiment orientation

To identify the mood of a sentence, first determine whether there is an adjective that reflects the author's mood, since it is often used to express mood only adjectives are considered opinions.

First, there are two sets of adjectives: positive and negative. The meaning of an adjective indicates its deviation from the norm. Positive adjectives (like good or perfect) are positive, while negative adjectives (like horrible or horrible) are negative (like tough or bad). The results show that the sentiment orientation of synonyms of opinion words is similar, but the sentiment orientation of antonyms is opposite. WordNet is then augmented with the first seed word. If the noun is synonymous with an affirmative adjective, add it to a positive word list. Likewise, a negative antonym is added to the original negative list.

A method for predicting text sentiment proposed by the author in Mingqing and Bing (2004). In this process, the position of the sentence can be judged by operating on the instances of viewpoint words. When there are more affirmative words than negative words, the sentence is regarded as affirmative, and vice versa. "No" can also be used as a modifier for negation. If the word "no" comes out, the feel of that sentence changes.

- product model

Step 1: Data preparation and pruning

In this step, there are two tasks to be done. First, divide the header pi(t) into an array of strings. Second, words that are not part of the product model (such as "Ona", "with", etc.) are removed from the string array.

Step 2: Inverse index generating

This step creates an inverse index for each possible model name. A reverse index is made of possible model names, including the words generated in the first step and a linked table with model names. If the linked list length of this item is 1, it should be used as the schema name because it is unique.

Step 3: pruning and define model name

Furthermore, if it cannot be decided whether these phrases comprise a model name or not, they must be kept. For example, "Ona 48CAMPANA 12W" is the name of a light. Because it is hard to tell whether the model name is "Ona" or "48CAMPANA," both words must be used. Following that, a list of prospective model name possibilities is compiled. "Lucene," as the model name suggests, is the open-source software employed in this study.

4.2.3.4 Features extraction using information theory

In this part, three heuristic rules are evaluated using information theory and useful features are extracted from them. Table 4.3 lists the properties obtained using information theory.

Before quantitatively measuring the above three indicators, the characteristics of a certain commodity should be evaluated first. This paper improves on the method proposed by Ding et al. (Dr., 2008). On this basis, the co-occurrence of product features and emotional words is used to predict them. Also, when a negative word is present, the functional sentiment of the product changes.

Table 4.3 Features extract

Feature Alias	Description
IT-SI	The self-information sum of product features
IT-DS	The divergence of sentiment sentences
IT-SS	The strength of sentiment sentences

Finally, the sentiment value threshold for product features is improved. When the sentiment value exceeds a certain threshold, positive sentiment is identified based on the characteristics of the product. Likewise, when a person's sentiment value falls below a certain level, the product is considered negative sentiment. If not, a neutral point of view will be considered.

- The self-information of product features

Different opinions regarding a product feature may be expressed in several reviews. Designers are intuitively given with diverse knowledge regarding usefulness. The probability of a product feature, prob (fj, sentiment), in a dataset is calculated as follows:

$$prob\ (f_j,\ sentiment) = \frac{numofsentence\ (f_i,\ sentiment)}{numofsentence\ (f_i)} \tag{4.2.1}$$

numofsentence (fj, emotion) is the total number of sentences used to express fj, and numofsentence (fj) is the total number of sentences in fj. According to information theory, SI(fj, sentiment) is calculated as follows when the product characteristic fj and its related sentiment are provided:

$$SI\ (f_j,\ sentiment) = -log\ (prob\ (f_j,\ sentiment)) \tag{4.2.2}$$

Because many product features can be mentioned in a single note, the overall self-information about the SI (reviewi) is as follows:

$$SI\ (review_i) = \sum SI\ (f_j,\ sentiment_{ji}) \tag{4.2.3}$$

reviewi is the ith review, fj is the jth feature, and sentimentji is the feeling that reviewi associates with fj. SI (reviewi) is the data collected about how different people feel about a product feature mentioned in reviewi.

- The divergence of sentiment sentences

Those reviews that mention both the benefits and the drawbacks will satisfy both designers and future consumers due to the abundance of information offered. Several phrases in a review of a table lamp might read, "... Extremely good product, the brightness adjustment unit works very well on its own, and it automatically adjusts the brightness based on the current lighting conditions, however the smart light app on my phone is not very user-friendly." Both the advantage and disadvantage of the brightness adjust are discussed in this evaluation. Online reviews provide insightful information.

Therefore, the perceived difference in the characteristics of a certain commodity can be expressed by three emotions (positive, negative and neutral):

$$DS\ (f_j) = \sum_{s \in \{positive,negative,neutral\}} SI\ (\ f_j\ ,\ )s \tag{4.2.4}$$

Since different product characteristics can be included in a single annotation, the difference information DS(note i) of annotation i can be determined as the sum of the difference information of the characteristics of each product, which can be expressed as:

$$DS\ (review_i) = \sum \mathrm{DS}\ (f_{ij}) \tag{4.2.5}$$

fij represents the jth feature in reviewi. DS (reviewi) is the information gathered from reviewi about the strengths and weaknesses of the product.

- The strength of sentiment sentences

People often suggest strong opinions on some specific product. It is clear that the greatest attitude towards a product's functionality is positive, negative or neutral. Taking the emotional strength SS(fj) of the product feature fj as the sum of the self-information of the three emotions, it is expressed as follows:

$$SS\ (f_j) = max\ (SS\ (f_j,positive),SS\ (f_j,negative),SS\ (f_j,neutral)) \tag{4.2.6}$$

Therefore, the sentiment strength of reviewi, SS(reviewi), indicates several product characteristics, which are calculated as follows:

$$SS\ (\mathrm{review}_i) = \sum SS\ (f_{ij}) \tag{4.2.7}$$

SS (reviewi) refers to what the designer gets by making intense and vehement reviews about the features of a particular product.

As described the used a regression model to predict the effectiveness of the network evaluations in this study. A guided clustering algorithm and a fast decision tree learner are introduced for regression analysis.

The algorithm uses the obtained information to construct a decision tree and prune it with the smallest error. The Bootstrap clustering algorithm is a comprehensive meta-algorithm for machine learning that can improve the stability and classification accuracy of classification and regression models (Leo, 1996). Given a standard training set D of size N, the bootstrap aggregation algorithm generates M additional training sets

Di, each of size N'N, by averaging and alternatively sampling examples from D. In each Di, some samples can be put back into sampling. Such samples are called pilot samples. M models are fitted with M bootstrap samples, and then fused by means of mean regression and classification output.

Note that there are many other commonly used algorithms such as Multilevel Perceptual Neutrality (MLP), Simple Linear Regression (SimpleLinear), SMOreg (SMOreg), Decision Tree (REPTree), etc. Both methods are machine learning techniques and are often used to describe complex interactions between multiple inputs and outputs. MLP is a mathematical model inspired by the network structure of biological brains. SimpleLinear is a least squares estimator, which is a linear regression model for a single predictor. A straight line is fitted with n points, and the sum of squares of the residuals of the model is minimized. SMOreg replaces all missing values globally and converts nominal features to binary features. REPTree constructs a decision or regression tree model that minimizes the gain of information.

4.2.4.2 Algorithms in Phase II

In the second stage, the main focus is on whether the patterns learned in the first stage can be transferred to different products in other fields, focusing on the effect of specific qualities. Specifically, a variety of feature analysis and feature selection algorithms are used to find the most effective and practical features. The following is the algorithm for feature selection:

Cosine similarity, Jaccard similarity and matching similarity measures are used. In the sample library, measures of Jaccard similarity and matching similarity are used. The attributes of each matrix and the normalized values of the instance objects are projected to predetermined numbers before using these indices. Then, apply these metrics to the modified matrix. So, these features are classified and the best feature is selected as the selected feature.

In statistical models, interactive information is a generic term for connection and related applications. This is a commonly used feature selection method, in which the mutual information of the feature and the target is close, and it has been widely used. Yang and the others are the same. (1997) determined that the feature selection method is not suitable for text classification, and no one will test whether the interactive information is suitable for evaluating customer feedback. On this basis, a feature selection strategy based on mutual information is adopted.

4.2.5 Test and discussions

4.2.5.1 Test setup

In this experiment, used 1,000 reviews on Amazon.co.uk as described in Section 3.3. Since Section 4.2.1 introduces two distinct phases, the performance is evaluated separately.

To evaluate the operability of the first phase, the average usability of the three designers was taken as the usefulness of the online evaluation. A total of 83 features were extracted, including 6 language features, 65 product features, 9 information quality features, and 3 information theory features. Guided aggregation techniques (- P100-S1-I10) and fast decision trees (- M 2- V0.001- N 3- S 1-L1) were used. In addition, MLP, SimpleLinear, SMOreg, REPTree, etc. are also evaluated, and the selected method is evaluated, and the results show that the method has good performance. In the experiment, a ten-fold cross-check method was used, based on the average of 1000 replicate experiments.

In step 2, we will decide whether the patterns learned in the first phase are sufficiently general to be applicable to other products that cannot be graded manually. In this step, we will investigate whether some feature selection methods are suitable for this problem.

4.2.5.2 Results and discussions

Table 4.4 demonstrates the comparison between the expected helpfulness and the designers' evaluation.

Table 4.4 Predicted results

MAE	*RMSE*	*PPMCC*
0.587	0.501	0.801

As can be seen from Table 4.4, the prediction results show that PMCC is stronger, with MAE and RMSE of 14.9% and 12.1%, respectively, which is the designer. Compared with Table 3.1, the model outperforms the proportion of online help voting. The model better illustrates whether the designer's point of view is feasible.

In the first-level algorithm selection, we also adopted other algorithms such as MLP, SimpleLinear, SMOreg, and REPTree. In Figure 4.3, the performance of the two schemes is compared.

In three evaluations (higher PMCC, lower MAE, lower RMSE), the better selection method was combined with the guided aggregation algorithm of the fast decision tree learner. In addition, we got better performance compared to the results of the first test and the actual average assist score.

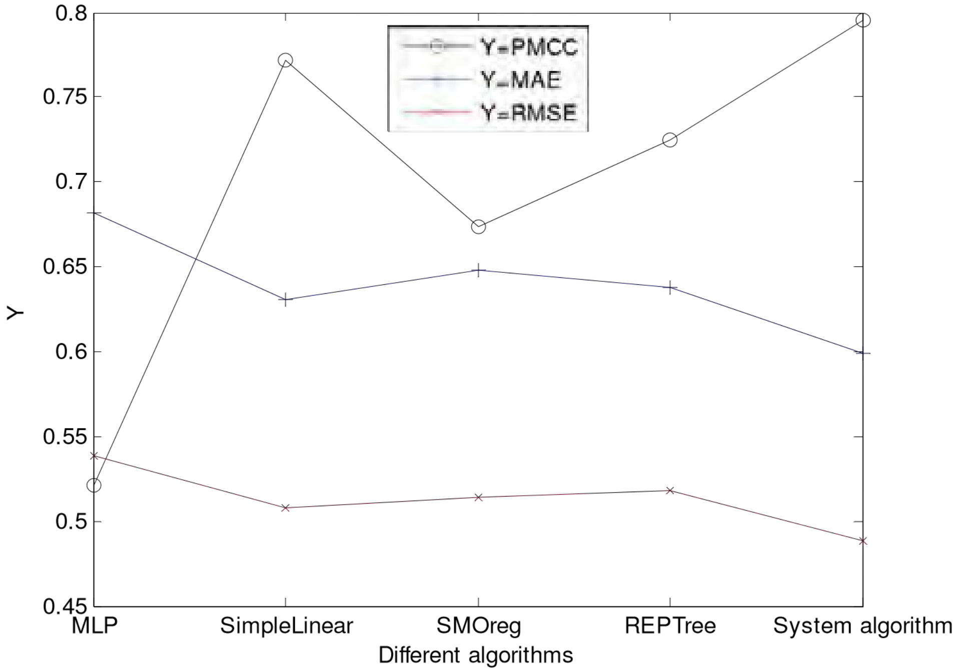
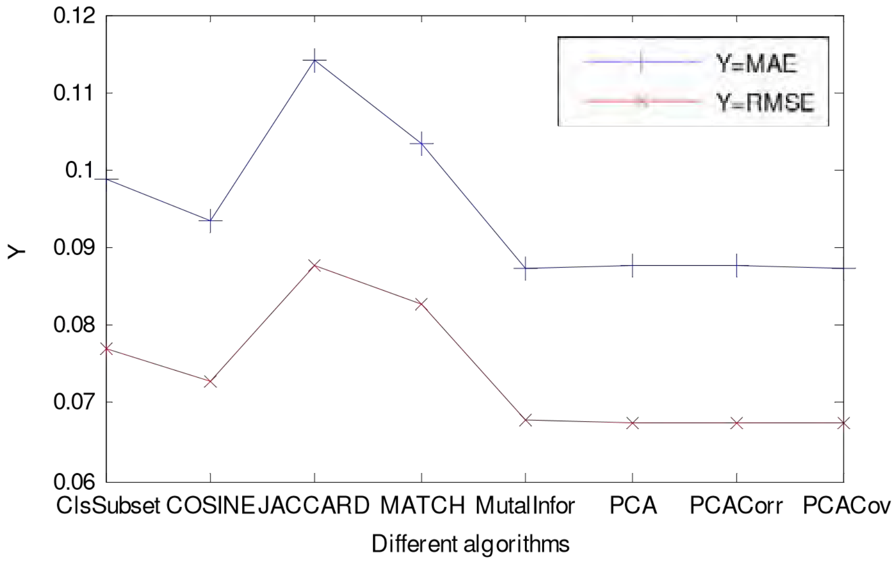


Figure 4.3 different algorithms

Figure 4.4 compares the evaluation effectiveness of the eight feature selection systems. All programs use high-quality features. The performance of mutual information and PCA of the three groups is the best. The distance between the two systems is the shortest. So, they chose as an app.



(a) MAE and RMSE results in phase II

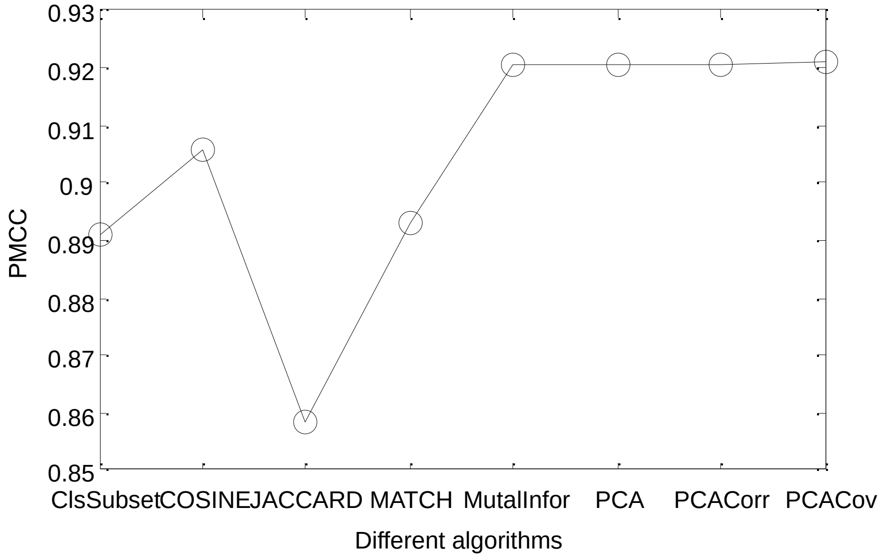
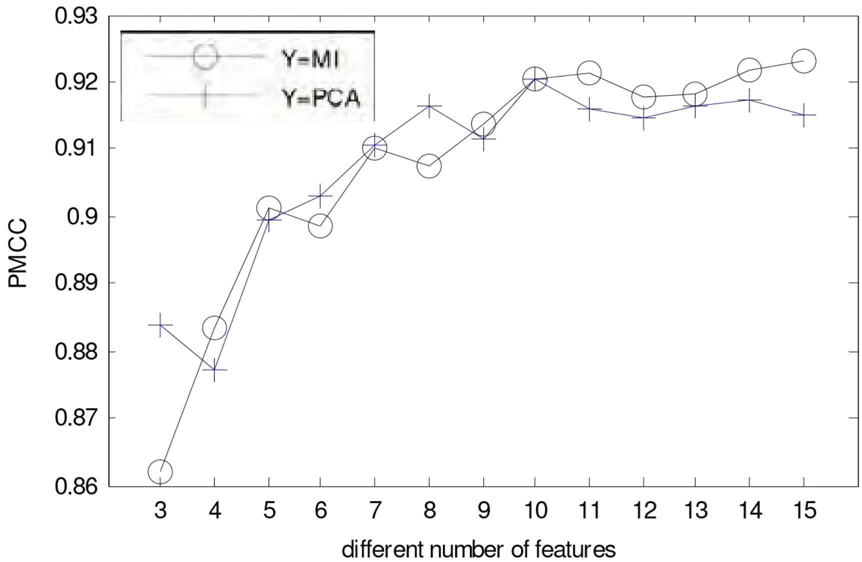
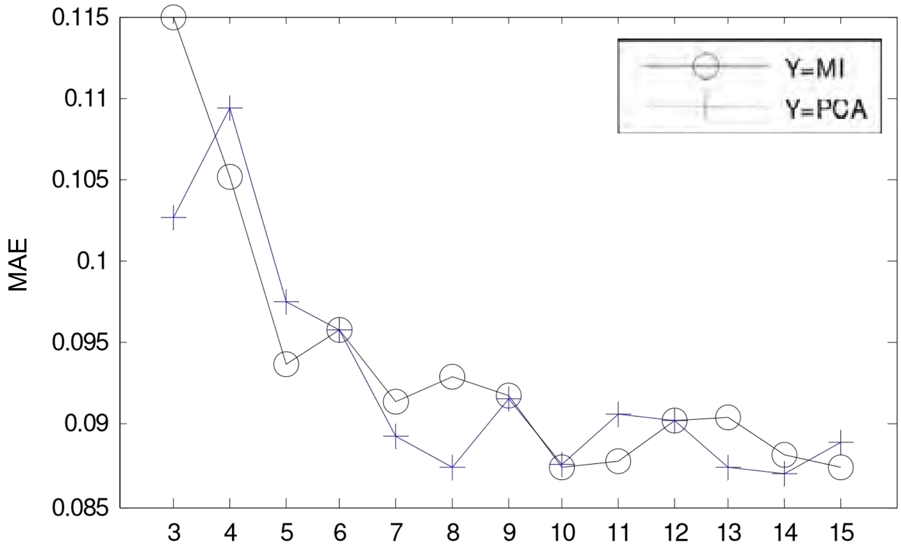


Figure 4.4 Phase II different algorithms

As can be seen from Figure 4.5, the more the number of features selected by the PMCC, the lower the MAE and RMSE. When the values of the two feature selection indicators are both 9 or 10, the curve will be in a relatively stable state. The results show that 9-10 features have the greatest impact on evaluation usefulness.



(a) PMCC at different numbers of features



(b) MAE at different numbers of features

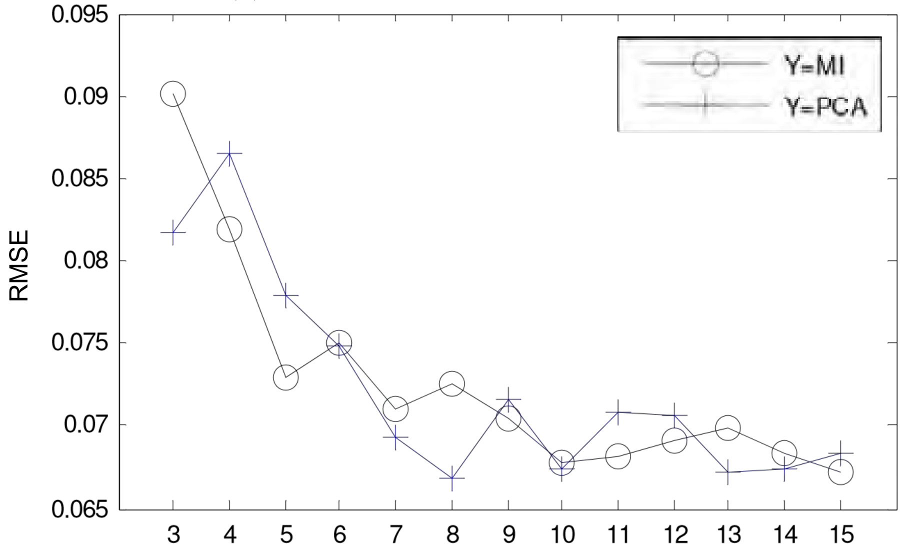


Figure 4.5 Performance

Table 4.5 shows the characteristics of these two options. We can see that, in fact, all of these qualities come from three different domains.

