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Do online reviews reveal mobile application usability and user experience? The case of WhatsApp

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***Abstract*—The variety of hardware devices and the diversity of their users imposes new requirements and expectations on designers and developers of mobile applications (apps). While the Internet has enabled new forms of communication platform, online stores provide the ability to review apps. These informal online app reviews have become a viral form of electronic word-of-mouth (eWOM), covering a plethora of issues. In our study, we set ourselves the goal of investigating whether online reviews reveal usability and user experience (UUX) issues, being important quality-in-use characteristics. To address this problem, we used sentiment analysis techniques, with the aim of extracting relevant keywords from eWOM WhatsApp data. Based on the extracted keywords, we next identified the original users' reviews, and individually assigned each attribute and dimension to them. Eventually, the reported issues were thematically synthesized into 7 attributes and 8 dimensions. If one asks whether online reviews reveal genuine UUX issues, in this case, the answer is definitely affirmative.**

I. Introduction

With the rapid development of mobile devices, increasing numbers of mobile applications (apps) are being manufactured and deployed, and these apps are accompanied by rich user reviews. This informal type of communication, directed at an unspecified number of people using internet-based technology and related to the usage of particular goods or services is defined as electronic word-of-mouth (eWOM) [1]. Undeniably, this phenomenon has attracted considerable attention from application users as well as their vendors. According to Mobile App Daily [2], the most trusted and largest media source of the mobile app industry, more than 70 percent of people read app reviews before downloading, while, more importantly, 75 percent identified reviews as a key driver for downloading, and 42 percent consider app store reviews as equally or more trustworthy than personal recommendations [3].

Inspired by these findings, in our study we investigate the content of online reviews. The broad area of topics gaudily reported by users roughly corresponds to a similar number of application properties. Therefore, in this study the focus is on quality-in-use issues, which are recognized as the subject of interest of usability and user experience (UUX) practitioners. The evaluation of the UUX of a mobile application has been identified by many as one of the main challenges [4,5,6], eventually determining the success of its continued acceptance by users.

On the other hand, while the majority of recent studies on the perceived quality of an app have focused on quality assurance from the perspective of its development or testing, this study, on the contrary, solely concentrates on the end user's attitude to an app, expressed by eWOM. In particular, we put forward one research question: do online reviews reveal mobile application usability and user experience? In other words, by assumption, we attempted to extract valuable information from eWOM data concerning the facets of UUX.

The remainder of this paper is structured as follows. We first review the background and relevant literature in Section 2. Sections 3 and 4 introduce the research methodology and experimental setup, respectively. Section 5 presents the empirical results obtained in the study, followed by a discussion of the findings and implications, given in Section 6. Finally, Section 7 concludes the study.

II. Theoretical Background and Related Work

In the light of the results obtained in our previous study [7], in the context of mobile applications, the majority of studies have pointed to the usability definition adapted from the ISO 9241-11 norm. Here, usability is defined as "the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" [8]. Furthermore, along with these three already articulated attributes, in some studies, other attributes have also been considered, namely: learnability, memorability, cognitive load, errors, ease of use, navigation and operability [7].

Under the umbrella of user experience, all of a "person's perceptions and responses resulting from the use and/or anticipated use of a product, system or service" [9] are a subject of concern. Based on the existing body of knowledge [10], we elaborated a list of UX dimensions, from which we elected eight unique dimensions: aesthetics, enjoyment, hedonics, trust, support, engagement, discomfort and frustration.

It is worth noting that, according to the above norm, usability, when interpreted from the perspective of a user's personal goals, can include the kind of perceptual and emotional aspects typically associated with user experience. Moreover, usability criteria can also be used to evaluate aspects of user experience.

To capture usability and/or user experience, there are two not mutually exclusive approaches [11], which are applicable either during or after application usage. The former mainly concerns laboratory testing, while the latter is a retrospective analysis of data, gathered in the form of a questionnaire [12,13,14], video recording [15,16,17], or, more notably, online reviews [18,19,20,21].

Iacob and Harrison [18] argue that 23.3 percent of mobile app reviews represent feature requests, where users either suggested new features or expressed their preferences for the re-design of existing ones. The prototype experimental tool (MARA) was used to mine and retrieve feature requests from the data of online reviews. In particular, the data are processed in a fixed sequence: review retrieval, feature request mining, feature request summarization, and feature request visualization. During the first phase, a web crawler extracts the source page which contains the reviews of a given app and parses their content. The meta-data, including the posting date, the user's rating, and other fields, are also collected. The meta-data, as well as the content of the review are normalized to reduce noise in the final results, where the latter is also split into sentences, using [22], a toolkit for processing text by use of computational linguistics. The second phase uses the split review content as input and mines for feature requests expressed by users. The mining algorithm utilizes a set of linguistic rules defined for supporting the identification of sentences which refer to particular requests. During the third phase, the system summarizes the extracted feature requests according to a set of predefined rules. The applied rules aim to rank the extracted user requests based on their frequency and length. The more frequent and lengthier feature requests would be first in the summary. Finally, during the visualization phase, the results of the summarization are displayed to the user.

