IDENTIFYING AFFORDANCES FROM ONLINE PRODUCT REVIEWS

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Abstract

Affordance based design is developed since the beginning of 21st century. Affordances being revealed properties of a system in a context, they may be much diverse and unexpected. Consequently, it is a utopia to think of enumerating all the existing precise affordances in advance. Presently, identifying affordances along a design or redesign process is based on experiments and focus groups, which are time and resource consuming. Although automatic identification strategies have been proposed, the lack of affordance database along with clear categorization technique makes it unpracticable and non-repeatable today. In this paper, the theoretical basis and technical basis of identifying affordances from online reviews are discussed. A framework of affordance identification is proposed by capturing constitutive affordance elements with natural language processing algorithms. Meanwhile, a case study of 303 review sentences of Kindle Paperwhite from Amazon.com is conducted with 1 expert in affordance based design and 6 participants. The result shows that the framework is effective in affordance identification. It provides basis for automating the identification process in the future.

Keywords: Design methods, Design engineering, Early design phases, Affordance based design, Online customer reviews

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1 INTRODUCTION

The concept of affordance was first put forward by Gibson (1979) in cognitive psychology to explain human's perceptual learning mechanism. Recently, Maier and Fadel (2001) introduced this concept into design engineering, insisting that the affordances should be the fundamental to artefact design. The affordance is defined as "relationships between two subsystems in which potential behaviours can occur that would not be possible with either subsystem in isolation". The affordance based design theory and process are then developed. It provides designers a complementary systematic process to design industrial products (Maier and Fadel, 2003).

In the affordance based design process, affordance identification is a crucial step (Maier and Fadel, 2005). It helps designers express customers' expectations, choose or create appropriate artefacts as well as find useful emerging roles of the artefact in its context. Various affordance identification methods are proposed in prior research. However, the interviews and focus groups based identification methods are not only time and resources consuming, but also dependent on participants' knowledge and experiences (Chou and Shu, 2014). Although some automated identification methods are proposed (Maier and Fadel, 2007), the lack of affordance database makes them unrealizable in practice.

To tackle these issues, online product reviews drew our attention. On one hand, the volume of information is greater than that available using traditional information gathering methods. In fact, the way that the clients use the product differs based on their knowledge, cognition, usage environment, etc. It is even possible to find misuses in online reviews. This information is highly valuable for designers to understand their product and thus make improvements or innovations. On the other hand, the online nature enables easier access for researchers, allowing for data aggregation and analysis with less time and resources.

However, do affordances really exist in online reviews? Is it thinkable to detect, interpret and encode in a unique manner a set of affordances from the analysis of customer reviews? To answer these questions, we observed a large amount of corpus of online reviews. In fact, customers are willing to share comments because making pertinent reviews gives them the sense of self-approval and belongingness (Cai et Chau, 2015). Whereas to make the reviews useful and persuasive, one way is to give examples of their own usage of product, which includes the user, the product and the interactions in certain usage conditions. Coincidentally, affordance can be understood as the action possibilities of a user interacting with a designed object (Gero and Kannengiesser, 2012). Thus, we believe that identifying affordances from online reviews is possible. The above observation provides the theoretical basis for our research.

In consequence, how to extract affordances from online reviews now becomes the key question. Obviously, reading and analysing manually such a large amount of online reviews is a laborious task. [Whereas automatically extracting information from online review text is always difficult (Wang and Dong, 2008).] In this paper, based on the affordance based design ontology proposed by Mata et al. (2015), we propose the constitutive affordance elements that can be captured from online reviews. Then, we build a framework to identify these elements with natural language processing. Afterwards, a case study is conducted to assess the effectiveness of the proposed framework in terms of correctly identifying affordances from online customer reviews.

2 RELATED WORK

2.1 Affordance based design

The concept of affordance was firstly put forward by perceptual psychologist Gibson (1979). He coined the term "affordance" of environment as "what it offers the animal, what it provides or furnishes, either for good or ill". Later, psychologist Norman (1988) took Gibson's theory of affordance and extended it into the design of everyday things. He simply gave some guidelines of what certain objects should afford and should not afford. Recently, Maier and Fadel (2001) argued that the affordances should be the fundamental concept in design engineering.