As mentioned earlier, our goal is to determine whether these three domain-independent features can be successfully applied to the prediction of online reviews without compromising the prediction accuracy of other aspects. We need to investigate the relationship between the predictive usefulness of the first stage and the designer's average score. The effectiveness of different types of domain features for network evaluation is investigated.

Table 4.5 features selection

	MI	PCA
1st	L-NW	IQ-NSPF
2nd	L-NADJ	L-NW
3rd	L-NS	L-NADJ
4	L-NADV	L-NS
5	IQ-NSPF	IQ-NPF
6	IQ-NOS	IT-SI
7	IT-SI	LN-ADV
8	IQ-NPF	IT-DS
9	IQ-NSS	IQ-NOS
10	VIDEO	IQ-NSS

In the follow-up interview for the case study, the most important question was, "What parts of this review make you think it was helpful?" Several designers, for example, said that the product "has many different features" and "highlights the likes and dislikes of the product." This is because adding these things to online reviews makes them more useful. In other words, the fact that some things are missing from the evaluation suggests that it may not be as helpful as others. In feature analysis, the importance of different traits is looked at. Zero means that the feature is not present in the Weka data file's feature vector construction, while a value that is not zero shows how important the feature is. Table 4.5 shows that the absence of some product features doesn't have a big effect on how helpful the product is expected to be. Other types of product features have different effects on how helpful the product is expected to be.

It can also be assumed that, regardless of the popularity of a product, there will always be a long-winded review of it by an experienced customer, and such reviews tend to be relatively Be brief.

Multiple extracted IQ features, such as IQ-NSPF, IQ-NOS, IQ NPF, and IQNSS, also significantly affect usability evaluation. IQ-NSPF and IQ-NPF confirm that "many of the product features mentioned in this review" are key to assessing usefulness. IQ-NOS and IQ-NSS represent the accuracy of information on the network. This shows that the authenticity of the evaluation information has a great influence on the usability of users. IT-SI is another important index for evaluating usefulness. This shows that this opinion is different from what most people feel, and is often beneficial. It is quite possible that these comments provide more information on this view and explain why.

Another study found that valid product reviews (IQ-NRP) may not always be comparable to other similar products, contradicting similar predictions that "good product reviews tend to involve many other products". We can assume that in a large number of online customer reviews, it is not necessary to list different products, but only mention one or two related products in useful reviews for better selection. Increasing the number of products does not necessarily lead to significant use effects.

On this basis, the feature selection strategy and PCA method based on mutual information are used to analyze the features and predict them. The following heuristic evaluation guidelines have been demonstrated: "Beneficial evaluations often reveal some functional tendencies of the product", "Beneficial evaluations are often longer", and "Beneficial evaluations often include the strengths and weaknesses of the project. "At the same time, we also found that features based on information quality were better predictors of usability.

4.3 Rating value for online reviews

4.3.1 Problem define

As the first exploratory case study in Chapter 3 shows, designers have very different ideas about how useful some reviews are. In the case study, an experiment was described in which one review was marked "2," "–2," and "1." The three annotators each gave their own opinion on how useful something was. Also, follow-up interviews show that the views of different designers may not always be the same.

This could mean that each designer looks at the usefulness of internet feedback from a different point of view or uses a different set of criteria. To meet each designer's needs, the main question is how to give rating values for online evaluations that take each person's opinion into account.

At first, different notations are used to define the recommended rating values in a formal way.

The group of designers is called "D," and the group of reviews is called "R." L is the set of rating values. For example, L = -2, -1, 0, 1, 2 is a set of rating values. A single designer (d) gives a certain review (r) a score (d, r). Based on a review, how would you suggest rating(d, r) as h(d, r) for a designer d? h(d, r) is the suggested rating, and rating(d, r) is the rating that designer d actually gave review r.

A regression or classification model can be used to answer this question. The goal is to learn the model or function f(d, r): D R L. This function is supposed to estimate rating(d, r) of a designer d based on a review r as h. (d, r). Now, the technical question is whether classification or regression methods are better.

The scoring scale is the main thing that makes the choice between classification and regression. When the evaluation index is not a discrete number, regression analysis is better. Classification is the best way to rate things that have different values. Another way to compare is to look at a situation in which all cases are handled the same way. In particular, the regression method tends to give a rating value that is close to the average rating of all reviews. On the other hand, the categorization will show that the most common label is "recommendation" (Christian and George, 2011). For example, let's say that r has marked a review as either helpful or not helpful. The regression tends to say that the average value is the safest choice, but the classification says whether the most common label is "helpful" or "not helpful."

In this study, a five-point scale is used to rate reviews. So, a classification is chosen to suggest star ratings for online reviews.

4.3.2 Overview of the rating value recommendation on online reviews

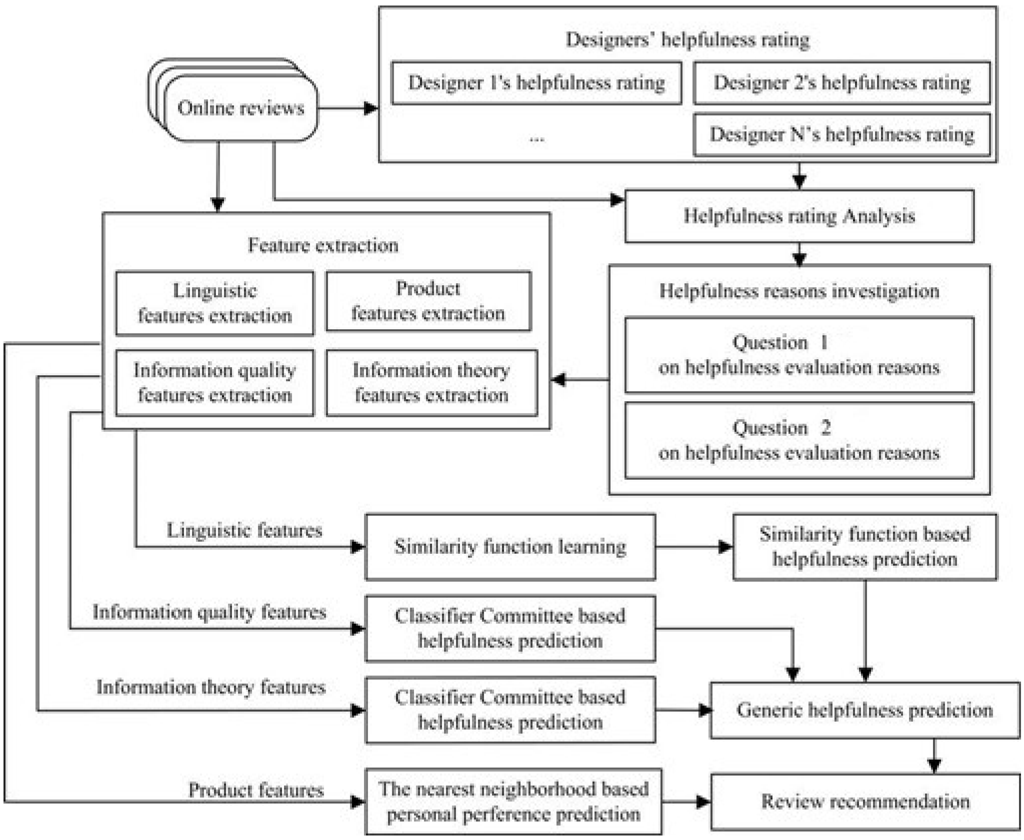


Figure 4.6 The technical blueprint

The case study shows that different designers have different opinions on whether online reviews are useful, and they also have their own criteria for determining whether some reviews are helpful. The fundamental reason is that different product designers have different needs, and according to intuition, different product features cause different designers to evaluate them differently. This paper assumes that rating(d, r) is the rating of the designer d according to the review r, from the general perspectives gh(d, r) and pp(d, r). In particular, the question is, after identifying the four characteristics, how to build a classification model to make recommendations; in general, both Gh (d, r) and the designer's personal judgment (d, r) are obtained considered. In the experimental study section, we will use the proposed model to test this hypothesis.

Overall, gh(d, r) is evaluated by three domain-independent dimensions: the language dimension, the information quality dimension, and the information dimension. These three domain-distinct features are all derived from reviews. This explains why they are used to illustrate universal properties. The pp (d, r) of individual evaluations was evaluated using the product feature dimension. Finally, a classification algorithm is used to aggregate the data of the two elements to provide a rating for online reviews.

4.3.2.2 Technical considerations

Intuitively, the ratings of two reviews can be compared and their content is the same. So, from a linguistic point of view, we can predict gh l(d, r) based on the learning of similarity functions. The similarity function is to judge the similarity between the evaluation contents through evaluation marks. If a similarity function can be specified and trained, then gh l(r) can be predicted as an annotation label l L that receives the largest average similarity to the unlabeled annotation r.

In terms of information quality and information quantity, only a few features were defined and extracted from the annotated data (e.g. 8 in xqual(r) and 3 in xquan(r) as described in Section 4.2.2). For example, gh quan (d, r) can get bad if you use three features and a fifth-order discrete classification classifier directly from x quan (r). The same result can happen for gh qual (d, r). However, it is a well-established fact of computational learning theory that the more autonomous a set of classifiers is, the better it will perform. In this way, a committee of four independent classifiers (three binary classifiers and one ternary classifier) determines the results in this dimension.

In terms of personal judgment, pp(d, r) is based on product characteristics, and the presence of different product characteristics is considered an important indicator. For example, view r gets the highest rating from the designer because it highlights some feature flaws. At the same time, it can get a minimum rating from other designers who claim that they are not talking about a person's concerns. Conversely, if Du and Dv also have similar evaluations, i.e., other evaluations are scored in a similar way; then du's evaluation ri and dv have the same score. Likewise, if other users provide ratings for ri and rj, du can also rate ri and rj as well. Therefore, the nearest neighbor method is used to predict pp (d, r).

In order to clarify the recommendation of the online review's rating value for different product designers, this research must address the following issues:

(1) Evaluate reviews from the linguistic dimension as $gh\_l(d, r)$

(2) Evaluate reviews from the information quality dimension as $gh\_qual(d, r)$

(3) Evaluate reviews from the information quantity dimension as $gh\_quan(d,r)$

(4) Estimate the generic helpfulness from the three dimensions as $gh(d, r)$

(5) Evaluate reviews from the personal assessment as $pp(d, r)$

(6) Recommend the rating value based on $gh(d, r)$ and $pp(d, r)$ as $h(d, r)$

4.3.3 Technical approach of review recommendation

4.3.3.1 Similarity learning method

In this part is to examine the language-related challenges of constructing a similarity function for client feedback.

Two completely similar evaluations should be rated as equally helpful. Review types include a ra, rb, rc, and rd. We give them ratings of 2, 2, -1, and -2 for how useful they are. Since both ra and rb are given a score of 2 for helpfulness, the first rule requires that they be more similar to one another than they are to rc, who receives a score of -1. Given that ra and rc are geographically closer together than ra and rd, it follows that the degree of similarity between ra and rc should be higher. The following are the formal rules:

- Rule one

$$h(d,r_a) == h(d,r_b) \ \&\& \ h(d,r_a) \neq h(d,r_c) \Rightarrow sim(r_a, r_b) \geq sim(r_a, r_c) \qquad (4.3.8)$$

- Rule two

$$h(d,r_a) \geq h(d,r_c) \ \&\& \ h(d,r_c) \geq h(d,r_d) \Rightarrow sim(r_a, r_c) \geq sim(r_a, r_d) \qquad (4.3.9)$$

Under these principles, the goal is to find a function that maximizes the similarity of annotations that get the same rating and the similarity of annotations that get the closest rating. On this basis, this paper presents the concept of similarity learning and describes it as a class of optimal problems (4.3.10).

$$\begin{aligned}
&\max \ \mu \sum_{\forall r_a,\, r_b,\, r_c \in c1} (sim(r_a, r_b) - sim(r_a, r_c)) + (1-\mu) \sum_{\forall r_a,\, r_b,\, r_d \in c2} (sim(r_a, r_b) - sim(r_a, r_d)) \\
&s.t. \\
&\quad sim(r_x, r_y) \in P \\
&\quad c1: sim(r_a, r_b) \geq sim(r_a, r_c) \qquad (4.3.10) \\
&\qquad \forall h(d,r_a) = h(d,r_b) \ \&\& h(d,r_a) \neq h(d,r_c) \\
&\quad c2: sim(r_a, r_b) \geq sim(r_a, r_d) \\
&\qquad \forall h(d,r_a) \geq h(d,r_c) \ \&\& h(d,r_c) \geq h(d,r_d)
\end{aligned}$$

The goal is to find a similarity function sim (rx, ry) in P that maximizes the model (4.3.10). A random variable of this optimization problem is a parameter that defines a similar function. But the uncertainty is building similar functionality. This paper uses the Taylor series method to define the similarity function. Its expression is as follows:

$$sim(r_a,r_b) = \sum C(t, k)[f(r_a)]^t[f(r_b)]^k \tag{4.3.11}$$

C(t, k) is a parameter that needs to be learned. f(ra) is a comment in a language. The power operators for language features are ra and t.

Solve the problem (4.3.10) using the optimal method given the training data. Get the best C(t, k). Then use the comparability function of C (t, k) to estimate g l (d, r) using the language feature x l (r)..

However, this is also a question worth thinking about. Many constraints make it difficult for beginners to complete the optimal solution in a suitable time. Another issue to consider is that for different online reviews, the level of designers is not necessarily fixed, because the evaluation system is unclear or uncertain. Therefore, certain compromises need to be made when calculating the similarity function.

Modify the problem to determine a similarity function that reduces the number of violations of constraints or maximizes constraints. However, this is an NP-hard task. Another adjustment must be made. First, by randomly dividing the constraints, the optimal solution is reduced by the minimum number of constraints in the initial stage. In stage 2, similar features learned from one separation are applied to another approach. Finally, the similarity function that meets the minimum conditions is selected as the final similarity function. Finally, predict gh l(d, r) as the largest average similarity:

$$gh\_l\ (d, r) = \arg\max(\ avg\ (sim(r, r_i\ ))) \tag{4.3.12}$$

4.3.3.2 Build classifier committee

As mentioned in the previous section, combining multiple classifiers in one committee can improve performance. Four classifiers were used in this study to make predictions for three binary classifiers 1, 2, 3 and one ternary classifier 4, (d, r).

For example, the annotation r is given the label c with the feature vector of x. Binary classifiers (1, 2 or 3) will score with a predicted value of 0 or 1. "1" indicates that annotation r is in category c, and "0" indicates that annotation r is not in category c. The score s indicates that in this example r is the determinable range of class C, there are three binary classifiers below.

φ1 tries to categorize annotations (contains "1", "2") (contains "0", "-1", "-2").

φ2 tries to classify annotations (containing "0", "1", "2") as "-1", "-2").

φ3 tries to annotate (including "0", "1", "-1") with two beneficial polarities (like "2", "-2").

Designers assigned numbers from "-2" to "2" to usability ratings. Some fractions can be logically derived from 1,2,3. Table 4.6 presents the three proposed binary classification methods.

Table 4.6 The suggested result from three binary classifiers

φ_1	φ_2	φ_3	Result
Helpful	NOT Unhelpful	Polarity	2
Helpful	NOT Unhelpful	NOT Polarity	1
Helpful	Unhelpful	-	UNDEFINED
NOT Helpful	NOT Unhelpful	-	0
NOT Helpful	Unhelpful	Polarity	-2
NOT Helpful	Unhelpful	NOT Polarity	-1

One such review r is as follows. When seen from either direction (helpful from 1, neutral from 2), and positively polarised (from 3), r is an all-around positive. The classification board agrees, and sets r equal to 2.

However, the five gradations cannot be reliably separated by with three binary classifiers. You can't reasonably determine r's rating, for instance, if you classify it as useful from 1, harmful from 2, and having a positive polarity from 3. As a result, ternary classifier φ4 is introduced.

4 classifies reviews as either useful (including "2" and "1"), useless (including "-2" and "-1"), or compromised (that is, "0").

When the three existing binary classifiers φ1, φ2 and φ3 cannot determine the rank, φ4 will make the final decision. In the above example, if the annotation r is classified by φ4, then "2" is represented by r (2", "-1", 2 "1", 3 "2"). Conversely, if the annotation r is classified as eclectic φ4, then "0" is represented by r.

Finally, using three binary classifiers and ternary classifiers, gh_qual (d, r) and gh_quan (d, r) are obtained respectively, and their corresponding relationships are given.

4.3.3.3 The nearest neighbor method

This study introduces the nearest neighbor method, which has the advantage of being simple and efficient for predicting individual grades from products.

The purpose of this study is that it will only review the validity of a small number of online reviews, while also recommending the evaluation of other reviews. In this case, the system is implemented by a specific online review by one designer and ratings by other designers. Therefore, designers can rely on the evaluation of other designers or other similar evaluations to evaluate their evaluation. To predict designer d's individual rating pp(d, r) for review r, the nearest neighbor method employs a comparison of designers' ratings and similar ratings.

The algorithm will be discussed step by step according to different formulas.

R is assumed to be the average of the total reviews (R) of the three designers. The average score for designer d is avg(d) and deviation (d) d. The deviation grade is the difference between the average grade of designer d and the average grade of designer d.

KNN is a simple and efficient way to assign an object to the K most common classes based on the majority vote of the neighborhood. The interpolation weights used by this collaborative screening method are:

$$pp(d, r_i) = bias(d, r_i) + \sum_{r_j \in KNN(r_i)} \theta \cdot residual(d, r_j) \quad (4.3.17)$$

However, in this collaborative screening process, there are only project proposals. Compared with item-based recommendation methods and other user-based recommendation methods, this paper adopts the nearest neighbor method to make predictions from two aspects: designer-centered expected pp d (d, r) and Review-oriented predictions pp r (d, r).

With the formulas described above, the two aspects of the two integrated hybrid proposal models can be defined:

$$pp\_d(d,r) = \frac{\sum_{d_a \in KNN(d)} sim(d,d_a) \cdot residual(d_a,r)}{\sum_{d_a \in KNN(d)} sim(d,d_a)} \quad (4.3.18)$$

$$pp\_r(d,r) = \frac{\sum_{r_a \in KNN(r)} sim(r,r_a) \cdot residual(d,r_a)}{\sum_{r_a \in KNN(r)} sim(r,r_a)} \quad (4.3.19)$$

$$\cos(X,Y) = \frac{X \cdot Y}{\| X \| \| Y \|} = \frac{\sum_{i=1}^{n} X_i \times Y_i}{\sqrt{\sum_{i=1}^{n} (X_i)^2} \sqrt{\sum_{i=1}^{n} (Y_i)^2}} \quad (4.3.20)$$

In this step, we also tested other similarities, these methods are not only inefficient, but also computationally intensive. Therefore, this paper adopts cosine similarity.

