Exploiting online customer reviews for product design

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Abstract. Online customer reviews (OCRs) are the text features of a consumer feedback on the crowdfunding platform. Utilization of OCRs as online survey provide an opportunity to obtain extensive and fast data about product information, experience of use and services. OCRs can be important information to identify consumer desires for a product design. This research proposes to utilize OCRs as input in developing products for start-up product. The object of this research is technology products. 34,006 OCRs were collected by scraping from kickstarter website. Opinion pros and cons are classified so as to produce 26,993 positive reviews and 13,203 negative reviews. extracted data use text pre-processing and Term Frequency-Inverse Document Frequency (TF-IDF) is used to select words through the classification of product design attributes. Our results show that the functional attributes and followed by aesthetics to be an important role in product design because these attributes have high reviews that customers consider when choice and buying products. More than that, the pros and cons based on relative value of product design reviews contained in online customer reviews are consideration for maintain and evaluate product design attributes. So that technology product produced by start-up product can be successful in the online market.

1. Introduction
The development of the World Wide Web provides accessibility for internet users and the opportunity to have web pages. These opportunities are used by start-ups to reach a wide and fast market. At the moment, people’s purchasing power is also increasing in the online market [1]. A crowdfunding based platform takes advantage of opportunities to help product start-ups compete in the online market. Start-up products use creative ideas to raise funds to be able to do mass production. Mass production can be done if crowdfunding investment reaches the goal. Failure is still unavoidable by start-ups. For example, Pasmawati et. al., [2] showed that only 7.35% of technology products were declared successful. Increased success occurred in 2020 by 20.66% [3]. The success of product design is very dependent on the initial concept at the conceptual design stage [4]. Product design is also a predictor of product preference [5].

Online surveys provide more information in a short amount of time, compared to conventional surveys that are limited. Online customer reviews (OCRs) are text features of feedback on crowdfunding platforms. OCRs in the form of information about user experience, the purchasing experience, and satisfaction with products and services [6]. Research on the use of OCRs for various applications has been carried out by several researchers, for example, sentiment analysis [7-10], product sales prediction [8,11], consumer purchase interest [12-15], consumer behavior [16-17], product development [18-20]. The object of research used is existing products that have reached the stage of mass production in e-
commerce, marketplaces, and crowdfunding. However, this research has not yet discussed the use of OCRs for product start-up applications in product development efforts at the design stage. Design attributes for technology products that are needed and desired by consumers in the online market. This study proposes how the use of qualitative OCRs can provide information to product start-ups as product design attributes in product development. Text pre-processing is used to extract unstructured data, then word selection uses the weight of the term frequency-inverses document frequency (TF-IDF). It is expected that by knowing the product design attributes, start-ups can compete with existing products to produce product designs according to consumer perceptions.

2. Method

OCRs are used as opportunities to identify product design attributes based on consumer perception. The Python 3.7 programming language is used as a tool for product design attribute analysis. This study went through 3 major stages outlined in Figure 1. The stages of the study began with data collection from the crowdfunding platform and the sentiment analysis process to find out the pros and cons of sentences. The next step is text pre-processing and text analysis.

2.1. Data Collection

Research data sourced from the kickstarter.com website. The object of research is technology products (drones, wearables, camera equipment, and 3d-printing). As many as 34,006 OCRs were taken by scraping from 100 technology products that had completed successful and failed campaigns. Natural language processing (NLP) is used for linguistic language analysis to find out sentiment reviews from OCRs. The OCRs data set was analyzed and yielded 26,993 positive reviews ($U^+_s$) and 13,203 negative reviews ($U^-_s$), as shown in Figure 2.
2.2. Text Pre-Processing
Text pre-processing uses Python with the NLTK Library. Text pre-processing through several stages, namely tokenizing, lower capitalization, stopwords, stemming, and spelling normalization. Text pre-processing stage, the process of extracting unstructured words into structured words is carried out. Nouns in Parts of speech (POS) are used and are considered to be the most representative tokens of a document [21]. But this study also uses adjectives as semantic networks because not all nouns relate to attribute features.