Based on this concept, affordance based design theory and process is developed by Maier and Fadel (2003). The process illustrates how to design a product that provides required affordances. Since then, researchers try to discover and explain the advantage of using affordances over functions. Although both are ways to convey behaviours, functions describe intended behaviours, while affordances describe all possible behaviours. However, not all the end-uses interact with the product in a designed manner. Thus,

the affordance based design is appropriate for investigating unintended or undesired behaviours. Research shows that affordance based design is more advantageous in explaining the evolution of artefacts, designing complex systems and redesigning existing products (Maier and Fadel, 2009). However, the trouble is that the spectrum of affordances is wide. Designers can consider the affordances of a device as the set of all potential human behaviours that the device might allow. Therefore, it is not easy for designers to reason out what they are at early design phase, as the search space is large (Brown and Blessing, 2005).

2.2 Affordance identification

Researchers have proposed various affordance identification methods for designers. Three kinds of strategies can be found in these methods.

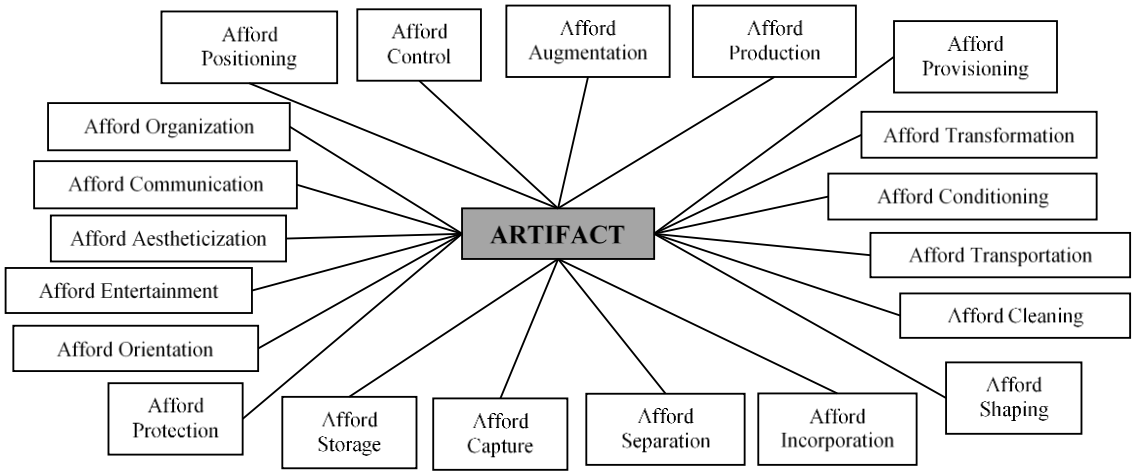

Figure 1 Generic affordance structure (Cormier et al., 2014)

The first strategy is pre-determination, in which a generic affordance structure is needed. Designers are recommended to use the generic structure as checklist to make sure all possible interactions have been considered. The generic affordance structures proposed by Maier and Fadel (2001) categorizes the affordances by product's life cycle stages and whether the affordance is desired or not by end-users. However, this classification leads to overlaps in affordance structure. For example, some affordances can be both in "human use" group and "desired use" group. In recent research, Cormier et al. (2014) propose another generic affordance structure with enlarged range and precisely defined categorizations (see Figure 1). Nevertheless, the inherent limitation of this strategy is that the affordance structure can only provide generic affordances that all the products possess or should possess, designers still face difficulties in identifying specific interactions.

The second strategy is through experimentation, which is widely used in design process. In these methods, participants are asked to manipulate the prototypes, and designers can identify the affordances through observations during the experiment or interviews after it. In a comparative study of function based design and affordance based design, this strategy is used to identify the affordances of computer docking station (Maier and Fadel, 2005). However, the first problem of this strategy lies on the availability of physical prototype. In fact, in the early design phase, physical prototypes are often not available for direct experiment. Whereas at the end of the design process, when physical prototypes are available, it will be costly to add unpredicted affordances or delete undesired affordances. Virtual prototypes seem to provide a solution, while the lack of physical interaction still limits the detection of affordance. The second problem is that the identification result depends on the knowledge and experiences of participants. Consequently, the quantity of samples should be large enough to ensure the pertinence of identification result. The entire process requires thus more time and resources.

The third strategy is automated identification using computer science. Maier and Fadel (2007) propose that using modern technology, maps between existing artefacts' properties (shape, material, etc.) and affordances can be stored in a database. Thus, expert knowledge about the affordances can be captured from this database and integrated into a computer assisted design environment. Unfortunately, constructing an affordance database is a huge work, we do not see such a database by now. Recently, Chou and Shu (2014) proposed a heuristic method to identify affordances from online product reviews.