In addition, linear combinations of pp d (d, r) and pp r (d, r) with 3 unknown values ω1, ω2 and ω3 are used for balancing.

$$\begin{aligned} & pp(d,r) \\ & = bias(d,r) + \omega_1 \cdot pp\_d(d,r) + \omega_2\, pp\_r(d,r) + \omega_3 \\ & = bias(d,r) + \omega_1 \cdot \frac{\sum_{d_a \in KNN(d)} sim(d,d_a) \cdot residual(d_a,r)}{\sum_{d_a \in KNN(d)} sim(d,d_a)} \\ & \quad + \omega_2 \cdot \frac{\sum_{r_a \in KNN(r)} sim(r,r_a) \cdot residual(d,r_a)}{\sum_{r_a \in KNN(r)} sim(r,r_a)} + \omega_3 \end{aligned} \tag{4.3.21}$$

Using this method, three parameters can be obtained. Therefore, by using the characteristics of the product, the individual evaluation of the designer can be predicted.

4.3.4 Experimental study and discussions

4.3.4.1 Experiment setup

It makes use of the one thousand evaluations of table lamps presented in Section 3.3.

First, this experimental analysis verifies the effectiveness of the learned similarity function. This is shown by the percentages of breaches of two heuristic rules created in Section 4.3.3.1 for different rating levels. In this study, we will evaluate and contrast many similarity measures, including the cosine similarity, Pearson product moment correlation coefficient (PMCC), and p-norm distance. If p=1, 2, or 3, then the p-norm distance is defined as follows:

$$\|(X,Y)\|_p = \left(\sum_{i=1}^{m} |X_i - Y_i|^p\right)^{\frac{1}{p}} \tag{4.3.22}$$

In this paper, support vector machine is used for evaluation, and the evaluation is based on this. SVM is a commonly used classification technique, but it is also widely used in regression algorithms such as epsilon-SVM. Due to the comparability of its structural loss and optimal strategy, C-SVM is used for classification and epsilon-SVM is used for regression.

In terms of evaluation indicators, the evaluation is based on two indicators: classification and regression.

Accuracy and recovery rate were used to measure the sorting effect. Accuracy refers to the percentage of instances retrieved, divided by the number of results obtained by the total number of results obtained.

$$Precision = \frac{|\{relevant\ instances\} \cap \{retrieved\ instances\}|}{|\{retrieved\ instances\}|} \tag{4.3.23}$$

$$Recall = \frac{|\{relevant\ instances\} \cap \{retrieved\ instances\}|}{|\{relevant\ instances\}|} \tag{4.3.24}$$

MAE and RMSE (see 3.3.2 and 3.3.1) are performance measurements on a regression basis.

In the experiment, we adopted the method of ten-fold cross-checking. All experiments were conducted and tested on a PC configured with an Intel(R) Core(TM) i9-9900K 3.60 GHz CPU and 32 GB of Windows 10 (64-bit) memory. Complete all quizzes within 60 seconds.

4.3.4.2 Results and discussions

Table 4.7 shows the performance of online evaluation evaluations. As can be seen from the table, this system has achieved good results in all four evaluation indicators. The average score of all three designers is above 0.9. In addition, in regression analysis, both MAE and RMSE scores were below 0.1, and RMSE was below 0.2.

Table 4.7 Performance of the designers' recommendations

Designer number	*Precision*	*Recall*	*MAE*	*RMSE*
D1	0.912	0.925	0.055	0.166
D2	0.915	0.913	0.080	0.186
D3	0.904	0.900	0.090	0.198

The proposed results are shown in Figure 4.7 by comparing the differences between two different classifications and regressions.

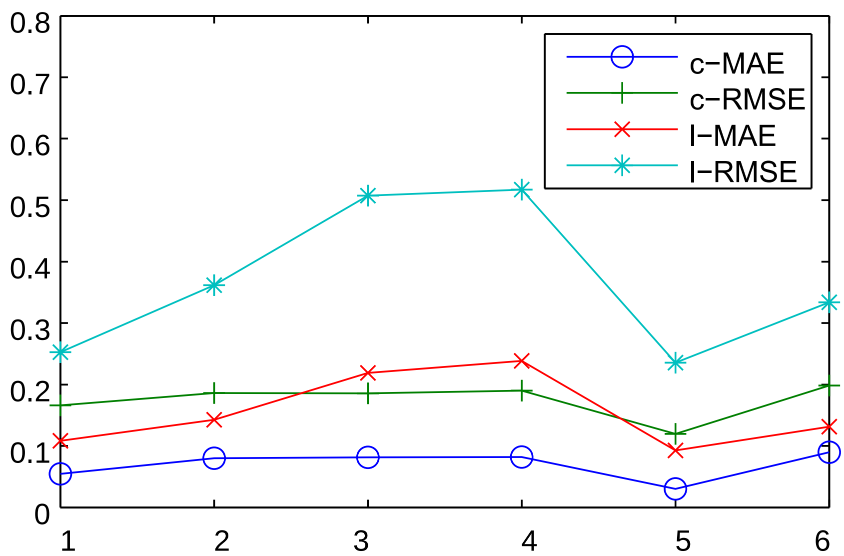
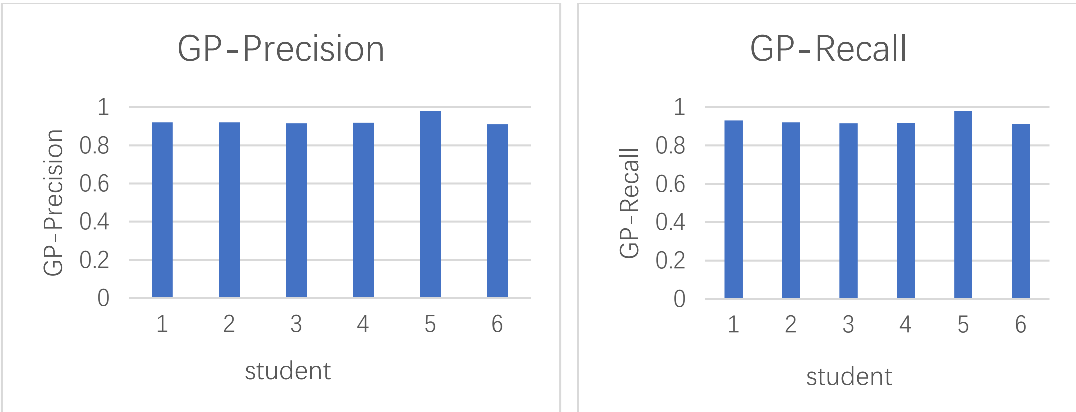


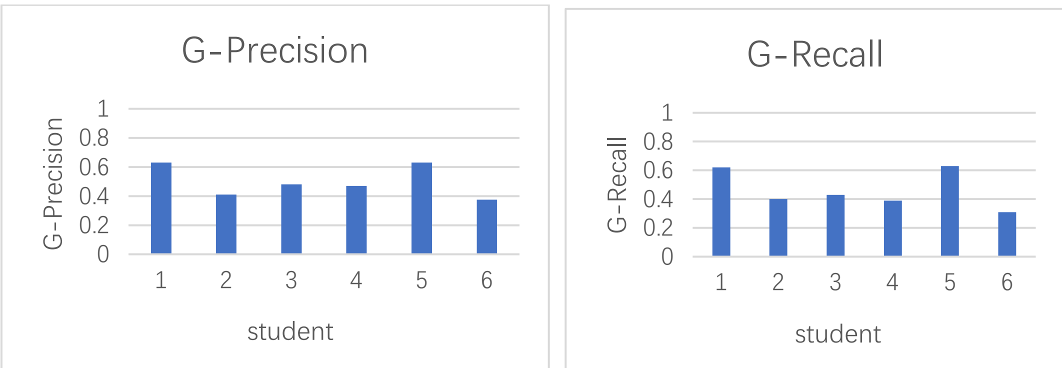
Figure 4.7 Classification vs. regression performance

Performance is measured using both MAE and RMSE. The "c-MAE" and "c-RMSE" metrics are utilised when the classification-based approach is used. Both l-MAE and l-RMSE refer to the regression-based technique. The graph clearly demonstrates that the classification-based strategy beats the regression-based approach. This further supports the idea that a classification-based method is the best way to provide ratings for this scenario.

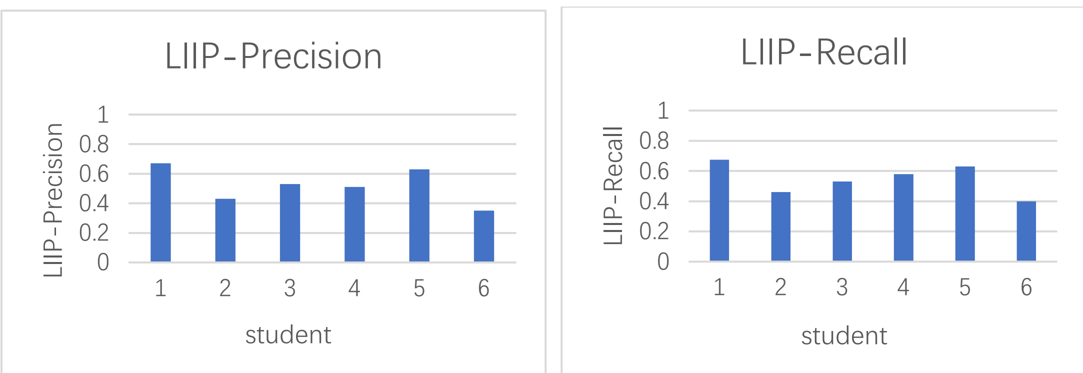
The disparity in accuracy and recall is seen in Figure 4.8. We refer to the accuracy and reliability of the proposed approach for recommending rating values as "GP-Precision" and "GP-Recall," respectively. If just three types of domain-independent characteristics are utilised to propose rating values, then we get "G-Precision" and "G-Recall."



(a) The proposed algorithm (GP)



(b) the generic helpfulness only algorithm (G)



(c) the classification algorithm that directly utilizes four categories of features (LIIP)

Figure 4.8 The performance comparison on different algorithms

Figures 4.8(a) and (b) show how factoring in users' opinions significantly boosts the recommendation's effectiveness (b). There is no one consensus among product designers on how crucial certain features are. That's why we think about the product's features. Applying just generic features will not provide satisfactory results. As a result, it's clear that product characteristics may help influence the values designers are advised to give ratings.

In Figures 4.8(a) and 4.8(b), we see how the efficacy of recommendations varies between methods (c). LIIP-Precision and LIIP-Recall are two assessment metrics that take into account how the four classes of features are integrated into a classifier like C-SVM to generate the recommendation. The suggested recommendation approach's assessment metrics are called GP-Precision and GP-Recall.

It is clear from the illustration that attempting to combine all four types of data into a single feature vector and then using a single classifier to generate the recommendation would not lead to satisfactory results. The suggested recommendation technique prioritises product characteristics, which is the root cause. These studies provide credence to the idea that certain characteristics of a product may have an impact on the values suggested for ratings.

4.4 Conclusion

From the point of view of the product designer, this chapter explains where to look for the best internet evaluations in terms of design. This study delves into the critical issue of how product designers perceive and evaluate online reviews.

The first topic covered in this chapter is how designers may anticipate the value of online reviews. A reliable technique for predicting review usefulness was established using a regression approach, based on research into why certain reviews are beneficial. In contrast to other attempts, this research acknowledges product designers' opinions as the gold standard for measuring usefulness. Online reviews are mined for data in four distinct feature areas. Validation of the efficacy of the proposed strategy is accomplished via the use of experimental categories. It's not only the usefulness forecast that's under scrutiny, but another fascinating topic as well. Whether or whether online testimonials may be considered neutral in terms of their utility is at issue here. The value of online reviews may be improved by considering whether or not domain-dependent attributes are included. The experiments found that domain-independent criteria may be used to assess the value of online reviews from the point of view of product designers without sacrificing much.

How to propose rating levels for various product designers based on internet reviews is the second subject addressed in this chapter. In this section, we developed a method of making suggestions based on categorization. The recommended method suggested here makes use of four sets of important characteristics. Values should be ranked from both an objective and subjective perspective while using this technique. Three types of domain-independent features are used to provide a broad evaluation of the advice. Language characteristics are used to train a similarity function, and a committee of classifiers is assembled to assess both the quality and amount of data. The suggestion is assessed based on the characteristics of the product as seen through the eyes of the individual. The categorization algorithm and the results from both factors are used to suggest stars for online testimonials. The effectiveness of the strategy was evaluated using several types of comparative experiments.

As a consequence of the presented models and encouraging findings, it is now clear that identifying online assessments that favour a certain design is possible from the perspective of product designers. In the next chapter, we'll dive into how to use online reviews to build a database with valuable information for designers.

Chapter 5: Mapping Customer requirements with Product Design Specifications

5.1 Introduction

The previous chapter discussed how to find online reviews of design preferences from the perspective of a product designer. This method mainly addresses two problems: one is to predict whether online reviews are useful from the perspective of product designers, and the other is how to provide ratings for different product designers through online reviews. On this basis, through the analysis of product designers, it discusses how to choose the optimal network for evaluation in the design process.

This chapter focuses on the second issue, creating a design-oriented knowledge base from online reviews to mapping customer requirement with PDS. As mentioned earlier, there are two questions in question 2, namely how to combine customer reviews with product design specifications and prioritize them based on online customer reviews. In the second case, there was only one keyword that could not describe the customer's topic. Encourages research into language technologies for automatically linking online reviews and product design specifications. In addition, the purpose of evaluation analysis is to assist product designers to improve the quality of their products to meet the needs of most consumers. So, web reviews are used to generate a way of prioritizing product design parameters. The following sections describe both types of queries in detail.

5.2 Problem definition

An important product design method is to "transform customer needs or requirements into product design specifications, and finally into a specific production process." In customer-oriented product design, the main purpose is often to satisfy customers needs. Take customer information as input and design work as the goal to achieve the best results of customer satisfaction. Product designers should combine customer requirements with product design specifications, and establish corresponding product design specifications. To illustrate the issues discussed in this chapter, we will gradually define several symbols.

Consumers are more and more inclined to address their product reviews through e-commerce platforms. In these sites, each item will have a series of annotations, r1, r2, ..., rp. In a comment ri, many sentences can be included: si1, si2, ..., siq. These online reviews provide useful information on customer needs. Due to the constraints of funds and time, designers can only position products according to the needs of customers. An objective analysis of all of this is impossible. PC=pc1, pc2, … pcn" is a common product design specification. An example is in Table 3.3, this list.

To understand customer needs, product designers need to analyze customer online reviews word for word. Please credit ri for one or more product design parameters. The term "WT" was considered the most critical word in this survey and can help product designers understand an article about a specific product design specification.

As mentioned in the case study, the same keyword can be associated with multiple product design parameters. In this study, product designers are expected to understand the underlined meaning of the word WT by reading Wc above. The context Wc is a text window that contains the NR word to the left and right of the WT.

However, it is very difficult for product designers to manually read, categorize and rate online reviews. An intelligent language technology is being developed that can automatically combine online reviews with product design criteria.

- (1) How to connect online customer reviews with product design specifications

Through the second exploratory case analysis, we found that some keywords are used as a product design criteria, while others are used as other product design criteria. In Section 3.4, there is an example illustrating this phenomenon. For example: "I love this light, it's colorful, well packaged, shipped without any scratches, and the light is bright enough to read at night." In the first sentence, "appearance" is "Bright" means, and in another sentence, it is called "performance".

In this study, a possible model will be developed to address this issue. It is assumed that the keyword WT in Wc is used as the product design specification pcp rather than pcq. Therefore, in the environment Wc, if the possibility of WT and pcp is defined as P(Wc, pcp), P(Wc, pcp) is greater than P(Wc, pcp). In other words, in the environment Wc, the connection between WT and pcp is larger than that between Wc and pcq. Mathematically, it can be expressed by the following formula:

$$P(W_c, pc_p) \geq P(W_c, pc_q) \tag{5.2.1}$$

Based on the design parameters of keywords and related products, we will conduct a probabilistic model of keyword analysis. This pattern will be used to automatically combine web reviews with product design requirements. Technical details will be discussed in Section 5.3.

When online reviews and product design guidelines are linked, designers need to decide how they should prioritize those design guidelines based on how users feel about online reviews.

In particular, in a particular ri, the customer may or may not be satisfied with the product design specification pcj. This information can be represented by (pcj, Oij). Oij is a comment on the product design specification pcj in ri. Correspondingly, a note ri can be expressed as "(pc1, Oi1), (pc2, Oi2), ..., (pcn, Oin)" as the product design specification opinion on the vector "(pc1, Oi1), (pc2, Oi2),...,(pcn, Oin)". Simply put, a vector can be expressed as Oi=«Oi». A positive value of Oij indicates that in the evaluation of ri, the consumer's satisfaction with pcj is negative, while for pcj, it is dissatisfied. In addition, in each product design specification, there can be one or more comment statements. If the consumer does not clearly mention the product design specification cpcj in ri, then the corresponding sentiment Oij is set to 0, that is, the user is assumed to be neutral about pcj. If there is more than one sentence discussing pcj in the review ri, the average of Oij is used as the consumer's last evaluation of pcj.

In addition, on the e-commerce website, customers will also give a comprehensive evaluation of their overall satisfaction. For example, in Figure 1.1, a consumer has a four-star rating. In this survey, the number of stars is based on the overall satisfaction of customers. It can be described like this: "In evaluation ri, csi is used to express the degree of satisfaction with the overall product. This level can be an ordered set of numbers (such as a five-to-one "star") or an ordered set of non-numbers Marks (eg very good, very good, almost unacceptable; very bad and very bad). The difference between the two is that in the first example the spacing between consecutive fractions is known, while in the second Not in this example.

The evaluation ri can also be expressed as (Oi, csi), which is based on the vector Oi in the product design specification comments and information on the overall satisfaction csi. In this way, "(O1, cs1), (O2, cs2)...(Op, csp)" can be used to express a set of customer reviews containing p comments. At present, based on information on customer sentiment and overall satisfaction, the key is how to prioritize product design specifications.

- (2) How to prioritize product design specifications based on customer reviews

In particular, by using "(O1,cs1),(O2,cs2),...,(Op, csp) to derive product design specifications pc1, pc2,..., the weights of pcn W = "w"), (O2,cs2),...,(Op, csp), the weights of product design specifications pc1, pc2,..., pcn, pcn are derived W = "w"). Here, the number of stars is considered as customer satisfaction, and the emotion vector of different product design specifications is considered as a feature vector. Mathematically, it goes like this：

$$cs_i = f\left(\sum_{j=1}^{n} w_j O_{ij}\right) \qquad (5.2.2)$$

where x represents their weighted opinion on the product's design.

It seems that only one regression model can learn w1,w2...wn. However, the use of regression models to analyze this issue is still controversial. Regression models are used to analyze problems with continuous numerical values, while csi is a discrete numerical value, which may be an ordered discrete degree or an ordered non-numeric marker.

The classification mode works better than the regression mode. Even so, the question is identified with a simple categorization pattern, which is a question. The rank information inherent in csi would be ignored by a simple classification model due to rank ordering or ordering, whether discrete or non-numeric is used. For example, at one point, a customer gave five stars. Suppose the rating is predicted to be four stars by the first model and three stars by the second model. In this case, the first model was more popular than the second because its rating was closer to the initial five-star rating.

Understanding rankings is another way to answer this question. Learning to rank is a challenge that uses training data to automatically build a ranking model so that new objects can be classified by relevance or importance (Bing et al., 2009). However, learning to order models neglects to put items in the same place. In this context, the learning ranking method cannot be used directly for prioritizing product design criteria.

Specifically, in this case, both categorization and ranking information should be considered. As a result, an ordinal classification model will be developed for this subject, with technical details described in Section 5.4.

5.3 Connecting customer reviews with product design specifications

5.3.1 A probabilistic keywords analysis model

This section introduces a probabilistic approach to linking online reviews and product engineering features. This mode of possibility will gradually explain a real paradigm to illustrate the idea.

For example: "There is a very magical feature. It has a USB slot on the front, which can be charged." Designers distinguish the word "usb" and think that "usb charging port" is a new product design standard. . However, as mentioned above, since "usb" can be used to represent other product design specifications, the consumer body in this article cannot be represented only by "usb".