2.3. Text Analysis
Text analysis conducted is extracting words and word selection. The word extraction is classified based on the product design attributes shown in Table 2. Whereas the data selection is based on the Term Frequency-Inverse Document Frequency (TF-IDF) weights. The data set used is the output of the spelling normalization process of $U_s^+$ and $U_s^-$. All extracted data is structured from $U_s^+$ and $U_s^-$ as words and attributes are calculated TF-IDF automatically using Python software. TF-IDF is used to find the value representation of each document in the collection. The greater the weight calculation value obtained, the higher the level of document similarity to the query. TF-IDF as an interpretation of backer responses on product campaigns. TF-IDF determines the relative importance weights of words in $U_s^+$ and $U_s^-$. TF-IDF for each word added up based on the classification of attributes. Furthermore, TF-IDF was analyzed based on the relative values between TF-IDF on $U_s^+$ and $U_s^-$. The relative value of TF-IDF ($N$,TF-IDF) < 0.5 means that the attribute has a negative opinion greater than a positive opinion. $N$,TF-IDF ≥ 0.5 means that the attribute has a positive opinion that is greater than a negative opinion.

3. Result and Discussion
3.1. Text pre-processing
Data used for text pre-processing are $U_s^+$ and $U_s^-$. Before carrying out the text pre-processing stage, the data is classified based on the pro ($U_s^+$) review and the cons ($U_s^-$). The results of the text pre-processing steps are shown in Table 1. Import OCRs data from $U_s^+$ and $U_s^-$ which are first saved in python cells. Import and process data classified by type of sentiment review. The tokenizing stage can be done after or before the case folding. In this study, tokenizing was done before case folding because it was considered more effective. Sorting review sentences into separate words and followed by sorted frequency for each word. Case folding stages can also be done after tokenizing. After the review sentence has been divided into words along with the frequency of each word, a lower capitalization is performed. This process is considered more effective because lowercase conversions are structured.

![Figure 2. Research data set](image-url)
words. At the stage of filtering/stopwords only removes Parts of speech (POS) such as the auxiliary verb, conjunction, pronoun, preposition, and interjection. This is because OCRs data sets use English. Words consisting of ≤ 1 or 2 or 3 are not automatically removed because there are attributes in the form of units. Numeric numbers are not omitted.

| Table 1. Text pre-processing results |
|-------------------------------------|
| Number of term                      |
| Positive | Negative |
|----------|----------|
| Tokenizing | 834,104 | 413,563 |
| Case folding (lower capitalization) | 26,993  | 13,203  |
| Filtering/stopwords                 | 6,653   | 3,942   |
| Stemming                             | 6,653   | 3,942   |
| Spelling normalization               | 6,653   | 3,942   |

In English text, the process of refining affixes such as prefix and suffix. The process of stemming by removing prefix can be done or also does not need to be done because it does not have the effect of being able to classify words. While suffix is not converted to basic words because there are some differences in meaning that can result in missclassification of attributes. For example, monitors are nouns, while monitored and monitoring are verbs. From the stemming process, there were 6,653 words from $U_s^+$ and 3,942 words from $U_s^-$. There are some texts from $U_s^+$ and $U_s^-$ which have incorrect spelling. The spelling normalization process is carried out to improve spelling substitution. A total of 6,653 words $U_s^+$ and 3,942 words $U_s^-$ at the end of the spelling, the normalization process is used to classify product design attributes at the feature extraction stage.

3.2. Feature Extraction
The extraction of words is classified using a manual check with Excel. Words are classified according to attribute groups. The results of the classification process of words on the product design attributes can be seen in Table 2 and Table 3.

| Table 2. Term classification based on product design attributes |
|---------------------------------------------------------------|
| Positive reviews | Negative reviews | Design product attributes |
|------------------|------------------|---------------------------|
| black, blue, beautiful, beam, brand, color, logo, unique, display, digital, design, ...... | appearance, blue, digital, metal, aesthetics | gold, display, unique, .... |
| ergonomics, compatibility, comfortable, lighting, tempature, vibrate, sounds, ..... | comfort, glow, contrast, lighting, ergonomics | noise, noise, vibrate.... |
| durability, adaptor, photochromic, smartscreen, stainless, video, ........ | ability, control, access, detector, functional | durability, setting, screen, ... |
| allergenic, irritating, allergy, photokeratitis, license, originally, authentic, copyright, certificate, .. | hazard, risk, .... health | authenticate, copyright, creative, innovation |
| authority, authorized, law, legality, legally, regulation, certificate, ........ | formal, legal, legality, ... | Regulation |
| safety, hazard, protection, dangerous, .... ratification, accreditation, quality, standard, certification, method, calibration, ...... | danger, hazard, safety, .... standard | instruction, method, module, quality, ... |
| trend, lifestyle, style, technology, high-tech,.... | technology, millenial, ..... | trend |
| reproduce, reproducible | environment, recycling, environment | reproduc |
| continue, sustainability | - | sustainable |