In this method, customer reviews are firstly categorised into "noise" group and "informative" group with K-mean clustering algorithm, based on their language features such as coordination conjunctions, proper nouns etc. Then, they found that novel affordances can be targeted in "informative" group with the help of cue phrases like "as opposite to" and "can actually", because unexpected usage are more probably to appear together with these cue phrases in online reviews. However, the precision of this method is relatively low. In their case study, of all the sentences that contain "as opposite to", only 32% of them come together with one or more affordances. Therefore, designers still have to read the entire customer review sentences to make sure what affordances the user is talking about.

As summarized above, to the best of our knowledge, all the identification methods have limitations. To be able to identify affordances within limited time and resource condition, new methods must be developed. Inspired by Chou and Shu (2014), we believe that online reviews are valuable sources for affordance identification. In fact, with mature technologies of scraping tools and natural language processing algorithms, extracting information from online reviews is much cheaper and faster than by physical experiments (Popescu and Etzioni, 2007). Meanwhile, comparing with virtual experiment, the real interactions between reviewers and products ensure the accuracy of identification results. Also, the variety of reviewers' experiences and usage conditions provide rich contexts of specific affordances related to a given product. The authors believe that the notion of affordance being more sophisticated than the one of sentiment, expectations are higher for the process of designing.

2.3 Natural language processing

To automatically extract information from raw text, we need to find the language features or language patterns and their relationship with target information. We summarize in this section the natural language processing methods which can provide information on language features and language patterns. The following methods are widely used in online review analysis.

POS-tagging (Part-Of-Speech tagging) algorithms is often used to pre-process the review sentences. Every word in the sentences is labelled with its lexical categories, such as subject, predicate, object, adverb, etc. Existing POS-tagging algorithms are mostly based on probabilistic model. The accuracy can prominently reach as high as 96% (Schmid, 2013). In online review analysis, feature extraction algorithms allow us to extract features of product from online reviews. Sentiment analysis algorithms assess the satisfaction of reviewers by giving a score to each phrase. Raghupathi et al. (2015) proposed a heuristic algorithm to evaluate the global sentiment of a review sentence. In this work, the basic database is a Dictionary of Affect Language (DAL) which associates an average score of pleasantness for human mind for each of the 200,000 English words (Whissel, 1989). The text is analysed word by word for globally rating sentiment. It appears that the data structure of a sentiment is here extremely basic, compared to what can be an affordance. Zhang et al. (2016) also proposed an unsupervised machine learning algorithm to jointly identify product features and sentiments words at the same time. The effectiveness of the algorithms is proved in each study. The above literature provides us the technical basis for automatically identifying affordances from online reviews.

3 CONSTITUTIVE AFFORDANCE ELEMENTS

As the language patterns and features can be found using natural language processing, the next task is to define the relation between language patterns and affordance to build information extraction rules. It is thus necessary to define how the affordance is described. To do this, we employ the affordance ontology proposed by Mata and Fadel (2015). In this ontology, the affordance class contains two objects and four properties (Figure 2).

The first object is denoted as “primary entity”. It defines the artefact which provides the affordance. The second object is denoted as “secondary entity”. It indicates the second entity involved in the potential action, which is either a human, an artefact, or an environmental material. These two objects are fundamental element of an affordance. The four properties are “affordance description”, “polarity”, “priority” and “quality”. Affordance description defines how affordances are represented in words. As shown in Table 1, three affordance descriptions already exist in previous research (Hu and Fadel, 2012). Polarity refers to the direction of influence of the affordance. It has two orientations: positive and negative. For example, the cut finger-ability of a knife is negative because it can hurt the user. Priority informs how important the affordance is compared with the other affordances of the product. It is usually defined by designers in the design process based on the target users. Quality defines how well an

affordance is achieved. For example, a chair and a briefcase both have the affordance of sitting-ability. It is expected that the sitting-ability of a chair has a higher quality than that of the briefcase. The ontology suggests quantifying the quality level with integers, ranging from 0 to 3.