Intuitively, certain contextual words can be used to describe the customer's topic. Therefore, in this study, the upper-lower Wc is defined as the text window surrounding the keyword WT, containing the NL words to the left of WT, the NR words to the right of WT, and the keyword WT itself. In this example, if there are only two words "usb", e.g. both NL and NR are 2, then Wc will contain 5 words, namely "feature", "there", "usb", "port,"," front".

On the other hand, in this case, "usb" is no longer "front-end port", but "function". So, in this example, "usb" is more likely to be connected to "feature" than "usb" and "front port". The above example can be expressed according to Equation 5.2.1:

$$P(W_c, \text{“feature”}) \geq P(W_c, \text{“front port”}) \tag{5.3.3}$$

In addition, when designers analyze the product design specification represented by the keyword "usb", not every word in the context Wc can play the same role. Assume that the word "usb" will have a big influence in making a decision. And those words that are farther away have less effect. For example, the words "nice" and "feature" will be less obvious than the "front" adjacent to the keyword "usb", because it is easier for designers to understand the user's attention to "usb port" . However, it should be noted that adverbs such as "only", "there" and "very much" are very common in customer reviews. Such terms are widely believed to have little effect on designers linking online reviews to product design specifications. Therefore, after removing the stems and stop words of the commented sentences, they become the power words for "WL" and "WR".

If an influence function is set for the comment statement, then the user topic can be automatically evaluated according to the specific context. However, for an arbitrary action function, we are still debatable because it is manually defined from the distance from the keyword to it. Therefore, from the annotation statement of the annotation, we can understand the influence function.

In general, given an environmental Wc, if it is identified as a product design specification pcp rather than a product design specification pcq, it is assumed that P(Wc, pcp) is greater than P(Wc, pcq). This paper aims to evaluate the weights of each word in the upper and lower layers Wc through a new parameter learning method.

If α, β, and γ are defined as the influence factors of the left word, right word of Wc and WT itself, according to Bayes' law, the connection between Wc and pcp can be equivalently deduced as:

$$\begin{aligned} & P(W_c, pc_p) \\ &= P(pc_p)P(W_c \mid pc_p) \\ &= P(pc_p)P(W_L, W_R, W_T \mid pc_p) \\ &= P(pc_p)P(W_L \mid pc_p)^{\alpha} P(W_R \mid pc_p)^{\beta} P(W_T \mid pc_p)^{\gamma} \end{aligned} \tag{5.3.4}$$

P(pcp) refers to the possibility that consumers are discussing the product design specification pcp. The context of a given keyword WT in relation to the product design specifications pcp, P(WL|pcp), P(WR|Pcp) and P(WT|pcP) can be interpreted as WT, the correct word for WT and WT itself.

Therefore, in the above example, if P (Wc, pcp) > P (Wc, pcq), it can be deduced that,

$$P(W_c, pc_p) > P(W_c, pc_q)$$

$$\sim \frac{P(pc_p)P(W_c \mid pc_p)}{P(pc_q)P(W_c \mid pc_q)} > 1$$

$$\sim \frac{P(pc_p)P(W_L \mid pc_p)_\alpha P(W_R \mid pc_p)_\beta P(W_T \mid pc_p)_\gamma}{P(pc_q)P(W_L \mid pc_q)_\alpha P(W_R \mid pc_q)_\beta P(W_T \mid pc_q)_\gamma} > 1 \qquad (5.3.5)$$

$$\sim \log \frac{P(pc_p)\ (P\ W_L \mid pc_p)_\alpha P(W_R \mid pc_p)_\beta P(W_T \mid pc_p)_\gamma}{P(pc_q)\ (P\ W_L \mid pc_q)_\alpha P(W_R \mid pc_q)_\beta P(W_T \mid pc_q)_\gamma} > 0$$

$$\sim \alpha \log \frac{P(W_L \mid pc_p)}{P(W_L \mid pc_q)} + \beta \log \frac{P(W_R \mid pc_p)}{P(W_R \mid pc_q)} + \gamma \log \frac{P(W_T \mid pc_p)}{P(W_T \mid pc_q)} + \log \frac{P(pc_p)}{P(pc_q)} > 0$$

In Model 5.3.5, a computational model for learning the left and right words of WT in Wc and WT influence factors α, β and γ is established. Computational models can be trained on the opinions of labelled customers.

From the training data, P(WL|pcp), P(WR|pcp), P(WT|pcp), P(Pcp) can be estimated. By adjusting the influencing factors α, β and γ, the model is expected to satisfy the inequality of customer evaluation (5.3.5) described in Model 5.3.5. After learning α, β and γ, given the environment Wc, the likelihood of WT being associated with a specific product design specification can be compared with the likelihood that WT is associated with other product design specifications. Ultimately, from the association of label keywords to product design specifications, customer topics can be predicted accordingly.

In fact, since P(〖pc〗 _p)/(P(〖pc〗 _q)), there is no need to accurately estimate P(pcp) from the training data. can be expressed in the following way:

$$\log \frac{P(pc_p)}{P(pc_q)} = \log \frac{|pc_p|}{|pc_q|} \qquad (5.3.6)$$

|PCP| is the number of PCPs in which consumers discuss product design specifications in training materials. Thus, item log(P(〖pc〗 _p))/(P(〖pc〗 _q)) is a determinant item, which can be directly derived from the training data.

The purpose of this paper is that, by adjusting the impact factors α, β and γ, the inequalities described in Model 5.3.5 can satisfy the customer's evaluation of all labels in the training data. That is to say, three parameter dependencies, α log (P (W_L│ 〖pc〗 _ p))/P (W_ L│ 〖 Pc〗 _ q)), β log (p (W_R│ 〖 p〗 _ p)/p (W_ R│ 〖 P)/(P (W_ T│ 〖 PC)_ q), P (W— T│ 〖 P〗 _ P)/P=(W_T│ 〖 pC〗 _ q)/P [W_R)/P<W_R?

Thus, a Ratio function is defined for parameter correlation in the training data:

$$Ratio(\alpha,\beta,\gamma) = \sum_{pc_p} \sum_{pc_q} \left\{ \alpha log \frac{P\left(W_L \middle| pc_p\right)}{P\left(W_L \middle| pc_q\right)} + \beta log \frac{P\left(W_R \middle| pc_p\right)}{P\left(W_R \middle| pc_q\right)} + \gamma log \frac{P\left(W_T \middle| pc_p\right)}{P\left(W_T \middle| pc_q\right)} \right\} \quad (5.3.7)$$

$$max\ Ratio\ (\alpha, \beta, \gamma) \quad (5.3.8)$$

If the Ratio function is maximal, then in 5.3.5, customer annotations can be used to try to satisfy the inequalities in the training data. In other words, the optimal α, β, γ determine the optimal differentiation function, which clearly distinguishes the most suitable product design specification from other specifications.

This concept is derived from support vector machines and gives an optimal policy. The support vector machine insists on taking the largest edge distance as the hyperplane and provides more possibilities for future data classification. The purpose of the method described in this paper is also to optimize the design parameters of the two products. Its goal is to enable visualization and precise coupling of WT and pcp in a WC environment.

A normalization term is introduced in the objective function of the support vector machine to avoid excessive adjustment of the hyperplane. To avoid overtraining, a normalization term must be applied to the objective function. To combine the scale and normalization terms, build a loss function as follows:

$$Loss(\alpha,\beta,\gamma) = -Ratio(\alpha,\beta,\gamma) + C_1\frac{\|\alpha\|^2}{2} + C_2\frac{\|\beta\|^2}{2} + C_0\frac{\|\gamma\|^2}{2} \quad (5.3.9)$$

- Ratio (α, β, gamma) is applied to Loss (α, β, γ) because max Ratio (α, β, γ) is essentially equal to minimizing the negative pole. For α, β and γ, the corresponding weights of normalized items are adjusted by C1, C2, C0. Note that gamma is a scalar, and both alpha and beta are vector parameters:

$$\alpha = (\alpha_1, \alpha_2, ..., \alpha_{NL})^T$$

$$(5.3.10)$$

$$\beta = (\beta_1, \beta_2, ..., \beta_{NR})^T$$

In the above discussion, it is assumed that words similar to WT have a greater impact on the determination of the relevancy of engineering features of products. Thus, at distance i to the left of the WT, the word's influence coefficient α i will be greater than the word at i+1. Similarly, at the position j on the right side of the WT, the word's influence coefficient βj should be larger than bj+1. These intuition laws are written like this:

$$\forall i \in [1, N_L - 1], \alpha_i > \alpha_{i+1}$$

$$(5.3.11)$$

$$\forall j \in [1, N_R - 1], \beta_j > \beta_{j+1}$$

$$M \cdot \alpha \le 0$$

$$M \cdot \beta \le 0 \quad (5.3.12)$$

$$0 \le \beta \le 1 \quad (5.3.13)$$

$$0 \le \gamma \le 1$$

$$\min Loss(\alpha, \beta, \gamma)$$

$$s.t. \quad M \cdot \alpha \le 0$$

$$M \cdot \beta \leq 0$$
$$0 \leq \alpha \leq 1 \qquad (5.3.14)$$
$$0 \leq \beta \leq 1$$
$$0 \leq \gamma \leq 1$$

Second, the study discusses the solution for P(WL|Pck) and P(WR|pck). On the basis of the N-gram method, two modes of "unigram" and "bigram" are obtained respectively. In statistical language modeling, N items are consecutive in a particular sequence. The word "unigram" means an N-gram, while "bigram" means a 2.

5.3.2 A Unigram model

The unary model is currently the most commonly used information retrieval method. Unigram mode can calculate the probability of a single word being hit without being affected by the keywords before and after. In this mode, the likelihood of each word is determined by the word itself. The following is an explanation of the unary pattern for the following words in the upper left:

$$P(W_L \mid pc_k) = \prod_{i=1}^{N_L} P(W_{Li} \mid pc_k) \qquad (5.3.15)$$

Assuming that the keyword WT is related to the product design specification pck, then P(WLi| pck) is the probability of generating the left word WLi. P(WLi|pck) can be estimated as:c(WLi , pck)

$$P(W_{Li} \mid pc_k) = \frac{}{\mid pc_k \mid} \qquad (5.3.16)$$

c(WLi, pck) is the number of times the word WLi is mentioned in pck. |pck| refers to the number of users discussing pck in the training data.

And when c (WLi, pck)=0, P (WLi| pck) is also equal to 0. Finally, the model cannot accurately predict the product's design specifications. To solve the zero probability problem of P(WLi|pck), Dirichlet Priors smoothing is employed. Based on the training data, Dirichlet Priors smoothing transforms the probability parameter into a prior probability:

$$P(W_{Li} \mid pc_k) = \frac{c(W_{Li}, pc_k) + \mu P(W_{Li} \mid \boldsymbol{C})}{|pc_k| + \mu} \tag{5.3.17}$$

μ is a constant that adjusts the smoothing item weighting.

P(WLi|C) is the probability of occurrence of the word WLi in the C language.According to Equation (5.3.17), $\alpha log\frac{P(W_L|pc_p)}{P(W_L|pc_q)}$ and $\beta log\frac{P(W_R|pc_p)}{P(W_R|pc_q)}$ can be written as:

$$\alpha \log \frac{P(W_L \mid pc_p)}{P(W_L \mid pc_q)} = \sum_{i=1}^{N_L} \alpha_i \log \frac{P(W_{Li} \mid pc_p)}{P(W_{Li} \mid pc_q)}$$
$$\beta \log \frac{P(W_R \mid pc_p)}{P(W_R \mid pc_q)} = \sum_{i=1}^{N_R} \beta_i \log \frac{P(W_{Ri} \mid pc_p)}{P(W_{Ri} \mid pc_q)} \tag{5.3.18}$$

$$Ratio_1(\alpha, \beta, \gamma) = \sum_{pc_p} \sum_{pc_q} \{ \sum_{i=1}^{N_L} \alpha_i \log \frac{P(W_{Li} \mid pc_p)}{P(W_{Li} \mid pc_q)} + \sum_{i=1}^{N_R} \beta_i \log \frac{P(W_{Ri} \mid pc_p)}{P(W_{Ri} \mid pc_q)} + \gamma \log \frac{P(W_T \mid pc_p)}{P(W_T \mid pc_q)} \} \tag{5.3.19}$$

$$Loss_1(\alpha, \beta, \gamma) = -Ratio_1(\alpha, \beta, \gamma) + C_1 \frac{\sum_{i=1}^{N_L} \alpha_i^2}{2} + C_2 \frac{\sum_{i=1}^{N_R} \beta_i^2}{2} + C_0 \frac{\| \gamma \|^2}{2} \tag{5.3.20}$$

5.3.3 A Bigram model

Binary mode is another common information retrieval paradigm. Binary doesn't evaluate how many words a word will hit; it combines the impact of each word before and after. In this mode, the likelihood of each word depends on its own word and neighboring words. Here is an example of a binary pattern, with the words below the left:

$$P(W_L \mid pc_k) = P(W_{L1} \mid pc_k) \prod_{i=1}^{N_L - 1} P(W_{Li+1} \mid W_{Li}, pc_k) \tag{5.3.21}$$

$$P(W_{Li+1} \mid W_{Li}, pc_k) = \frac{c(W_{Li+1}, W_{Li}, pc_k) + \mu P(W_{Li+1} \mid \boldsymbol{C})}{c(W_{Li}, pc_k) + \mu} \tag{5.3.22}$$

According to Equation 5.3.22, $\alpha log\frac{P(W_L|pc_p)}{P(W_L|pc_q)}$ and $\beta log\frac{P(W_R|pc_p)}{P(W_R|pc_q)}$ can be written as:

$$\alpha\log\frac{P(W_L \mid pc_p)}{P(W_L \mid pc_q)} = \alpha_0\log\frac{P(W_{L1} \mid pc_p)}{P(W_{L1} \mid pc_q)} + \sum_{i=1}^{N_L-1}\alpha_i\log\frac{P(W_{Li+1} \mid W_{Li}, pc_p)}{P(W_{Li+1} \mid W_{Li}, pc_q)}$$

$$\beta\log\frac{P(W_R \mid pc_p)}{P(W_R \mid pc_q)} = \beta_0\log\frac{P(W_{R1} \mid pc_p)}{P(W_{R1} \mid pc_q)} + \sum_{i=1}^{N_R-1}\beta_i\log\frac{P(W_{Ri+1} \mid W_{Ri}, pc_p)}{P(W_{Ri+1} \mid W_{Ri}, pc_q)} \quad (5.3.23)$$

$$\begin{aligned} Ratio_2(\alpha,\beta,\gamma) = \sum_{pc_p}\sum_{pc_q}\{&\alpha_0\log\frac{P(W_{L1} \mid pc_p)}{P(W_{L1} \mid pc_q)} + \beta_0\log\frac{P(W_{R1} \mid pc_p)}{P(W_{R1} \mid pc_q)} + \\ &\sum_{i=1}^{N_L-1}\alpha_i\log\frac{P(W_{Li+1} \mid W_{Li}, pc_p)}{P(W_{Li+1} \mid W_{Li}, pc_q)} + \\ &\sum_{i=1}^{N_R-1}\beta_i\log\frac{P(W_{Ri+1} \mid W_{Ri}, pc_p)}{P(W_{Ri+1} \mid W_{Ri}, pc_q)} + \\ &\gamma\log\frac{P(W_T \mid pc_p)}{P(W_T \mid pc_q)}\} \end{aligned} \quad (5.3.24)$$

$$Loss_2(\alpha,\beta,\gamma) = -Ratio_2(\alpha,\beta,\gamma) + C_1\frac{\sum_{i=1}^{N_L}\alpha_i^2}{2} + C_2\frac{\sum_{i=1}^{N_R}\beta_i^2}{2} + C_0\frac{\|\gamma\|^2}{2} \quad (5.3.25)$$

In summary, the whole algorithm can be described as following algorithm.

Algorithm : Impact factor learning Algorithm

$\alpha, \beta, \gamma \leftarrow$ {Random numbers between zero and one}
for Each keywords W_T connecting with multiple product engineering characteristics **do**
  $S \leftarrow$ {All review sentences labeled with W_T}
  $PC \leftarrow$ {All possible product engineering characteristics for W_T}
  for $S_i \in S$ **do**
    Stemming, stop words removal on S_i
    POS tagging S_i and words filtering with certain POS
    $W_L \leftarrow$ {Left N_L words of W_T }, $W_R \leftarrow$ {Right N_R words of W_T }
    $pc_p \leftarrow$ {the product engineering characteristic that W_T relates in S_i }
    for $pc_q \in PC$ **do**
      Calculate $\log\frac{P(W_L \mid pc_p)}{P(W_L \mid pc_q)}$, $\log\frac{P(W_R \mid pc_p)}{P(W_R \mid pc_q)}$, and $\gamma\log\frac{P(W_r \mid pc_p)}{P(W_r \mid pc_q)}$
      Calculate $\log\frac{P(pc_p)}{P(pc_q)}$
      Save these results in a vector V_i, and append V_i in a matrix MT
    end for
  end for
end for
Using MT as the training data, solve the optimization problem as described in Equation 5.3.14
return α, β, γ

5.4 Prioritizing product design specifications based on customer reviews

5.4.1 An ordinal classification approach

Another goal of this chapter is to show that product specifications (PC) priorities can be seen from online reviews. It is precisely how to learn the weight W of PC by utilising consumer happiness on web evaluations.

As mentioned in the previous section, due to the discrete nature and ranking information of customer satisfaction, many modern solutions are not suitable for this problem. Therefore, the sorting strategy is to solve this problem.

Different learned ranking algorithms are used to modify data parameters using internal ranking information. Other learning classification algorithms are based on pairwise basis, such as RankSVM (Thorsten, 2002) and several related methods (Yoav et al., 2003, Thorsten, 2006). The pairwise algorithm expands the initial assignment of training samples D to candidates P that contain a set of document pairs. This set of file pairs uses a learning technique, generally a number from +1 to -1 to represent a pair of file pairs. Figure 2.15 illustrates a matching technique. This method uses the training data in RankSVM to extract the feature weighting vector W, so that the distance between the hyperplanes can be optimized. Next, W will be used to predict which text to choose in the test data.

If different product design specifications are used as features, and customer satisfaction is regarded as the expected ranking and positioning, the feature weights can be adjusted. In contrast, the prediction bias in RankSVM clearly distinguishes the two articles. So, the difference in vision research is that two articles cannot be expected to have the same preference. Because the customer's evaluation of the product is the same, the opinions of multiple customers are not the same in terms of customer satisfaction.

However, knowing W and maximizing the distance between the hyperplanes can help us solve this problem. This paper transforms the learning W of PCs in evaluation space D into W in evaluation space P. However, please note that the W stands for comments related to product design specifications. Formally, the set P of annotation pairs is hidden in the annotation set D. P is the set of annotation pairs (Oi, csi), (Oj, csj)) in the comment group D.

To clearly describe the proposed classification, we will introduce an example step by step. In this example, it is assumed that the designer focuses on six product design specifications, namely pc1, pc2, ..., pc6, which are all critical in product design. The design specifications of the six products, W1, W2, ..., W6, should be estimated. In addition, on the commercial website of this product, we also collected nine user-related opinions, r1, r2, ..., r9. Customers can rate a review from one to five stars to indicate their overall satisfaction with the product. It is represented by csi {1, 2, 3, 4, 5}. In Table 5.1, there are 9 notes about csi, which represent the customer satisfaction level of the whole product.

Table 5.1 An example of the customer satisfaction of nine reviews

cs_1	cs_2	cs_3	cs_4	cs_5	cs_6	cs_7	cs_8	cs_9
5	2	3	4	5	2	4	1	3

For a specific product design specification, you can find some different perspectives in a specific note. As described in Chapter 3, annotators can manually identify the attitudes of different product design principles. In addition, relevant data can be automatically collected by means of different viewpoint exploration and sentiment analysis.