Based on the results of the classification, it is known that there are no reviews that discuss the sustainable attribute of negative reviews. The classification of words/term is based on the definitions
and synonyms of all the words contained in positive or negative reviews. Furthermore, the word is weighted based on TF-IDF.

3.3. Product Design Attributes Based On TF-IDF

TF-IDF attribute is the sum of TF-IDF synonym words that are included in the classification of product design attributes. TF-IDF on $U^+_s$ and $U^-_s$, as shown in Figure 3.

![Figure 3. TF-IDF of product design attributes](image)

The results showed that the TF-IDf values of positive reviews are in the range of 0.0002 to 2.3083. While the TF-Idf values of negative reviews are in the range from 0.000 to 1.8667. TF-Idf values that have $U^+_s > U^-_s$ are aesthetics, ergonomics, functional, innovation, sustainable, and trend. Whereas $U^+_s < U^-_s$ are environment, health, regulation, safety, and standard. Sustainable hasn't negative reviews from backers. If the TF-Idf value of $U^+_s > U^-_s$ means that the attribute has backers perception tend to be positive and vice versa. The higher TF-IDF, the greater the similarity in product design attributes. Tf-Idf also shows backer perceptions about product design in reviews. Figure 3 also shows the response rate of backers based on Tf-Idf. Tf-Idf value of backers response is 0.0025 - 4.1750. The highest response is functional and followed by aesthetics, standard, ergonomics, regulation, innovation, safety, trend, health, sustainable and environment. The next stage is to determine the product design attribute based on the number of the relative value ($N_r$ TF-IDF). The results of the $N_r$ TF-IDF calculation are shown in Figure 4.

![Figure 4. $N_r$ TF-IDF of product design attributes](image)

$N_r$ TF-IDF of attributes ranges from 0.026 - 1.00. The highest $N_r$ of 1.00 was sustainable and followed by innovation, trend, functional, aesthetics, standard, ergonomics, regulation, safety, environment, and healthy. The high $N_r$ TF-IDF, the high the level of positive responses. While the low $N_r$ TF-IDF show that the low level of negative responses. Attributes that have $N_r$ TF-IDF < 0.5, among
other, regulation, safety, environment, and health. These attributes indicate that \( U_1^+ < U_1^- \) or in other words have negative dominant backer perceptions. This attributes are attributes that are maintained in the development of product design. Attributes that have \( N_{\text{TF-IDF}} > 0.5 \) are sustainable, innovation, trend, functional, aesthetics, standard, and ergonomic. Sustainable is an attribute that has the highest \( N_{\text{TF-IDF}} \), because sustainable only has pros perception without any cons. This Attributes indicated that have positive dominant perceptions. This attributes must be evaluated in developing product design.

4. Conclusion

Online customer reviews are reviews in the form of text, which has the potential to provide information and insight to the designer or start-up in product development. Our results show that functional attribute an very important role in product design because these attributes have the highest reviews and responses that customers consider when choosing and buying products. The attributes that must be evaluated in developing product design are regulation, safety, environment, and health because has negative dominant response. While, the attributes that must be maintained in the development of product design, among other, sustainable, innovation, trend, functional, aesthetics, standard, and ergonomic because has a positive dominant response. This evaluations used so that technology product produced by start-up product can be successful in the online market. This research only determines the attributes of product design based on OCRs. The future research, attribute validation needs to be done to predict success of technology products from start-up product in crowdfunding platform. customer reviews are reviews in the form of text, which has the potential to provide information and insight to the designer or start-up in product development. Our results show that functional and followed by aesthetics attributes an important role in product design because these attributes have high reviews and responses that customers consider when choosing and buying products. Moreover, aesthetics and functional are a priority for evaluated product design attributes so that technology product produced by start-up product can be successful in the online market. This research only determines the attributes of product design based on OCRs. The future research, attribute validation needs to be done to predict success of technology products from start-up product in crowdfunding platform.

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