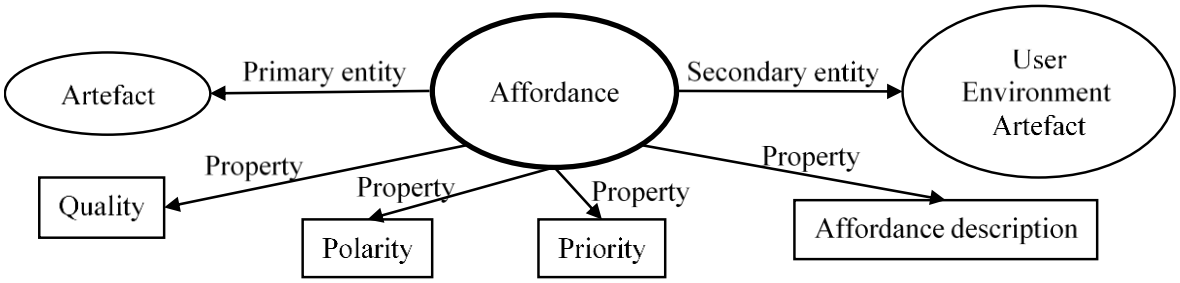

Figure 2 Affordance based design ontology proposed by Mata and Fadel (2015)

Table 1 Existing affordance description formats (Hu and Fadel, 2012)

Format	Alternative format	Example
Verb + -ability	-	Grab-ability, twist-ability
Verb + noun + -ability	Noun + verb + -ability	Lift handle-ability, rotate gear-ability
Transitive verb + noun	Intransitive verb	Collect water, lubricate part

According to this ontology, an affordance instance is fully defined when these objects and properties are specified. However, we make some changes to adapt the online review context. First, as the priority of affordance is determined by designers based on the requirement of design project, we are not going to identified this element from online review. Second, as reviewers focus on their direct interactions with the product or indirect interactions with the product through an artefact, the secondary entity is always the user or artefact. Third, for the affordance description, we adopt the "format transitive verb + noun" or "intransitive verb" followed by an adverb which precis the usage condition or usage purpose, because the adverbs further define the environment of interaction. Finally, instead of using integer as indicator of affordance's quality, we evaluate it by two levels: "low" and "high". Thus, based on the ontology, five elements can be captured from online reviews to construct an affordance.

- Affordance description: verb + noun + adverb
- Primary entity: the product or feature of the product
- Secondary entity: user or artefact
- Quality: low/high
- Polarity: beneficial/harmful

4 AFFORDANCE IDENTIFICATION FRAMEWORK

In this section, an affordance identification framework with natural language processing is proposed based on the constitutive elements (Section 3). Figure 3 shows a synoptic of the framework.

4.1 Pre-processing online customer reviews

The unguided review environment leads to significant amounts of irrelevant information when seeking useful affordance-related insights. It is worthwhile to develop methods to extract potentially useful information. Chou and Shu (2014) provide an effective algorithm to eliminate uninformative review sentences, which contain only buying information, personal preference, product comparisons, etc. For example, in the sentence "I still recommend that you buy a Kindle without special offers", the reviewer describes a personal preference. No affordance can be tracked from this uninformative sentence.
The algorithm consists of three steps. First, the online reviews are vectorised by language features, such as frequency of adverbs, purchase words, etc. Second, a k-mean clustering is processed to generate two clusters that decompose the text meaningfully. Third, by POS-tagging algorithms, the words in informative review sentences are labelled with part of speech and dependency trees are constructed for future use.

4.2 Identification of affordance description

With POS-tag, all the verbs in the informative sentences are targeted. The verbs like “be”, “have”, “wish”, “hope” are considered as uninformative verbs and are neglected, because they describe a status rather than an interaction. The remaining verbs are regarded as interacting verbs and are added to the affordance description. Then, adverbs which further describe interacting conditions should be included in the description. Finally, if the verb is a transitive verb, the object of the verb is also extracted to construct the entire affordance description. Adverbs and objects can be identified with POS-tag and dependency tree.