This research uses the five-degree index, from negative two to positive two, to analyze the product design standards in the online evaluation, with negative two as the lowest and two as the highest. It is expressed as Oij {-2, -1, 0, 1, 2}.

In this example, it is assumed that Oi = "Oi" is the customer satisfaction with the six product design specifications in review ri. The training instances in D can be expressed in terms of settings, depending on the settings:(O_1, cs_1), (O_2, cs_2), ..., $(O_9, cs_9) \in D$

(5.4.26)

Based on customer satisfaction information, a set of reviews can be created. In both reviewri and rj, if csi > csj ranks better than rj, then (Oi-Oj,1) is put into P. If the rank of csi is higher than that of ri, fill in (Oi- Oj,-1) into P. If csi is equal to csj, then ri and rj are equivalent, then, add (Oi-Oj,0) to P. So there are (■(9@2))=9×8/2=36 annotation pairs:$((O_1, cs_1), (O_2, cs_2))$, $((O_1, cs_1), (O_3, cs_3))$, ...,

$$((O_2, cs_2), (O_3, cs_3)), ((O_2, cs_2), (O_4, cs_4)) \ldots,$$

$$\ldots$$

$$((O_8, cs_8), (O_9, cs_9)) \tag{5.4.27}$$

For example, in Table 5.1, the customer satisfaction information is cs4>cs6, then (O4-O6,1) puts (O4-O6,1) in P. So, in P, all annotation pairs can be found in Table 5.2.

Table 5.2 Review pairs in P

$(O_1 - O_2, 1)$	$(O_1 - O_3, 1)$	$(O_1 - O_4, 1)$	$(O_1 - O_5, 0)$
$(O_1 - O_6, 1)$	$(O_1 - O_7, 1)$	$(O_1 - O_8, 1)$	$(O_1 - O_9, 1)$
$(O_2 - O_3, -1)$	$(O_2 - O_4, -1)$	$(O_2 - O_5, -1)$	$(O_2 - O_6, 0)$
$(O_2 - O_7, -1)$	$(O_2 - O_8, 1)$	$(O_2 - O_9, -1)$	$(O_3 - O_4, -1)$
$(O_3 - O_5, -1)$	$(O_3 - O_6, 1)$	$(O_3 - O_7, -1)$	$(O_3 - O_8, 1)$
$(O_3 - O_9, 0)$	$(O_4 - O_5, -1)$	$(O_4 - O_6, 1)$	$(O_4 - O_7, 0)$
$(O_4 - O_8, 1)$	$(O_4 - O_9, 1)$	$(O_5 - O_6, 1)$	$(O_5 - O_7, 1)$
$(O_5 - O_8, 1)$	$(O_5 - O_9, 1)$	$(O_6 - O_7, -1)$	$(O_6 - O_8, 1)$
$(O_6 - O_9, -1)$	$(O_7 - O_8, 1)$	$(O_7 - O_9, 1)$	$(O_8 - O_9, -1)$

Once P is established, identifying W, the equivalent opinion of the product design specification, is a tri-classification exercise. It makes an effort to classify review pairs as "-1," "0," or "1" depending on how customers feel about certain aspects of a product's design.

A complete review pair in P is represented formally as (OPk, crk), where OPk = Oi - Oj. Here, Oi = [Oi1, Oi2,..., Oin], and [(pc1, Oi1), [(pc2), [(pcn, Oin])] is a review ri pair vector giving an opinion on the product's design. Product design specification opinion pair vector, or Oi for short, is a set of expert opinions on the product's design. This means that OPk may be written as Oi1 - Oj1, Oi2 - Oj2,..., Oin - Ojn>. Alternate notation for this is OPk = OPk1, OPk2,..., OPkn>, where OPks = Ois - Ojs. The correlation between reviews ri and rj, as represented by the customer satisfaction metric crk, is discrete, taking on the values -1, 0, and 1. This is a three-classification issue where the feature vector is OPk and the desired class is crk.

The question may be reduced to a binary one, though, if one takes the next step. Keep in mind that when csi csj, a binary classification will be shown if the inverse subtraction of the opinion vector for ri and rj is used, for example, by entering (Oj - Oi, 1) into P rather than (Oi - Oi, -1). The change will have no effect on W's value. However, this eliminates the ranking link between two reviews. To determine whether review boasts a more satisfied client base, it's important to keep track of whether csi > csj or csj > csi in the customer satisfaction index.

Now the customer satisfaction relationship of two reviews crk is either "1" or "0," and OPk is either "Oi - Oj" or "Oj - Oi." Two reviews with the same number of stars should be projected to have the same level of customer satisfaction, but "1" indicates that the reviews do not rank equally or have different labels of client happiness.

Accordingly, all review pairings in P may be created using the aforementioned transformation methods, as shown in Table 5.3, using the preceding nine reviews as examples.

Table 5.3 Review pairs in P after applying transformation rules

$(O_1 - O_2, 1)$	$(O_1 - O_3, 1)$	$(O_1 - O_4, 1)$	$(O_1 - O_5, 0)$
$(O_1 - O_6, 1)$	$(O_1 - O_7, 1)$	$(O_1 - O_8, 1)$	$(O_1 - O_9, 1)$
$(O_3 - O_2, 1)$	$(O_4 - O_2, 1)$	$(O_5 - O_2, 1)$	$(O_2 - O_6, 0)$
$(O_7 - O_2, 1)$	$(O_2 - O_8, 1)$	$(O_9 - O_2, 1)$	$(O_4 - O_3, 1)$
$(O_5 - O_3, 1)$	$(O_3 - O_6, 1)$	$(O_7 - O_3, 1)$	$(O_3 - O_8, 1)$
$(O_3 - O_9, 0)$	$(O_5 - O_4, 1)$	$(O_4 - O_6, 1)$	$(O_4 - O_7, 0)$
$(O_4 - O_8, 1)$	$(O_4 - O_9, 1)$	$(O_5 - O_6, 1)$	$(O_5 - O_7, 1)$
$(O_5 - O_8, 1)$	$(O_5 - O_9, 1)$	$(O_7 - O_6, 1)$	$(O_6 - O_8, 1)$
$(O_9 - O_6, 1)$	$(O_7 - O_8, 1)$	$(O_7 - O_9, 1)$	$(O_9 - O_8, 1)$

Note: "–1" and "1" are two types in SVM or RankSVM. In SVM or RankSVM, use "-1" and "1" to clearly define the hyperplane. So, for brevity, the two examples specified in the previous steps are "-1" instead of "0". Now, crk's annotation class information is "-1" or "1", which can be expressed by crk {-1,1}.

D to review pair set *P* is summarized as:

$$(O_i - O_j, 1) \quad \text{P, if } cs_i > cs_j$$

$$(O_j - O_i, 1) \quad \text{P, if } cs_i < cs_j$$

$$(O_i - O_j, -1) \quad \text{P, if } cs_i = cs_j \qquad (5.4.28)$$

According to these rules, the review pair set *P* from the nine reviews in *D* is shown in Table 5.4.

Table 5.4 The final review pairs in P

$(O_1 - O_2, 1)$	$(O_1 - O_3, 1)$	$(O_1 - O_4, 1)$	$(O_1 - O_5, -1)$
$(O_1 - O_6, 1)$	$(O_1 - O_7, 1)$	$(O_1 - O_8, 1)$	$(O_1 - O_9, 1)$
$(O_3 - O_2, 1)$	$(O_4 - O_2, 1)$	$(O_5 - O_2, 1)$	$(O_2 - O_6, -1)$
$(O_7 - O_2, 1)$	$(O_2 - O_8, 1)$	$(O_9 - O_2, 1)$	$(O_4 - O_3, 1)$
$(O_5 - O_3, 1)$	$(O_3 - O_6, 1)$	$(O_7 - O_3, 1)$	$(O_3 - O_8, 1)$
$(O_3 - O_9, -1)$	$(O_5 - O_4, 1)$	$(O_4 - O_6, 1)$	$(O_4 - O_7, -1)$
$(O_4 - O_8, 1)$	$(O_4 - O_9, 1)$	$(O_5 - O_6, 1)$	$(O_5 - O_7, 1)$
$(O_5 - O_8, 1)$	$(O_5 - O_9, 1)$	$(O_7 - O_6, 1)$	$(O_6 - O_8, 1)$
$(O_9 - O_6, 1)$	$(O_7 - O_8, 1)$	$(O_7 - O_9, 1)$	$(O_9 - O_8, 1)$

Now, the problem shifts to learning a weight W to classify pairs of annotations in P into two classes (“–1” and “1”). This is very similar to the method in SVM. In the support vector machine, the distance between two parallel hyperplanes is maximized by adjusting the weight W.

An example of SVM is illustrated in Figure 5.7.

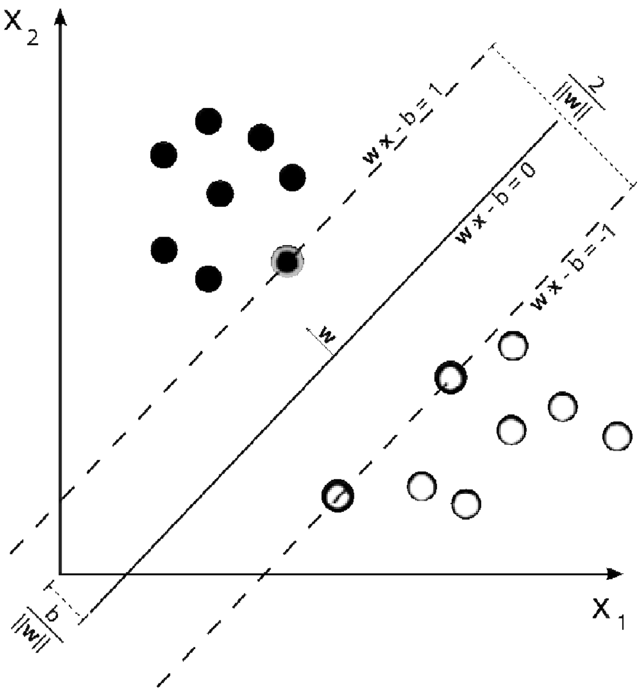


Figure 5.7 The linear separation of two classes with SVM

On this basis, a sorting algorithm based on support vector machine is proposed to classify the evaluation pairs into two categories.

The purpose of SVM is to maximize the separation between hyperplanes. But SVM does not contain cross-category sequence information. The classification problem of sequence numbers is first transformed into binary. In the support vector machine, W represents the feature weight, and there are no other restrictions on W. However, in this example, W refers to a review related to the product design specification, or a weight on the product design specification. This means that W must be positive, due to the polarities of emotions across different products. For example, "-2" is the largest negative number and "2" is the largest positive number. So, new constraints are introduced.

Also, in cases where separation by hyperplane is not possible, a compromised marginal maximization method can be used. The slack variable k in the SVM is selected. The relaxation variable is a measure of compromise. This idea is also applied to the design of sequence taxonomy.The complete model for this problem is shown as follows:

$$
\begin{aligned}
&\min \sum \xi_k + \frac{C}{2} W^T W \\
s.t.\ &\hat{cr}_k = \sum_{j=1}^{n} w_j OP_{kj} \\
&\hat{cr}_k cr_k \geq 1 - \xi_k \\
&W \geq \mathbf{0} \\
&\xi_k \geq 0
\end{aligned}
\qquad (5.4.29)
$$

Models (5.4.29) for more details: k is a relaxation variable that estimates the degree of compromise. The coefficient C is the importance of the sum of the rule term and the trade-off term. 1/2 W TW is a regularization method used to suppress overfitting. To avoid overfitting due to over-tuning of the coefficient W, it is added to the error function. Used to estimate the customer satisfaction relationship between two annotations cr^k. Like a support vector machine, both hyperplanes are spaced 2-2 apart, and they should be as large as possible so that they can be distinguished well. Under the third constraint, the weight wi of the product design specification pci is constrained to be above 0. "0" is zero vector, non-scalar zero.

Accordingly, the weights of the six product design specifications, w_1, w_2, ..., w_6, for the nine reviews can be calculated by the optimization problem in Model (5.4.30):

$$
\begin{aligned}
&\min \sum_{k=1}^{36} \xi_k + \frac{C}{2} \sum_{t=1}^{6} W_t^2 \\
&s.t.\ \hat{cr}_k = \sum_{j=1}^{6} W_j OP_{kj} \\
&\quad \hat{cr}_k cr_k \geq 1 - \xi_k \\
&\quad W \geq \mathbf{0} \\
&\quad \xi_k \geq 0
\end{aligned}
\tag{5.4.30}
$$

Rendering order sorting is a matching technique. In this strategy, we compared the customer satisfaction of two groups. Although pairwise comparisons are possible, this method is not suitable for AHP. AHP can do pairwise comparisons, but AHP can provide many comparisons. In this classification method, pairwise comparison results are only determined binary. In particular, the overall relationship of customer satisfaction is equal or unequal. If this classification method were used directly for AHP, it would only show which product design parameter is most important. Therefore, how to adjust this classification system so that it can be applied to the AHP method is the future research direction.

5.4.3 Experimental study and discussions

5.4.3.1 Experiment setup

In Sections 5.4.1 and 5.4.2, we propose a categorization of pairs to prioritize product design specifications in online reviews, and analyze these criteria. Two different performance indicators of classification and classification are tested to test their performance.

Prior, post-test and F-degree estimates are generally used to evaluate the performance of classification algorithms. See 4.3.23 and 4.3.24 for the definitions of before and after. F-measure is a weighted average of precision and recall. Here, we use the F1 score, the optimal and optimal harmonic mean. An F1 score at 1 is the best and at 0 is the worst.

$$F_1 = 2 \cdot \frac{|\,Precision \cdot Recall\,|}{|\,Precision + Recall\,|} \tag{5.4.35}$$

MAP and NDCG are a popular evaluation method. MAP is a rank-based measure of relevance and irrelevance across a range of queries. The method is implemented according to the measure of P@n and AP(q). The accuracy shown by P@n is only obtained for the first n examples in the sorted list. In the first n instances, there are rn associated files, P@n=rn/n. AP(q) averages P@n over n possible values of n. Denote rq as all instances of query q, |Q| is the total number of instances in query q, and r(n) is a function that will return 1, or 0, in n sorted instances.

$$AP(q) = \frac{1}{r_q} \sum_{n=1}^{|Q|} P@n \cdot r(n)$$

$$MAP = \frac{1}{|Q|} \sum_{q \in Q} AP(q) \tag{5.4.36}$$

NDCG is a method for evaluating the quality of grading. The availability or usefulness of documents depends on their position in the results list. The gain goes from the top to the bottom, and each effect will have a discount.

$$DCG = \sum_{i=1}^{n} \frac{\log_2(1+i)}{2^{rel_i} - 1}$$

$$NDCG = \frac{DCG}{IDCG} \tag{5.4.36}$$

reli is the rank correlation of results at position i that is irrelevant, correlated, and extremely correlated. In this survey, "reli" was the first "star" indicating customer satisfaction. IDCG is the normalization term of DCG, which guarantees a full NDGC score of 1. That is, in an error-free sorting algorithm, the DCG will be the same as the IDCG, and the resulting NDCG value will be 1.

In Section 3.4, all lamp data are presented as experimental data.

5.4.3.2 Results and discussions

The performance of model 5.4.29 is shown in Figure 5.8. C is that in model 5.4.29, the parameter wi is adjusted too much in order to avoid the weights in the product design specification. As shown in Figure 5.8, all prediction accuracy is above 70% except "Cobalt".

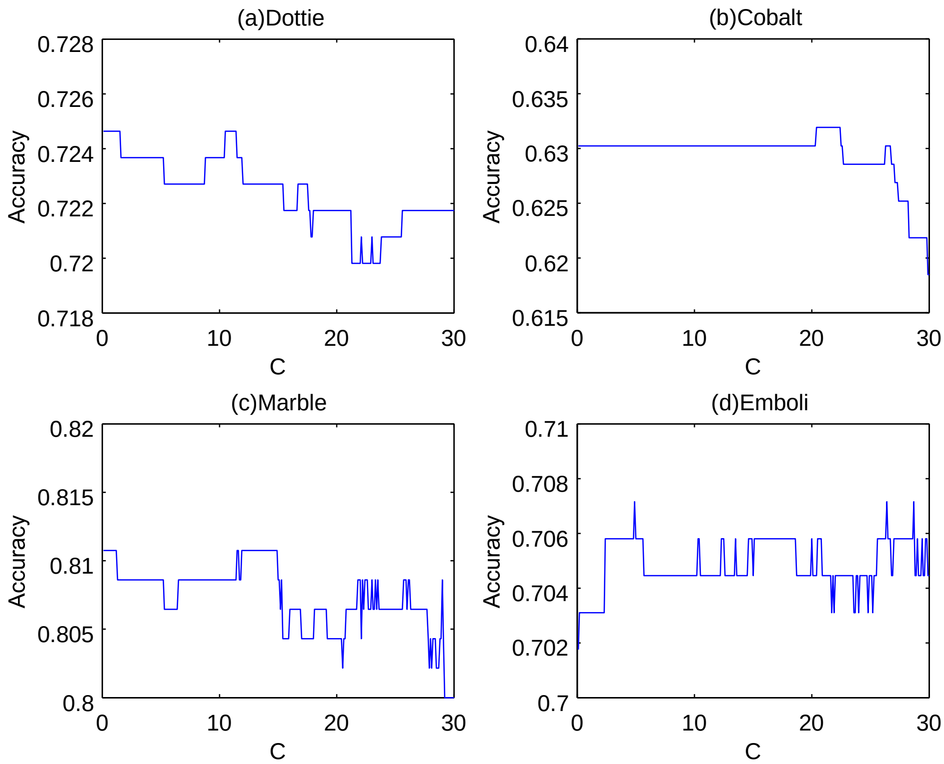


Figure 5.8 Accuracy vs. regularization term C

The most important product design specifications of the table lamp datasets are listed in Table 5.5. In all these experiments, *C* equals to 15, where the performances are relatively stable in Figure 5.8. Compared with top frequent product design specifications in Table 3.5, somewhat different yet interesting results are presented in Table 5.5.

Firstly, as seen from Table 5.5, those mentioned frequently product design specifications in customer reviews are not necessarily predicted as important product design specifications. For example, “design” is frequently discussed by consumers, according to Table 3.5. However, it does not appear in Table 5.5 in all these table lamp datasets. Generally speaking, “design” is a hot topic in lamp reviews, but product designers do not necessarily pay more attention on this product design specification when they launch a new lamp. It illustrates that a high degree of “design” perhaps not necessarily lead to the same degree of customer satisfaction. From these experiments, when designers plan to design a new lamp or improve the current model, which product design specifications should be given more attention are suggested.

Table 5.5 Top five important product design specifications

	Dottie	Cobalt	Marble
1	Easy to assemble	Recycle materials	Price
2	Size	Weight	Weight
3	Stable	Price	Easy to assemble
4	Package	Easy to fit	Recycle materials
5	Recycle materials	Switch	control

	Embolic	Panau	Ele
1	Recycle materials	Recycle materials	Stable
2	Easy to fit	Structure	Price
3	Size	Package	Easy to assemble
4	Price	Easy to fit	Adjust position
5	Package	size	

But it does not mean “design” is not important for a table lamp design. Although “design” receives relative lower priority, generally, the modern design of a table lamp is considered as a must when it designed. It points to another relevant question, how to classify product design specifications into different categories, such as, must-be, one dimensional and attractive attributes in Kano’s Model. This is one future work of this research.

Secondly, important product design specifications may not be talked about by a large proportion of consumers. Take the “Ease of fit” in Table 5.5 as an example. This term appears three times in Table 5.5, but it does not appear in Table 3.5. It interprets that, although this item is not frequently mentioned by consumers, the overall customer satisfaction is impacted by this product design specification in a certain degree. Product designers need to pay more attention to improve the fit of lamps, and the high degree of customer satisfaction depends on these product details.

Thirdly, there are also some product design specifications in both Table 5.5 and Table 3.5. For instance, “price” and “Easy to assemble” appear in the two tables. Admittedly, these two product design specifications, especially “price”, is the essential of a new product. Without the “easy to assemble”, a lamp still can work very well. Similarly, with a little complex setting up for some amateur, a table lamp may still be a good product. However, with these creative product design specifications, the user experience must be improved. These product design specifications are preferred by many consumers, and there are many comments on it. Customer satisfaction will be boosted with these novel product design specifications.

5.5 Summary

In this chapter, build a design-oriented knowledge base for mapping customer requirements with product design specifications is described. The key question about how online reviews is utilized in the viewpoint of product designers is explored.

The first question to be addressed in this chapter is how to integrate online reviews with product design specifications. A second exploratory case study in Chapter 3 revealed that a keyword is not necessarily associated with the same product design specification. Therefore, there is no one-to-one relationship between keywords in online reviews and product design descriptions. However, online reviews will automatically be linked to product design specifications, so new product designs will attract consumers' attention. This paper proposes a probability-based keyword analysis method to solve this problem. On this basis, this paper establishes two models of unary and binary, which combine online evaluation with product design specifications. Using the optimal weighted learning method, keywords and context words in the two models are compared.

The second question in this chapter is how to prioritize product design specifications based on online reviews. Specifically, it is to weigh different product design specifications through the overall customer satisfaction of the product and the user's evaluation of the product design specifications. By using different design specifications, designers can optimize existing products for a new model. This study introduces a ranking method to solve this problem. The method is to achieve the maximum goal by discussing the overall customer satisfaction and customer sentiment of the product in the evaluation pair. In addition, this study also proposes an optimization model using integer nonlinear programming to convert the results into the initial customer satisfaction level for each evaluation, which cannot be explained by many pairwise methods at present. Finally, after some experiments, the algorithm is proved to be effective.

Chapter 6: Environmental Life Cycle Assessment

6.1 Introduction

Sustainability development has become a significant and a major concern across many industrial sectors, especially the manufacturing industry (Zheng et al., 2015). Manufactured products influence in three dimensions of sustainability: economy, environment and society throughout their entire life cycle including design, material extraction, manufacture, transportation, use and disposal. It was found that about 80% of sustainability impacts from the product are decided in the product design and development stage (Kulatunga et al., 2015). The life-cycle assessment (LCA) methodology has been evolved to retrieve the environmental impact information (Iso, 2006), which enables the environmental performance of materials to be evaluated during their entire life cycle, encompassing extraction and processing resources, manufacture, distribution, use, recycling, and final disposal. Because the LCA assesses the environmental impact, it is also referred as environmental LCA (E-LCA).

This study presents an approach for integrating LCA into the sustainable design of lighting products. The environmental performance of the materials is evaluated through the product life cycle, encompassing extraction and processing resources, manufacture, distribution, use, recycling, and final disposal. Based on the LCA results, the sustainability performances of different materials and processes for lighting products are assessed and the assessment results are utilised in optimum design of the lighting product.

In the following sections, the research method is presented first, followed by discussion based on the comparative LCA results obtained, and further topics to be covered in the forthcoming full paper are highlighted.

6.2 Life cycle assessment

Life-cycle assessment (LCA) is an effective tool to evaluate the environmental impact of a product during its life cycle. The LCA analyses were conducted for all Ona existing domestic lighting products (the details of existing products LCA analysis results can be found in a journal paper “Application of life-cycle assessment to the eco-design of LED lighting products” (Shuyi et al., 2020), Euro-Mediterranean Journal for Environmental Integration (2020) 5:41).

This research integrates LCA methodology into the sustainable design of lighting products. A comparative LCA between different materials is conducted in the initial design of a LED luminaire “Medusa” shown in Figure 6.1, with three versions of casing made of plastic, wood and aluminum.

Figure 6.1 different casing materials for “MEDUSA” luminaires

The LCA is carried out according to ISO 14040 (Iso, 2006), which comprises the following four phases:

Goal and scope definition: this research aims to evaluate the life cycle environmental performance of luminaire Medusa featured with sustainable concepts, in order to achieve optimum design solutions, with particular attention in the materials selection. The results obtained will also be used to develop the production and consumption strategy towards more sustainable domestic luminaires.

Inventory analysis: compiling a complete record of the important materials and energy flows throughout the lifecycle, in additional to releases of pollutants and other environmental aspects being studied. The inventory data are listed in Table 6.1.

Impact assessment: Online LCA Platform http://h2020.circ4life.net/ is used for the LCA modelling. It links the reference flows with the life cycle inventory (LCI) database, and then utilises the LCI flows with relevant characterization factors. The ReCiPe single score method (Goedkoop, 2009) is applied in this study, and the total environmental impact is expressed as a single score.

Interpretation: identifying the meaning of the results of the inventory and impact assessment relative to the goal of the study.

The LCA is conducted with following steps:

- Obtain the bill of materials (BoM) of the products, and define the functional unit informed by the light analysis;
- Define the boundaries of the assessment according to the goal and scope;
- Identify the limitations and omissions of the data included in the assessment;
- Select the life cycle impact assessment method;
- Input the BoM specified in step 1 into the LCA software;
- Conduct the assessment with the LCA software;

Analyse and interpret the LCA results of all luminaires obtained;

Derive recommendations for reducing the environmental impact of the assessed lighting products.

Table 6.1. Inventory data for the luminaires in this study

Medusa (wood)		Medusa (aluminum)		Medusa (plastic)	
Wood	0.81 kg	Aluminum	1.944 kg	Plastic	0.754 kg
Lamp holder	0.0182 kg	Lamp holder	0.0182 kg	Lamp holder	0.0182 kg
Hood	0.0096 kg	Hood	0.0096 kg	Hood	0.0096 kg
Cable Dam	0.0026 kg	Cable Dam	0.0026 kg	Cable Dam	0.0026 kg
Electrical connection	0.0614 kg	Electrical connection	0.0614 kg	Electrical connection	0.0614 kg
Washer	0.0049 kg	Washer	0.0049 kg	Washer	0.0049 kg
Electricity, low voltage	400 KWh	Electricity, low voltage	400 KWh	Electricity, low voltage	400 KWh
Road transportation	314.4 kgkm	Road transportation	707.6 kgkm	Road transportation	295 kgkm
End of life	0.9067 kg	End of life	2.0407 kg	End of life	0.8507 kg

6.3 Results and discussion

The single score results of LCA assessment for the luminaires are shown in Table 2. The results show that the plastic version has the highest environmental impact score (38.9Pt), while the wood and aluminum versions have much less environmental impacts (19.1 Pt and 21.1 Pt). The major environmental impacts are dominated by the impacts of two stages:

- The manufacturing stage, including the flow of materials in each process, the quantity and type of materials required, the source of raw materials; the means of transportation used and the energy (electricity, gas, fuel) consumed during production;
- the consumption of electricity during the use stage.

However, all of them have the same lifetime and electricity consumption, which mean they have same environmental impact during the use stage. The reason for the different scores is the manufacturing process for different materials, and the treatment of the materials at the end of life stage where the wood and aluminium are recyclable while the plastic is more difficult in recycling.

Table 6.2-1. ReCiPe Midpoint results of Medusa Wood

Characterization	Explanation	Unit	Value
mCCHH	Climate change Human Health	kg CO2 eq	1.64E2
mOD	Ozone depletion	kg CFC-11	1.41E2
mHT	Human toxicity	kg SO2 eq	8.6E0
mPOF	Photochemical oxidant	kg P eq	9.21E-
mPMF	Particulate matter formation	kg N eq	9.45E1
mIR	Ionising radiation	kg 1,4-DB eq	1.11E2
mCCE	Climate change Ecosystems	kg NMVOC	1.29E5
mTAF	Terrestrial acidification	kg PM10 eq	6.61E-
mFEP	Freshwater eutrophication	kg 1,4-DB eq	2.02E-
mTET	Terrestrial ecotoxicity	kg 1,4-DB eq	5.33E0
mFET	Freshwater ecotoxicity	kg 1,4-DB eq	4.64E0
mMET	Marine ecotoxicity	kBq U235 eq	3.38E1
mALO	Agricultural land occupation	m2a	7.46E0
mULO	Urban land occupation	m2a	1.24E0
mNLT	Natural land transformation	m2	7.07E-

mWD	Water depletion	m3	1.22E0
mMD	Metal depletion	kg Fe eq	1.22E2
mFD	Fossil depletion	kg oil eq	4.05E1

Table 6.2-2. ReCiPe Midpoint results of Medusa Metal

Characterization	Explanation	Unit	Value
mCCHH	Climate change Human Health	kg CO2 eq	1.64E2
mOD	Ozone depletion	kg CFC-11	1.41E2
mHT	Human toxicity	kg SO2 eq	8.6E0
mPOF	Photochemical oxidant	kg P eq	9.21E-
mPMF	Particulate matter formation	kg N eq	9.45E1
mIR	Ionising radiation	kg 1,4-DB eq	1.11E2
mCCE	Climate change Ecosystems	kg NMVOC	1.29E5
mTAF	Terrestrial acidification	kg PM10 eq	6.61E-
mFEP	Freshwater eutrophication	kg 1,4-DB eq	2.02E-
mTET	Terrestrial ecotoxicity	kg 1,4-DB eq	5.33E0
mFET	Freshwater ecotoxicity	kg 1,4-DB eq	4.64E0
mMET	Marine ecotoxicity	kBq U235 eq	3.38E1
mALO	Agricultural land occupation	m2a	7.46E0
mULO	Urban land occupation	m2a	1.24E0
mNLT	Natural land transformation	m2	7.07E-
mWD	Water depletion	m3	1.22E0
mMD	Metal depletion	kg Fe eq	1.22E2
mFD	Fossil depletion	kg oil eq	4.05E1

Results from LCA Online Platform -ReCiPe Endpoint results

The results for the endpoints (ecological points) are shown in Table 3. The wood plate is worth 19.1 pounds, the metal plate is worth 21.1 pounds, and the end (ecological point) results of each Ona lighting product are on its website (https://onaemotion.com). Figure 6.2 shows the contribution to the life cycle. As can be seen from the graph, in the overall environment, the utilization period is the main contribution, after the production period.

Table 6.3-1 The endpoint (eco-point) results of Medusa wood

Characterization	Explanation	Unit	Value
sTotal	Total	Pt	1.91E1
sHH	Human Health	Pt	1.26E1
sES	Ecosystems	Pt	5.47E-1
sRS	Resources	Pt	5.96E0

Table 6.3-2 The endpoint (eco-point) results of Medusa Metal

Characterization	Explanation	Unit	Value
sTotal	Total	Pt	2.11E1
sHH	Human Health	Pt	1.33E1
sES	Ecosystems	Pt	5.45E-1
sRS	Resources	Pt	7.2E0

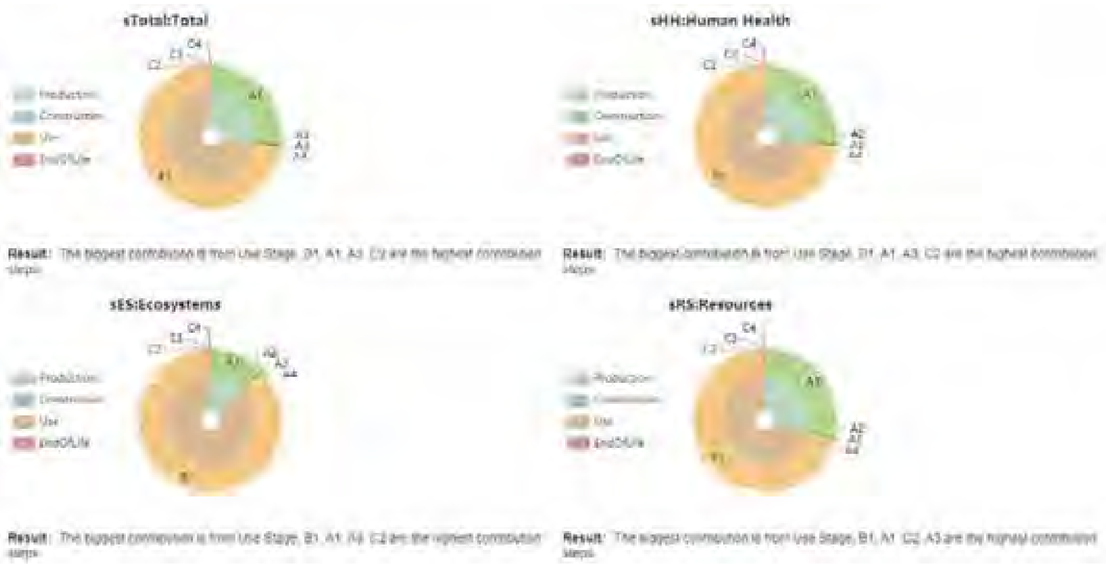


Figure 6.2-1 Life cycle stage contribution analysis results (Medusa Wood)

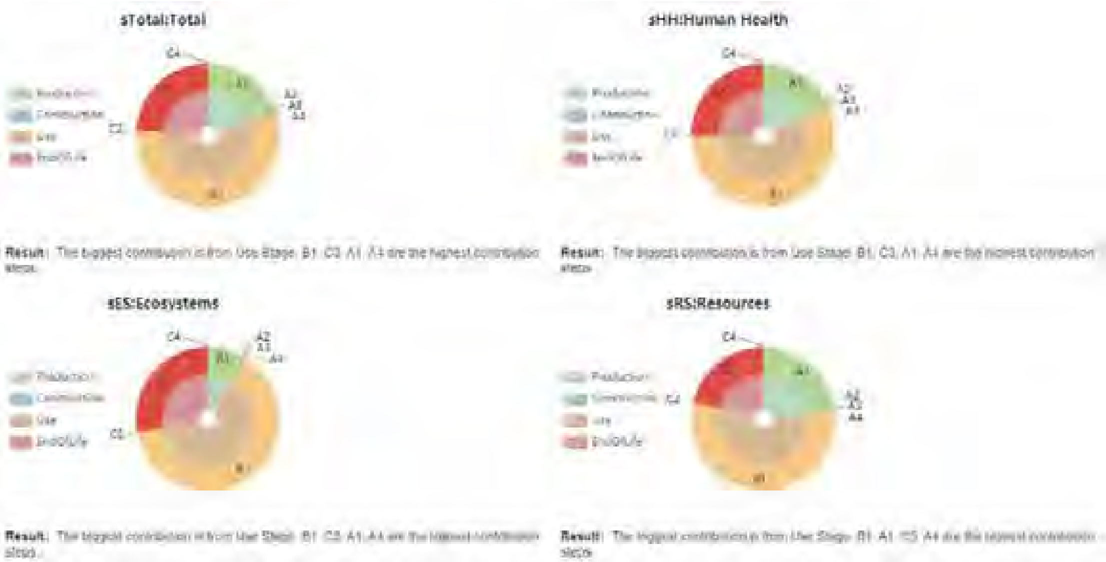


Figure 6.2-2 Life cycle stage contribution analysis results (Medusa Metal)

In terms of waste properties, the benefits of recycling them differed: aluminum had a positive effect of 57.54%, a negative effect of 0.29%, and plastics accounted for 14.08%. As can be seen from the results of the LCA study, recycled aluminium and wood have a small environmental impact (19.1 and 21.1), while now processing plastics has a significant effect (38.9).

From the results, in the final design, only wood and aluminum were considered, and no plastic was included; in addition, the structure was optimized by adding the top so that all the casings were of the same length, see fig. 6.2.

On the basis of evaluation and feedback, the main features specified in the Product Design Specification (PDS) of the new LED lighting product (Medusa) are as follows:

- Low energy consumption during the manufacturing stage (easy to manufacture).
- Prolong the lifespan by enabling repairability—the product is expected to have a 10-year lifespan.
- Modular design.
- Easy to assemble/disassemble (the consumer can assemble the product by themselves).
- Made from low-impact materials; postconsumer/recycled materials are preferred.

- Refine the dimensions of the product to reduce weight.
- Fully recyclable at end of life.

The sustainability of the Medusa lamp is addressed through the following characteristics:

- High availability of data. This product comes in two different materials: wood and metal. The selected raw materials are standard raw materials, which are easy to obtain and regenerate.
- Modular architecture. The eco-friendly design aims to achieve a clean building that uses relatively few materials, but still visually appeals to customers. The exterior structure of the lamp is composed of many parts of the same shape and size. These parts are attached to the two inner rings. For safety and aesthetics, the front end of the exterior parts is curved. The modular structure of the lighting device also facilitates installation/removal of the lighting device (which the user can assemble by himself) and access to its internal components when repairs or maintenance are required.
- Easy to produce. The main parts used in the lamp are made of renewable plastics and are extruded. No connecting parts are required, reducing the complexity of the luminaire and reducing energy consumption in production. A special glue holds all the parts together. The innovation of this design is that chemicals can be used to dissolve the glue so that possible disassembly and recycling can be avoided.
- High recycling/recycling. The bulb is made from a single material and requires no additional connecting parts (although three materials are available). Therefore, the bulb can be recycled as a whole, and the WEEE program does not need to disassemble it during its disposal phase.

6.4 Conclusion

This research integrates environmental LCA into sustainable design of lighting products by conducting comparative LCAs with different materials. Three table lamps are investigated, which all have the same structures, but their casings are made of wood, aluminum and plastic materials. The LCA results indicate that the lamps of wood and aluminum have much lower impact scores (19.1 Pt and 21.1Pt, respectively), which are approx. 50% less than that of plastic version (38.9 Pt). Therefore, the plastic one has not been considered in the final design.

Chapter 7: Social Life Cycle Assessment

7.1 Introduction

This chapter introduces a paradigm for analysing the positive social consequences of a product on consumers during its use phase. This is the first of three research chapters that describe the research activities carried out in this thesis. This chapter begins with a definition of social benefit and an explanation of what it entails. The second section of the chapter covers the framework's development and how it links to earlier 'environmental and social' assessment studies and frameworks, particularly LCA. The last section of the chapter outlines the form of the societal benefit assessment framework, as well as the processes and data necessary for such evaluation, and compares it to the IS014040 LCA methodology to highlight major distinctions and illustrate the originality of this research.

Social elements are assessed from a Life Cycle Assessment perspective in order to assess the sustainability of residential lighting products. Thus, ISO 14040/44 standards establish the basis for social life cycle assessment (S-LCA). Thus, S-LCA is a process for assessing social and socioeconomic properties of goods, as well as possible positive and negative consequences, throughout their life cycle (Andrews, 2009).

7.2 Definition of social benefits

The analysis revealed that existing sustainable product design techniques do not take into account beneficial societal benefits, particularly in regard to the product's functioning during usage. While research in positive impacts assessment has emerged in recent years, notably in SLCA, there is little evidence to imply that the study community has a consistent definition of positive social impacts. Previous attempts to identify and evaluate these have been restricted to the life cycle stages of resource, production, and disposal, with the usage phase generally overlooked in terms of positive effect evaluation. This study aims to fill this knowledge gap by creating a framework and decision support tool for assessing positive social effect.

To begin, it is critical to define positive social benefits in order to construct this framework and design decision support tool. In this thesis, the positive social effect of a product is defined as the social benefits of a product. A product's social benefits are defined as the advantages that the product provides to society or its collective consumers throughout its use. This will be focused specifically on the planned advantages flowing directly from the product's numerous features. While increased supply networks throughout the product's lifespan may provide advantages, it should be noted that they are not direct benefits to society. The greatest advantages that a product may provide its consumers and the larger community are presumably derived from its functions; after all, why should costly resources be dedicated to the production of a product that does not successfully benefit society? Regardless of whether or not excellent environmental practises exist and the job prospects that result.

7.3 Methodology for the social life cycle assessment

SLCA has several methodological peculiarities that are outlined afterwards and are modified to the features of the demonstrators (UNEP/SETAC/LCI, 2009). The social impact assessment is performed in a manner comparable to and consistent with the environmental life cycle assessment, since the basic steps for analysis design and configuration are the same. Figure 7.1 depicts the relationships between the four major phases of a Life Cycle Assessment (ISO, 2006b).