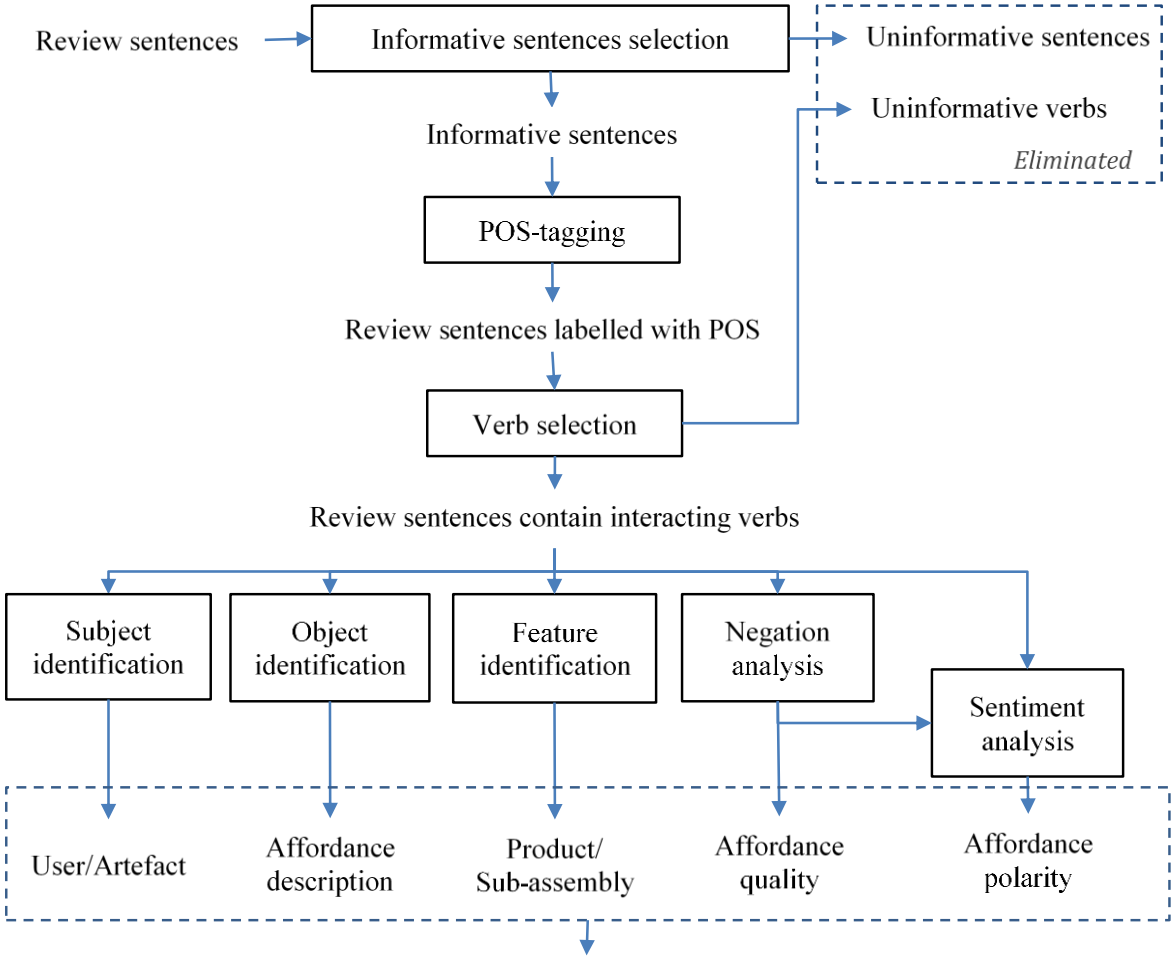

Figure 3 Synoptic of proposed framework

4.3 Identification of primary entity

The feature in review sentences can be extracted by feature extraction algorithms. A product feature lexicon can help extract features from online reviews. If no feature word is found in the present sentence, the feature(s) in the previous sentence is considered, as reviewers talk about a topic with continuity. In the case that no feature is found in the present sentence or previous sentences, the primary entity is by default the product.

4.4 Identification of secondary entity

The secondary entity is captured from the subject of the review sentences. The subject can be identified from dependency tree. If the subject is a human, then it is "user". If the subject is an artefact, then the name of artefact should be specified.

4.5 Identification of quality

This element can be identified with the help of negation analysis algorithms. In the online reviews, reviewers only describe whether the product has potential ability to realise the desired interaction or not. Thus, if a negation word (not, hardly, wish + could, etc.) is found in sentence, the affordance quality is "low", otherwise, the affordance quality is "high".