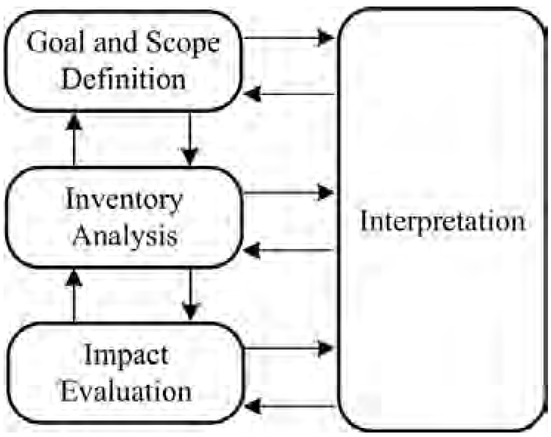


Figure 7.1 Principal phases of an LCA study

The first phase outlines the goal and scope of the analysis, beginning with the assessment's functional unit. In this scenario, the evaluation is centred on items, and the functionality is provided by one full unit of ready-to-use product: one table lamp (domestic lighting product). The scope of the analysis is also decided in this stage depending on the study's objectives. The broadest scope is a cradle-to-cradle study, which includes all life cycle stages, including material disposal and product end of life. The inventory of inputs/outputs of each life cycle stage per functional unit is retrieved based on the stated scope, either from own sources or from relevant databases. The effect evaluation for an SLCA consists of aggregating all social consequences and weighting them according to national and sectoral risk variables, and it is presented in similar medium risk hours. Assessments of the most impactful phases and actions, as well as comparisons with feasible scenario planning, are conceivable. Finally, the interpretation of the results permits the analysis to be iterated among the preceding processes.

However, in order to undertake a thorough and comparative social evaluation, the SLCA technique is subdivided into subcategories that are socially significant subjects or elements. These divisions are divided into impact categories and stakeholder categories. Stakeholders are a collection of agents who are likely to have shared interests due to their interaction with the product system under consideration (Fontes et al., 2014). Figure 7.2 depicts the links between the major players involved in business and goods. Given the scarcity of scientific or internationally approved inventory categorization methods, as stated by (Hsu, Wang, and Hu, 2013), this technique can serve as a strong foundation for subcategory structuring.

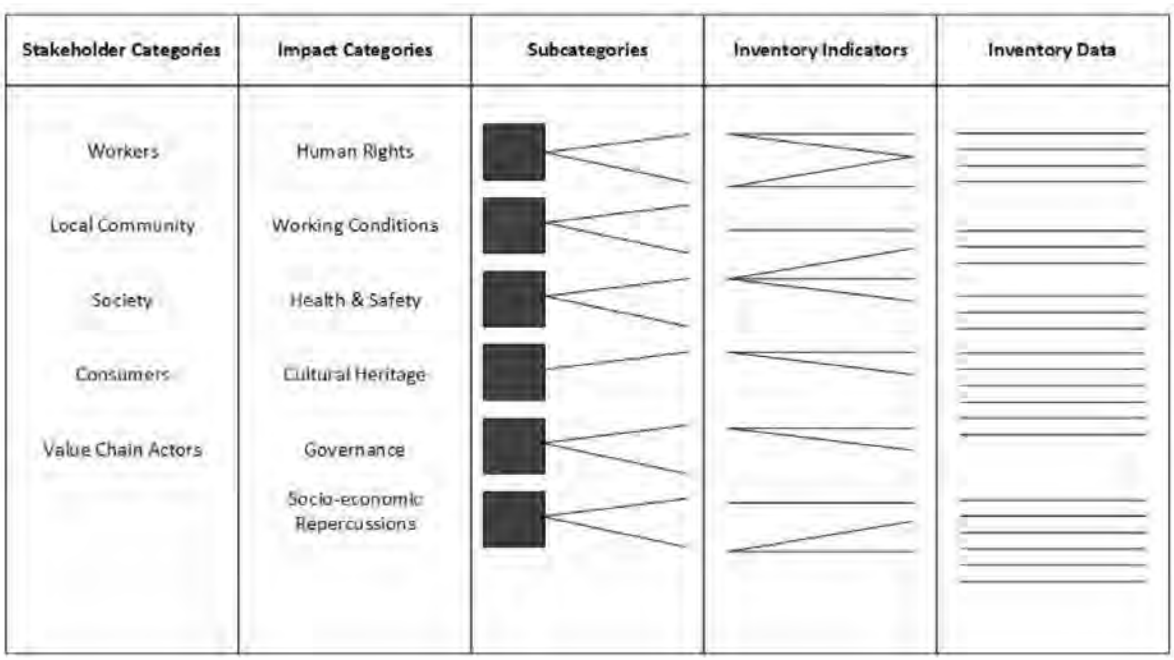


Figure 7.2 Relationship between stakeholders (UNEP/SETAC/LCI, 2009)

To give a systematic strategy to understanding and analysing the societal benefits of products, a framework is necessary. This ensures that the procedure can be replicated and that comparisons can be made between research that use the same step-by-step technique. This framework's main considerations have been recognised as three important factors:

1) Intended users of the product
2) The functions of the product
3) The benefits relating to those functions

Firstly, it is recognised that society is not a homogeneous collection of similar individuals, but rather a highly diversified collection of social groupings with multiple overlapping memberships. Some groups within a chosen range, such as age, are exclusive, and a person can only belong to one group at a time. In other cases, such as occupation, where an individual may have many jobs, organisations may be more open to various affiliations. It is also obvious that justifying the requirements of one collective society group above another would be immoral and divisive. One option to resolving this quandary would be to draw a line around the societal group being evaluated. This would narrow the emphasis of the evaluation to to those aspects directly related to the requirements of that group that are being addressed. Furthermore, the evaluation focuses on the intended functions of the product rather than unanticipated ones. The core of societal benefits is how the specified functionality helps the whole population. As a result, the other two main considerations for an assessment are the functionality of the product under consideration. To accurately represent the product and acquire a complete grasp of the link between functions and benefits, it is critical that all intended functions of the goods be recorded. For the same reason, it is critical to include all of the items' possible benefits.

7.3.1 Stakeholders and subcategories

The initial set of subcategories was used to identify appropriate subcategories for the S-LCA investigation. The stakeholders and subcategories were chosen based on relevancy, data availability, and bibliographical validation requirements. ONA lighting (Spain) provided national, sector, and company-specific statistics and comments for each subcategory in all five stakeholder categories, which were subsequently confirmed if data was available for all subcategories. Finally, the findings of one of the most cited papers in the field (Jrgensen, et al., 2008), an updated S-LCA review (Siebert, et al., 2018), and the most recent report on S-LCA done by the Joint Research Centre in 2018 (Mancini, et al., 2018) were consulted to validate those subcategories. The three studies provide a total of 24 S-LCA cases that serve to identify the most relevant social indicators.

All five categories of stakeholders were considered: 'workers,' 'local community,''society,' 'consumers,' and 'value chain players.' To analyse the social sustainability of the LED lighting product supply chain, 16 subcategories were examined: 'fair wage,' 'working time,' 'discrimination,' 'health and safety,''social benefits,' and 'legal concerns.' 'Workers' rights,' 'fair competition,' 'promoting social responsibility,''supplier relationships,' 'contribution to economic development,' 'Access to material resources,' 'Safe and healthy living conditions,' 'Local employment,' 'Health and Safety,' 'Transparency,' and 'End of life responsibility'

7.3.2 System boundary

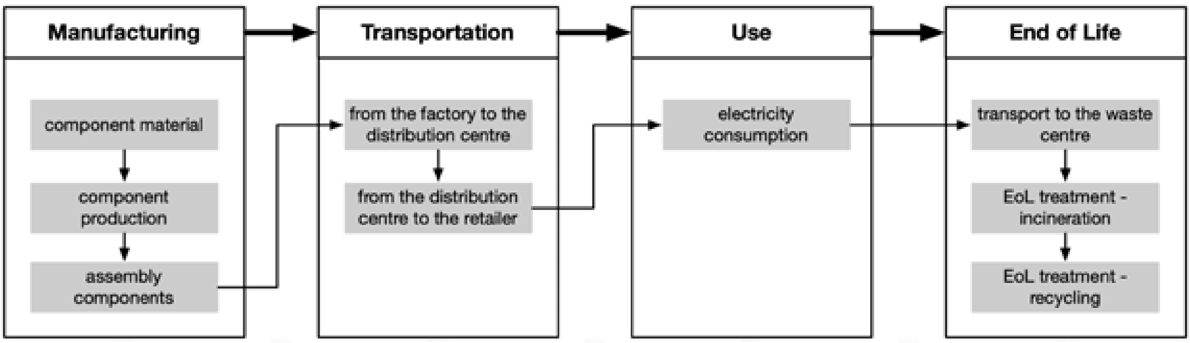


Figure 7.3 ONA lighting product system boundary

ONA designs and manufactures the lighting product, which has the same functional unit as E-LCA. Figure 7.3 depicts the product's simplified life cycle process flowchart.

The evaluation takes into consideration all stages. The production/assembly stage includes 18 primary components as well as packaging materials. LED lighting board, housing, LED driver, fasten members, and packaging are the five components. The examination also includes background industrial processes such as basic material production and material extraction. Transportation, useful life, and EoL situations are also taken into account.

7.3.3. Social life cycle inventory data

Inputs for the social life cycle inventory are stated in monetary terms, with 1 GBP equaling 1.34 USD and 1 USD equaling 6.8 CNY. The product's ultimate price includes capital items, overheads, waste, materials, and labour costs associated with producing one functioning unit. The data source spans the years 2018 to 2019. Given the data quality, the study collects enough information to model the product system. Overall, the data availability for the S-LCA research meets the evaluation aim and scope. The final product business assessed all reference costs after collecting case-specific data. However, where case-specific information was missing, generic statistics were used. The PSILCA database was used to get the background process data. Table 7.1 displays the end product's social life cycle inventory data.

Table 4.1 Life cycle inventory

Value chain step	Substep	Material/activity	Quantity	Unit	Country Supplier / Waste Destination	Cost €
Reference annual production			300	units		136,11€/unit
Materials	Metal pieces	Virgin stainless steel	2836	g	Spain	70
		Iron	344	g		
	Shade	Parchment	104	g	Spain	59
	Cable	PVC	52	g	Spain	1,68
		Copper	42	g		
	Plug	ABS	7	g	Spain	0,69
		Copper	2	g		
	Lamp frame	ABS	25	g	Spain	0,52
		Cast Iron	3	g		
	Base	Pig iron	872	g	Spain	
	Switch	ABS	7	g	Spain	0,57
		Copper	1	g		
	LED lamp	Iron	12	g	Spain	3,65
		ABS	18	g		
		Aluminium	38	g		
		ABS	1	g		
		PET	11	g		
		Printed Circuit Board (PCB)	5	g		
		LED power supply	3	g		
		Capacitor	4	g		
		Inductors	1	g		
		Resistor	0,6	g		
		Stainless Steel	1	g		
		LED	1	g		
Manufacturing Process	Number of employees dedicated to annual production		2	people	Spain	19800€/year per people

Value chain step	Substep	Material/activity	Quantity	Unit	Country Supplier / Waste Destination	Cost €
Labour	Operator		100	h/year	Spain	18€/h
	Administration		50	h/year	Spain	18€/h
	Transport / Handling		25	h/year	Spain	22€/h
Waste	Recycling	Plastics	91	g	Spain	
		Metal	3180	g	Spain	
		Paper cardboard	104	g	Spain	
	Packaging waste		373	g		
Packaging	Bags	Plastics	1,5	g	Spain	1
		Paper	78	g	Spain	1
	Labels		0,3	g	Spain	0,2
	Boxes		373	g	Spain	5
Transport	Market 2018 Main destination countries	1st Main destination country	100	%	Spain	15
Use	Consumers	Total Electricity consumption in 40.000 hours	268	kWh	Spain	0.145 €/kWh
End of Life	Disposal (domestic bin)		4390	g		
Capital Items	Use of Assembly line dedicated to annual production		100	h/year	Spain	
	Estimated % use of Building dedicated to annual production (considering 100% use for all products)	Laboratory R&D	1	%	Spain	-
		Office	0,25	%	Spain	-
		Assembly shop	6,09	%	Spain	
		Storehouse	0	%	Spain	
		Product trials	1	%	Spain	
	Estimated % use of tools dedicated to annual production (considering 100% use for all products)	Welder	0,2	%	Spain	0,9€/h
		Polishing Machines	0	%	Spain	2,69€/h
	Online Sale	Table lamp	300	units/year		266,20€/unit

The chosen product is produced to order. As a result, they do not have a large supply of the goods. Regarding power usage for the production phase, it was not considered in the LCI because the product does not have a significant volume inside the organisation. The total number of employees in the firm is four. Half of them are female. The median pay for men is 1,068.37 € and the median wage for women is 1,328.44 €. Because of the size of the firm, they are not required to have a labour union. In terms of water use, the total annual consumption is 12m3 at a cost of 9,31€/m3. The yearly cost of personnel/annual turnover ratio is 0.75. This value represents a corporate characteristic in which the primary activity is product design. Employees are paid an average hourly rate of 38€/h. It should be noted that the fee paid to AMBILAMP for the recycling activity of the product is 0.5€ per unit, which corresponds to the producer's expanded obligation.

Finally, in order to examine the ONA's risk levels in relation to its performance, Table 7.3 displays the data obtained in relation to the indicators investigated. Given that the PSILCA database provides reference data from certain sectors at the national level, ONA values are utilised to adjust the reference data to a business level, with the assumption that this information may be extended to the lighting industry in Spain.

The usage of functional units is an important part of LCA. The functional unit in LCA guarantees that items are compared fairly as long as they fulfil the same functional statement. For example, a reusable bottle that can carry 100mL of water every day for a year. This would enable a water bottle, a cup, and a plastic bag that can hold water to be properly compared based on the declared use. In summary, the LCA functional unit determines the function of items, as well as the amount of materials used and the time span of the product's lifetime.

7.4 Assessment of Social life cycle impact

PSILCA uses a multi-regional input/output database with data from 189 nations and almost 16,000 activity sectors split across industries and commodities. Eora includes raw data from the UN System of National Accounts, Eurostat, the Comtrade database, and several national organisations (Eisfeldt, 2017). Eora, as an Input-Output database, employs money flows to connect activities. All process inputs are expressed in US dollars, and effect outputs are computed in comparable medium risk working hours. This technology facilitates the linking of disparate operations as well as the comparison of impact results. PSILCA includes a total of 88 qualitative and quantitative indicators, which are quantified in various units such as single values or percentages, and some of which are also qualitative. The indicators/sub-indicators are grouped into 25 social and socioeconomic subgroups (topics). PSILA material includes a comprehensive list of stakeholders, subcategories, and indicators (Eisfeldt, 2017).

The social life cycle evaluation of the reference products was carried out based on the stakeholders' selection and inventory creation. The amount of risk for each selected indicator was determined using case-specific social data obtained from the firm and industry. The 'Activity variable' 'worker hours' has been used in PSILCA to'reflect the share of a certain activity connected with each unit process' (UNEP/SETAC, 2009), which is computed as follows (Eisfeldt, 2017):

$$\textit{Worker hours} = \frac{\textit{Unit labour costs}}{\textit{Mean hourly labour cost (per employee)}}$$

Following that, life cycle simulation models for social evaluation were created using the software application OpenLCA. The simulation model is constructed on self-construct processes that are supported by built-in industries and commodities data from the country's database, such as 'electronic element and device-CN.' The social performance was calculated using the Social LCIA approach (GreenDelta, 2020).

7.4.1 Results and discussion

The social implications are weighted according to the risk level in Table 7.2, which corresponds to the PSILCA Social Life Cycle Impact Analysis technique v1.00 as implemented in openLCA software.

Table 7.2 PSILCA risk level weights. (PSILCA Social Life Cycle Impact Analysis method v1.00)

RISK LEVEL	WEIGHT
VERY HIGH RISK	5
HIGH RISK	2
MEDIUM RISK	1
LOW RISK	0.5
VERY LOW RISK	0.25
NO RISK	0
NO DATA	0.5

The findings of the SLCA of the table lamp conducting the LCI assessment are shown in Tables 7.3, 7.4, and Figure 7.4. It should be noted that the LCI has been calculated in monetary terms. As a result, all cost figures and product prices were translated into 2011 US dollars using the 0.75 €/US dollar conversion rate.

Table 7.3 ONA´s LED domestic table lamp SLCA absolute results per impact indicator

Impact Category	Unit	Total	Cable	Lamp frame	LED lamp	Metal pieces	Plug	Shade	Switch	Packaging	Manufacture of domestic appliances /Commodities /ES	Other transport material n.e.c./ Commodities/ES	Other business services/ Commodities/ ES	Production and distribution of electricity/ Commodities/ ES	Recycling /Industries/ ES
Minerals consumption	MC med risk	30.17	0.33	0.05	0.32	6.35	0.10	8.95	0.07	1.04	1.42	0.88	7.85	2.73	0.05
Non-fatal accidents	NFA med risk	64.17	0.42	0.14	0.85	17.86	0.18	16.52	0.15	2.01	3.31	1.91	14.70	6.01	0.12
DALYs indoor/outdoor air & water pollut.	DALY med ris	7.90	0.08	0.01	0.08	1.51	0.02	2.80	0.02	0.32	0.34	0.21	1.86	0.64	0.02
Association and bargaining rights	ACB med risk	20.31	0.43	0.03	0.16	2.93	0.11	9.17	0.06	1.02	0.60	0.58	4.13	1.07	0.03
International migrant stock	IMS med risk	34.88	0.26	0.06	0.40	8.18	0.10	8.25	0.07	0.99	1.68	1.03	10.08	3.72	0.06
Youth illiteracy	YI med risk	27.82	0.28	0.04	0.25	5.11	0.08	10.61	0.06	1.19	1.15	0.68	6.19	2.11	0.06
Weekly hours of work per employee	WH med risk	20.08	0.14	0.03	0.21	4.45	0.05	5.45	0.04	0.64	0.95	0.57	5.53	1.97	0.04
Violations of employ. laws & regulations	VL med risk	30.71	0.24	0.05	0.36	6.53	0.08	9.44	0.06	1.09	1.35	0.97	7.48	3.00	0.05
Net migration	NM med risk	15.63	0.12	0.03	0.19	3.90	0.04	3.35	0.03	0.41	0.76	0.42	4.57	1.79	0.03
Indigenous rights	IR med risk	16.00	0.19	0.02	0.12	2.14	0.05	8.17	0.03	0.90	0.44	0.42	2.80	0.69	0.03
Pollution	P med risk h	25.62	0.39	0.04	0.23	4.54	0.11	9.98	0.07	1.12	1.12	0.71	5.51	1.75	0.05
Frequency of forced labour	FL med risk	7.15	0.07	0.01	0.07	1.42	0.02	2.50	0.02	0.28	0.26	0.19	1.69	0.61	0.02
Goods produced by forced labour	GFL med risk	0.73	0.01	0.00	0.01	0.09	0.00	0.34	0.00	0.04	0.01	0.01	0.15	0.05	0.00
Anti-competitive behaviour	AC med risk	11.44	0.11	0.02	0.12	2.51	0.04	3.38	0.03	0.39	0.55	0.30	2.98	1.00	0.02
Corruption	C med risk h	92.81	0.86	0.16	1.17	20.82	0.28	29.96	0.21	3.45	4.74	2.47	20.83	7.70	0.17
Illiteracy	I med risk h	60.28	0.67	0.09	0.54	10.99	0.19	23.77	0.13	2.66	2.27	1.39	12.96	4.48	0.14
Fossil fuel consumption	FF med risk	7.44	0.07	0.01	0.07	1.45	0.02	2.46	0.02	0.28	0.41	0.22	1.81	0.60	0.01
Workers affected by natural disasters	ND med risk	9.31	0.15	0.01	0.09	1.76	0.04	3.24	0.03	0.37	0.42	0.27	2.21	0.71	0.02
Internt. migrant workers. in sector/site	IMW med risk	32.07	0.25	0.05	0.36	7.44	0.08	8.27	0.06	0.96	1.27	1.01	9.05	3.22	0.06
Unemployment	U med risk h	68.17	0.39	0.13	0.88	18.22	0.17	12.06	0.14	1.52	3.42	1.85	20.68	8.57	0.13
Biomass consumption	BM med risk	59.93	0.48	0.09	0.58	11.43	0.16	20.71	0.12	2.36	2.33	1.74	14.97	4.84	0.11
Child Labour	CL med risk	23.74	0.44	0.03	0.19	3.50	0.11	11.07	0.07	1.23	1.07	0.55	4.30	1.14	0.04

Impact Category	Unit	Total	Cable	Lamp frame	LED lamp	Metal pieces	Plug	Shade	Switch	Packaging	Manufacture of domestic appliances /Commodities /ES	Other transport material n.e.c./ Commodities/ES	Other business services/ Commodities/ ES	Production and distribution of electricity/ Commodities/ ES	Recycling /Industries/ ES
Drinking water coverage	DW med risk	14.14	0.14	0.02	0.13	2.48	0.04	5.52	0.03	0,62	0.99	0.37	2.84	0.92	0,03
Education	E med risk h	41,53	0.36	0,07	0,46	9,21	0.12	11,66	0,09	1.36	1,99	1.13	10,92	4.07	0.08
Fair Salary	FS med risk	86,23	1.01	0.13	0.83	16,46	0,30	30.57	0.20	3.47	3,79	2.23	20.37	6.71	0.16
Safety measures	SM med risk	36.47	0,43	0,09	0,43	10.94	0.15	10.33	0,12	1.27	1.43	1,00	7.32	2.87	0,09
Gender wage gap	GW med risk	45.86	0.28	0.07	0.37	8,49	0.11	13.46	0.08	1.55	1.63	1,02	14,98	3.71	0.10
Trafficking in persons	TP med risk	15.64	0.21	0.02	0.14	2.72	0.06	6.12	0.04	0.69	1.03	0.37	3.22	1.00	0,03
Fatal accidents	FA med risk	9.92	0.10	0.02	0.11	1.91	0.03	3.55	0.02	0.40	0.41	0.30	2.30	0.76	0.02
Social security expenditures	SS med risk	25.77	0.36	0.04	0.22	4.40	0.10	10.66	0.06	1.19	0.99	0.64	5.33	1.73	0.05
Industrial water depletion	WU med risk	43.37	0.38	0.07	0.43	8.40	0.12	13.82	0.09	1.59	2.33	1.51	11.03	3.51	0.07
Trade unionism	TU med risk	99,28	0.66	0.17	1.11	22.19	0.25	27.40	0.20	3,22	4.47	2.81	26.74	9.88	0.19
Sanitation coverage	SC med risk	42.55	0.49	0.06	0.33	6.29	0.14	20.22	0.10	2.25	1.43	0.92	8.07	2.17	0.07
Health expenditure	HE med risk	76.42	0.71	0.12	0.76	15.32	0.23	25.97	0.16	2.97	3.31	1.87	18.38	6.46	0.15
Certified environmental management syst.	CMS med risk	76.22	0.55	0.10	0.57	11.78	0.18	26.35	0.13	2.97	3.67	2.41	21.66	5.71	0.14

Table 7.4 Comparative results of the table lamp SLCA vs PSILCA reference sector

Impact Category	Unity	Manufacture of domestic appliances/Commodities/ES	SLCA table lamp w/o use
Minerals consumption	MC med risk	16.97	27.44
Non-fatal accidents	NFA med risk	17.85	58.16
DALYs indoor/outdoor air & water pollut.	DALY med ris	3.96	7.26
Association and bargaining rights	ACB med risk	6.26	19.24
International migrant stock	IMS med risk	20.85	31.17
Youth illiteracy	YI med risk	13.26	25.71
Weekly hours of work per employee	WH med risk	9.00	18.12
Violations of employ. laws & regulations	VL med risk	15.79	27.70
Net migration	NM med risk	9.55	13.84
Indigenous rights	IR med risk	4.57	15.31
Pollution	P med risk h	12.59	23.87
Frequency of forced labour	FL med risk	3.14	6.54
Goods produced by forced labour	GFL med risk	0.15	0.67
Anti-competitive behaviour	AC med risk	6.55	10.44
Corruption	C med risk h	54.59	85.11
Illiteracy	I med risk h	24.94	55.80
Fossil fuel consumption	FF med risk	4.71	6.84
Workers affected by natural disasters	ND med risk	4.79	8.60
Interntl. migrant workers. in sector/site	IMW med risk	15.00	28.85
Unemployment	U med risk h	22.94	59.60
Biomass consumption	BM med risk	27.67	55.10
Child Labour	CL med risk	11.22	22.61
Drinking water coverage	DW med risk	10.79	13.21

Education	E med risk h	24,15	37.46
Fair Salary	FS med risk	51.67	79.52
Safety measures	SM med risk	9.03	33.60
Gender wage gap	GW med risk	15.06	42.15
Trafficking in persons	TP med risk	11.19	14.64
Fatal accidents	FA med risk	4.68	9.16
Social security expenditures	SS med risk	11.20	24.04
Industrial water depletion	WU med risk	25.62	39.86
Trade unionism	TU med risk	54.95	89.39
Sanitation coverage	SC med risk	16.79	40.38
Health expenditure	HE med risk	39.20	69.95
Certified environmental management syst.	CMS med risk	46.54	70.51

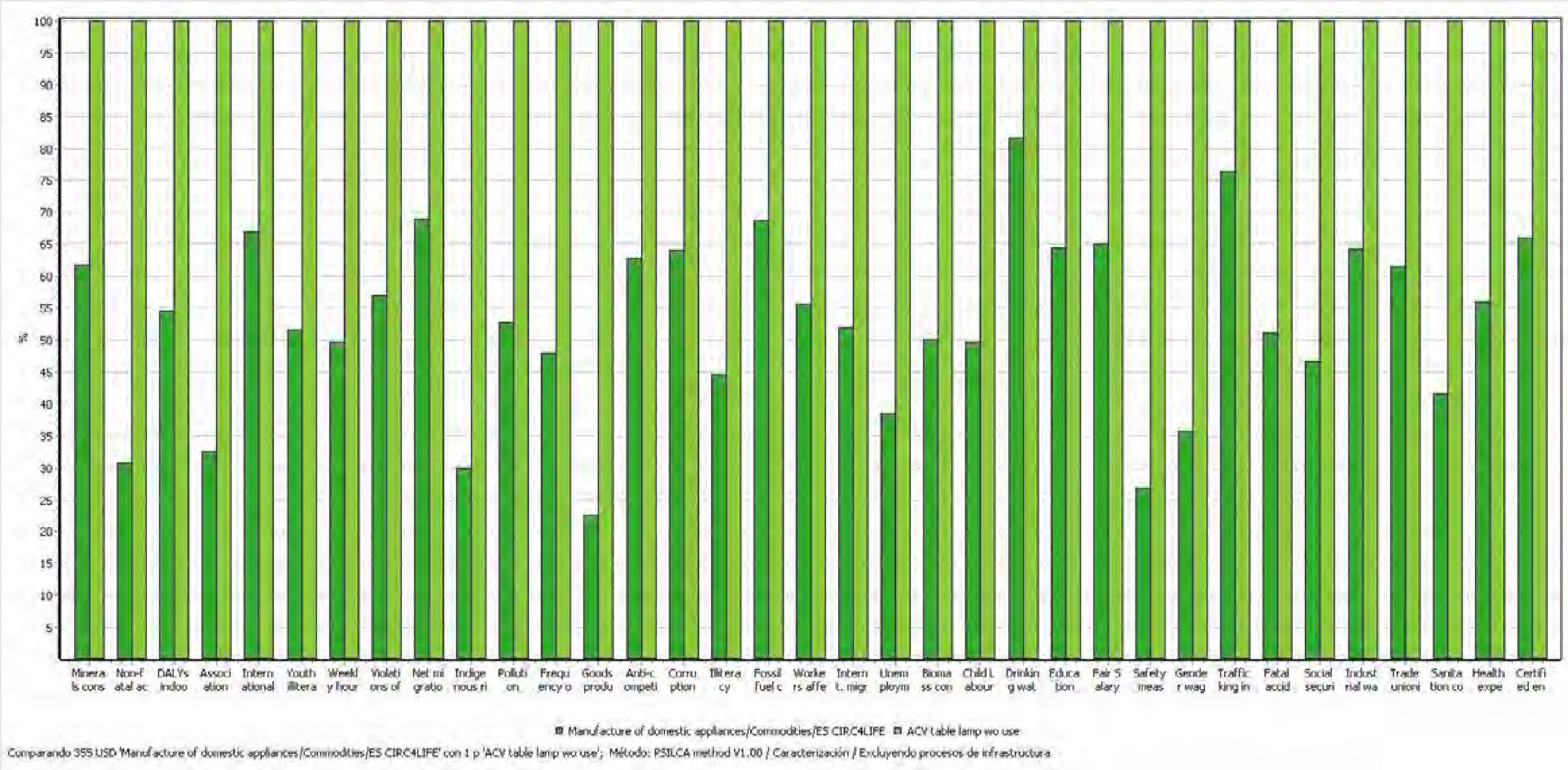


Figure 7.4 The table lamp (ONA) SLCA vs PSILCA reference sector

The social life cycle consequences were acquired and compared to the electronic industry in Spain because the production facility and component suppliers are located in Spain. The comparative results demonstrate that, overall, the reference product has a stronger social performance in 30 of the 49 impact areas, as shown in Table 7.4. However, shared significant concerns (in Table 7.4) are highlighted, notably 'association and bargaining rights,''sanitation coverage,' 'public sector corruption,' and 'pollution.' The extraction of metal elements to make electrical components puts'sanitation coverage' and 'pollution' at risk for local community stakeholders. A high risk associated with sanitation and polluting issues during the extraction and manufacturing processes was identified, as were attributions of the environmental burden in local communities; Austria, China, and the Netherlands are the most affected countries by the environmental burden along the supply chain. Furthermore, 'Industrial water depletion' is identified as a dangerous social issue relating to the local populations that produce power and electric equipment. In the material supply nation, the worker right problem of 'association and bargaining rights' was recognised as a danger. However, this might be attributable to the political system rather than an issue at the firm level. According to the comparison results, emphasis might be devoted to improving worker health and safety measures in the manufacturing line of metal and plastic components, as well as promoting fair wages connected to extraction labour and lowering the gender wage gap to reduce the risk of 'worker' stakeholder. Another important issue identified in the contrasted findings is 'public sector corruption,' which is difficult to address by taking steps at the firm level. However, improved implementation might be accomplished by addressing social responsibility issues along the supply chain, since distribution operations and electrical supply networks in Spain have been linked to somewhat irresponsible social behaviours.

Further examination of the identified social concerns from the social impact results revealed that the production/assembly stage is the most important contributor to the social performance of the reference product among all life cycle activities and processes. Housing, LED driver, and LED panel manufacture, as well as power, have been recognised as important areas to enhance the social performance of the reference product. Figure 7.4 emphasises the essential processes related to the identified critical societal challenges. The production of house components poses the greatest threats to major socioeconomic challenges. Furthermore, the manufacture of LED drivers and LED panels is one of the key contributors to serious societal dangers.

During the usage phase, the electricity supply chain is highlighted as the key contributor of social responsibility along the supply chain,' 'industrial water depletion,' and 'contribution to environmental load' hazards. As the usage stage is designated to occur in Spain, it is proposed that more attention be made to reducing the dangers posed by electricity generating processes to local populations and value chain participants. Plastic component production and distribution operations have small effects on the impact of societal concerns.

There are no pressing social issues among the stakeholder groups ‘society' or 'consumers.' In compared to the results of the cited industry in China, the positive social effect was 18% higher (approximately -4.1 per unit) under the category 'contribution to economic growth.' Because it is currently the only indicator in the PSILCA database that analyses positive social impact, the finding gives a way to distinguish the positive effect from other impacts. As indicated in Figure 4.14, manufacturing operations have the most beneficial impact; the primary contributors are the manufacture of LED drivers (37%), housing (31%), and LED panels (22%). China is the country that gets the most from the good influence because it is where the majority of the manufacturing activities take place.

7.4.2 Discussion

Classification in LCAs and S-LCAs refers to how inventory data connects to affects, and allocation technique is used when one inventory relates to several impacts. This is due to the fact that functional inventories might be related to many benefits in a variety of ways, and dividing the inventory scores by allocation does not accurately reflect the reality. As a result, an alternate approach is devised: a classification matrix, as illustrated in Table 7.5. For characterization, the function types are divided into function benefits, with scores ranging from 0 to 5. A score of 0 indicates that the function type does not contribute to those advantages, while a score of 5 indicates that it greatly contributes to those benefits. This assessment stops at the primary advantages of functioning since determining the link between the core benefits and subsequent benefits proved challenging. The time and data necessary for this research are not feasible, and it will be used in subsequent studies and recommendations.

Each benefit's Societal benefits score is the total of the weighted inventory scores of each function type multiplied by the appropriate categorization scores. Table 7.5 displays the scores, with the functional inventory (FI) score and weighted functional inventory scores to the left of the classification model and the societal benefit scores (SC) shown on the first line below the model. To determine the "potential fulfilled" of each function benefit, the scores of each function benefit are divided by a theoretical maximum score. The theoretical maximum scores (TC) are determined by scoring all function types to the maximum, i.e. 10. Table 5 shows the benefit potential as a percentage of the original scores; an overall average may be derived as a single societal benefit score. Overall, ONA lighting products received a score of 63%, which is 22% better than the Spanish average (39%).

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Table 7.5 Social analysis results characterisation calculation for ONA lighting product

Functional Inventory Scores	Theoretical Maximum Functional Inventory Scores	Priority Weights	Weighted Functional Inventory Scores	Weighted Teoretical Maximum Functional Inventory Scores	ONA lighting product	Fair Salary	Working time	Fair competition		Contribute to economic development		Safe and healthy living conditions		
								Presence of anti-competitive behaviour or	Sector average wage, per month	Contribute of the sector to economic	Presence of certified	Pollution level of the country	Drinking water coverage	Sanitation coverage
6					Workers	0	0	0	1	2	4	2	1	4
1					Value chain actors	[illegible]	2	0	2	[illegible]	4	1	2	3
1					Society	3	1	2	2	[illegible]	3	2	2	4
5					Local community	2	2	2	3	3	1	2	0	[illegible]
3					Consumers	2	[illegible]	[illegible]	4	3	0	0	0	[illegible]
					Social benefit score per category (SC)	12	10	9	12	18	12	7	5	21
					Theoretical max score per category (TC)	32	30	32	27	60	32	15	9	63
					Benefit potential =SC/TC	37%	33%	28%	44%	30%	38%	49%	58%	33%
					Average	39%								

7.5 Summary

The social life analysis results for ONA lighting products are significantly superior. This is due to the incorporation of the eco-design idea and recycling methods. In general, electrical components are made in Spain, which contributes greatly to total social performance. Previous LCA studies on lighting goods, on the other hand, indicated that the environmental effect of the battery-powered integrated lighting product is significantly greater than without (Muoz et al., 2008). As a result, for a holistic sustainable strategy, outcomes should be assessed holistically, and subsequent actions should be considered alongside economic and environmental assessment findings. Furthermore, the evaluation might be repeated if the targeted user groups are older, in which case the importance ranking would be reassessed. This will aid in determining the correctness of the evaluation.

Chapter 8: Conclusions

8.1 Achievements

Understanding customer requirements will assist designers in developing new product in customer-driven product design. There are several methods for gathering customer requirements. Customer requirements are traditionally derived from customer surveys or customer service data. These data are manually gathered, processed, and evaluated in order to determine customer requirements for the new product design. However, this takes time and is labour-intensive.

Customers post their particular interests and preferences through online reviews, along to the rapid growth of information technology. These online reviews/comments include a wealth of information regarding customer requirements. However, there are a great number of online reviews that are created on a regular basis. It is impossible to analyse by hand. According to the complete literature evaluations, online reviews are infrequently used in the requirement analysis of product design, despite the fact that they are universally acknowledged to be advantageous to product designers. Several important algorithms addressing online reviews offered by computer science researchers mostly focus on opinion mining, whereas models built by product design researchers exclusively use customer survey data. Online reviews, on the other hand, are fundamentally different from survey data. In comparison to limited survey data, online reviews data give a lot of vital information about consumer preferences that have been taken into account in product design. In this case, an intelligent system is presented to assess a big number of online product reviews.

Before delving into the technical intricacies of the intelligent system, it is crucial to understand how product designers might benefit from online reviews. This study investigated how the author viewed the helpfulness of the review and observed how online reviews may be used to analyse customer requirements. The experiment yielded useful information and fascinating findings.

8.2 Contribution to knowledge

The following are the key contributions made by this research in online reviews data mining and sustainability evaluation for sustainable lighting product creation, according to the author:

- In comparison to existing methodologies, two intelligent ways to analysing internet reviews in terms of detecting client requirements are offered. The suggested technique efficiently identifies consumer requirements from the examination of internet reviews. A regression model for identifying useful online reviews, a classification model for rating the values of online reviews, a probabilistic method for automatically connecting online reviews with product design specifications, an integer nonlinear programming optimization model for prioritising product design specifications have all been successfully developed.
- Contribution to mining online reviews for user desired product design criteria. Product design and development have effectively used total consumer sentiment of distinct product engineering features. A pairwise approach has been presented to prioritise product engineering attributes based on customer-related information.
- Highlighting the major benefits of environmental life cycle assessment, which may be utilised not only to compare the environmental performance of goods, but also in the product design process.
- Highlighting the major benefits of environmental life cycle assessment, which may be utilised not only to compare the environmental performance of goods, but also in the product design process.

8.3 Future work

One significant restriction is that numerous methodologies described in this study is several annotators were recruited in the two case studies to either analysis or examine the product design parameters provided in online reviews. It took many days to complete the annotated data. As a result, obtaining a high number of training samples is impossible. As a result, a semi-supervised strategy may be preferable, alleviating the load of corpus development.

Only online reviews are taken into account in this study. Consumers now have new ways to express themselves because to the rapid advancement of information technology. Consumers also express their views on public discussion boards, personal blogs, and social networking sites. A growing number of tweets and microblogs about specific items may also be found on numerous Websites. Consumers express their experiences in many forms, whether positive or negative, which are unavoidably viewed by their friends or admirers. Their feelings will inevitably translate into powerful comments or ideas that will impact potential customers' decisions. How to automatically identify important information from various channels for product designers will undoubtedly be a prominent study issue.

The attitude stated in internet evaluations may not reflect their genuine feelings. Comparing numerous sources of consumer information, as well as several traditional customer survey data, would be an excellent way for designers to undertake customer analysis. A difficult topic for designers is how to incorporate many sources of client information and create a holistic approach.

Another intriguing aspect is that some good evaluations may have come from product marketers. In order to gain a larger market share, they provide various suitable terms to characterise their items. On the one hand, before undertaking customer analysis in product design, it is critical to provide a solid rationale for how to detect genuine customers and extract their demands. On the other side, the product descriptions in these evaluations give a wonderful opportunity for rivals to learn more about the product. As a result, understanding how to evaluate the degree of exaggeration in these internet evaluations can assist rivals in making product changes.

Finally, a completely automated system should be created. Although numerous methodologies for product designers have been presented and validated, they have not been easily incorporated into a completely autonomous system. Product designers are expected to use this completely automated system directly. If product designers can use this approach, they will acquire additional customer requirements and ideas for product design by mining online reviews, which will encourage the development of new algorithms, models, and applications.

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