4.6 Identification of polarity

With sentiment analysis algorithm, the review sentences are categorised into two levels of satisfaction: negative and positive. The SENTRAL algorithm proposed by Raghupathi et al. (2015) provide a possibility to evaluate the overall satisfaction of the whole sentence. If the affordance quality is high, positive sentiment means that the affordance is "beneficial", negative sentiment means that the affordance is "harmful". If the affordance quality is low, positive sentiment means that the affordance is "harmful", negative sentiment means that the affordance is "beneficial". For example, for an e-reader, in the review sentence “I’m loving it because it doesn’t hurt my eyes”, the e-book provides low ability of “hurt eyes” affordance, and the reviewer is satisfied with that. Thus, the affordance “hurt eyes” is harmful to user.

4.7 Constructing structured affordance

After all the elements are extracted from online reviews, the affordance is finally formulated as follows: *The [product or sub-assembly] provides [affordance polarity] affordance with [affordance quality] capable for the [user/artefact/environment] to [affordance description]*.

5 CASE STUDY: IDENTIFY AFFORDANCES OF KINDLE PAPERWHITE

To evaluate the proposed framework, a case study is performed with the online reviews of Kindle Paperwhite. Kindle Paperwhite is a product sold only online. Thus, a large amount of customer reviews is available. The device is designed to be used in various usage conditions, which means that the affordances mentioned in online reviews are likely to be various.

We downloaded 5 most useful customer reviews from the product description page of Amazon.com. They are likely to contain more informative sentences. The reviews are compiled by 5 different reviewers. All the reviewers are recognized as owners of the product with the label "verified purchase”. The length of reviews varies from 10 to 135 sentences and totalled 303 sentences.

5.1 Experiment design

The experiment is divided into two parts. The first part is to assess the effectiveness of the proposed framework. To do so, one expert in affordance based design reads the 303 review sentences and identify the affordances in these sentences with the expert's experience (without using the framework). These affordances are regarded as ground truth once validated by another expert in affordance based design. Then, the expert simulates the framework to identify affordances. The identification results are then compared with ground truth to assess the effectiveness of proposed framework.

As the framework is simulated manually by the expert in the first part of the experiment, there might be subjective identification result. Therefore, the second part of the experiment aims at evaluating the repeatability of the identification results in the first part of the experiment. It ensures the possibility of automatization of the framework. To do so, 6 participants are involved in the experiment. Each participant is firstly trained to use the framework in 15 minutes. Then, they are asked to analyse 20 consecutive review sentences randomly selected from the 303 review sentences following the framework. Therefore, 120 (6×20) review sentences in total are analysed simultaneously by the expert and participants. After the experiment, the identification result of participants is compared with that of the expert. The expert discusses the dissimilarities with participants, if the dissimilarities comes from unconscious mistake, the participants are asked to correct the mistake. Finally, the expert and participants are interviewed to collect feedbacks (clarity of the definition of each element, difficulties following the proposed framework, etc.) on the identification framework.

Third,

To assess the effectiveness of the framework in identifying affordances from online reviews, recall rate and precision rate are used as two main indicators. Recall is defined as the fraction of affordances that are identified, while precision is the fraction of identified affordances that are correct. They are

calculated with Equations (1) and (2) as follows. It is obvious that higher the two indicators, better the effectiveness of the identification framework.

$$recall = \frac{\text{number of affordance elements correctly identified from review sentences}}{\text{number of affordance elements exist in review sentences}} \quad (1)$$

$$precision = \frac{\text{number of affordance elements correctly identified from review sentences}}{\text{number of affordance elements identified in review sentences}} \quad (2)$$

In the second part of the experiment, the repeatability is evaluated by the similarity of the identification results. Higher similarity means a better repeatability of proposed framework and thus a higher possibility to automatizing the framework.

5.2 Experiment result

For the ground truth, 145 affordances are identified from online reviews and verified by another expert. For first part of the experiment, 133 affordances are captured from 91 review sentences. 58 sentences contain 1 affordance, 25 sentences contain 2 affordances, 7 sentences contain 3 affordances and 1 sentence contains 4 affordances. The identification result for each affordance element is listed in Table 2.

Table 2 Identification result of expert

	Affordance description	**Primary entity**	**Secondary entity**
Ground truth	145	145	145
Elements captured by expert	133	133	133
Elements correctly identified	130	133	127
Recall rate	90%	92%	88%
Precision rate	98%	100%	95%
	Quality	**Polarity**	**Affordance**
Ground truth	145	145	145
Elements captured by expert	133	133	133
Elements correctly identified	133	129	125
Recall rate	92%	89%	86%
Precision rate	100%	97%	94%

For second part of the experiment, 50 affordances are captured from 41 sentences. 30 sentences contain 1 affordance, 7 sentences contain 2 affordances, 2 sentences contain 3 affordances. The identification result and comparison with expert's result for each element is listed in Table 3.

Table 3 Identification result of participants

	Affordance description	**Primary entity**	**Secondary entity**
Elements captured by participants	50	50	50
Elements that are identical with expert	40	50	47
Similarity	80%	100%	94%
	Quality	**Polarity**	**Affordance**
Elements captured by participants	50	50	50
Elements that are identical with expert	50	47	39
Similarity	100%	94%	78%

6 DISCUSSION ON THE EXPERIMENT RESULTS

The whole experiment takes about 5 hours for the expert and 45 minutes for each participant, which means about 1 minute per sentence for the expert and 2 minutes for each participant. 125 affordances are correctly identified using the framework by the expert from 91 informative sentences amount 303 review sentences. The result illustrates that comparing with other methods, identifying affordance from online reviews seems to be a better method which consumes less time and fewer resources.

We can conclude that the affordance identification framework is effective, as the recall and precision reach over 85%. However, the definition of affordance description is still to be detailed before

automating the framework. Indeed, 20% of affordances description cannot be identified repeatedly. This number is rather high. Meanwhile, some difficulties are identified from the results and the interview of expert and participants.

1. Affordance described by an adjective cannot be identified by the framework

We found that not all the affordances are described with a verb. Ten affordances are defined by an adjective word with postfix "-able". For example, in the sentence below, it can be concluded that the Kindle Paperwhite affords the user the ability to notice the unevenness of background light. Two affordances are described by other adjectives like "waterproof". That's why the recall of affordance description is not as high as other elements (90%).

Example: The unevenness of background light is noticeable.

2. Identification of subject in passive form and infinitive

As customer reviews are freely expressed, many sentences are written in passive voice. This makes the subject identification difficult because the subject is omitted. The same observation can be concluded for infinitives (to do). That is why the recall and precision of "user/artefact/environment" element (88% and 95%) are the lowest among all the elements. For example, in the sentence below, the participant has to read the whole sentence to determine the subject.

Example: This can be turned on or off if you find it distracting.

3. Identification of ironic tone

Ironic tone is often used by customers in online reviews to express their dissatisfaction towards the product. However, it cannot be tracked only by sentiment words. In this case, participants have to analyse the whole sentence, even previous sentence to make sure whether the reviewer express irony.

Example: Actually, it should be named as "kindle PAPERYELLOW". it is yellow like the page of a century-old book when the light is set to near maximum.

4. Identification of informative sentence

The low similarity identification results of "affordance description" element between expert and participants (80%) suggests that a clearer definition of interacting verb is required. This observation is highlighted by expert and participants in the final interviews. For example, in the sentence below, the verb "forgot" looks like an interacting verb, as it involves the chargers and the user. However, by reading the adjacent sentences, we can figure out that "forget charger" is only a description of user's status. Thus, a robust categorisation of informative and uninformative sentences is needed to eliminate this kind of phrase when automating the framework.

Example: September 2015 update: I was on a week-long vacation trip but forgot my chargers.

7 CONCLUSION AND FUTURE WORK

To conclude, this paper discusses the theoretical basis and technical basis of using online review to identify affordances. Theoretically, the online reviews contain information on the interaction between user and product, which can be interpreted by affordance. Technically, an automatic affordance identification framework is proposed to capture the affordance elements using natural language processing. The advantages of using online reviews to identify affordances over existing identification strategies are then discussed. The framework can be used as a complementary method for affordance identification. A case study with 303 online reviews of Kindle Paperwhite involving 1 expert and 6 participants shows that the proposed framework is effective. Therefore, the framework provides basis for automating the identification process.

In the future work, we will process to implement the framework in Python with the help of public available natural language toolkits. After the automatization, we will further study how to use the affordances to help designers.

However, some problems remain in this research for automating affordance detection in customer reviews. First, due to the limit of time and resource, the process of framework is processed manually. The use of "most useful" online reviews as samples for the experiment may leads to bias in affordance identification. Thus, the efficiency and accuracy of the framework are to be verified after automatization with random selected online reviews. Second, the recall and precision of the framework can still be improved, as it is found that the adjective that describes the affordances usually possess postfix "-able".

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