He et al. [19] propose a feature-opinion mining approach to automatically summarize the reviews, based on dependency parsing. The approach utilizes a regression model to generate sentiment words, consisting of a phrase and its sentiment weight. Next, the feature is extracted, based on the dependency relationship between the feature and sentiment words. Eventually, a score is assigned to the feature according to the dependency relationship. In general, the applied approach consists of three phases: (1) sentiment word generation, (2) feature extraction, and (3) feature scoring.

Jin et al. [20] illustrate a framework to select pairs of opinionated representative yet comparative sentences with specific product features from online reviews of competitive products. Sentiment analysis techniques were applied to identify opinionated sentences referring to a specific feature from product online reviews. To select a "small" number of representative yet comparative opinionated sentences from those identified, the authors investigated the representativeness, comparativeness and diversity of the information. The contribution of this study lies in three greedy algorithms to analyse the optimization problem for suboptimal solutions.

A comprehensive study of existing solutions for mining online opinions is given by [21]. There are several methods identified, including LDA (Latent Dirichlet Allocation), ASUM (Aspect and Sentiment Unification model), statistical analysis, SVM (Support Vector Machine), EMNB (Expectation Maximization for Naïve Bayes), decision trees, manual tagging, keyword extraction with grouping and ranking, and others.

To sum up, having briefly depicted the main ideas from arbitrarily selected studies, in this study we performed a semi-automated review analysis, methodologically similar to the framework developed by Vu et al. [23].

III. METHODOLOGY

In our study, the sentiment analysis is aided by the WordStat Sentiment Dictionary, designed by combining negative and positive words from three different sources: Harvard IV dictionary, the Regressive Imagery Dictionary (RID) and the Linguistic and Word Count dictionary. Eventually, more than 9526 negative and 4669 positive word patterns were gathered [24].

A user's sentiment is not measured by those two lists of words and word patterns, but instead by two sets of rules which are intended to take into account the negations preceding those words. For example, negative sentiment is measured by applying the following two rules:

- negative words are not preceded by a negation (e.g. no, not, never) within four words in the same sentence;
- positive words are preceded by a negation within four words in the same sentence.

On the other hand, positive sentiment is measured in a similar way by alternatively checking the following two rules:

- positive words are not preceded by a negation;
- negative terms are followed by a negation.

However, some argue that the latter rule shows less predictive properties, and in some cases, might even deteriorate the sentiment measurement [25,26].

In general, the sentiment analysis was carried out in a fixed sequence of five stages [27], as depicted and described below (Fig. 1):

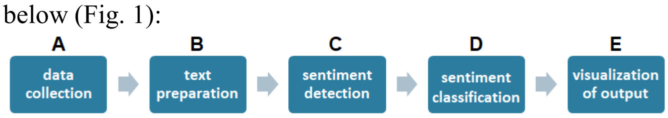

Fig. 1 The sentiment analysis process

Data collection (A) involves downloading the text data from the Web and assembling one consolidated data set.

Text preparation (B) aims to clean and transform the collected data, comprising the following two tasks:

- data parsing, which means analyzing data and breaking them down into smaller blocks, which separately can be easily interpreted and managed, and

- data pre-processing, which concerns: (*i*) performing tokenization, where the words are transformed from the text into a structured set of elements (tokens); (*ii*) executing a stop word list, where the words which have low informative value or are semantically insignificant (e.g. *and*, *also*, *or*) are removed; and (*iii*) reducing the words by individually extracting a stem word (a root of words).

Sentiment detection (C) is to identify sentences with subjective expressions (opinions, beliefs and views) and to reject objective communication sentences (facts, factual information).

Sentiment classification (D) is the task of classifying a text in a document into a positive or negative class on various levels (e.g. document, sentence and aspect of entities).

Visualization of output (E) aims at transforming data, information and knowledge into a visual form (e.g. pie, bar, line graph) to take advantage of natural human visual capabilities [28,29,30].

In the next step, we assumed, after [31], that in textual analysis research, a higher negative (positive) word frequency indicates a more pessimistic (optimistic) sentiment. Therefore, we extracted all negative and positive words with the highest frequency of occurrence. Next, we consequently mapped these words to a particular usability attribute and/or user experience dimension. Finally, identifying the original reviews, based on keyword searching, enabled us to individually assign them to the relevant attributes and dimensions.

IV. Experimental Setup

In total, we collected 399 reviews by WhatsApp users from the Google Play website using a self-made web crawler. The data set is both human and computer readable due to the JSON (JavaScript Object Notation) format applied.

Let $i = \{1, 2, \ldots, n\}$ be the ordinal number of a user's review. Each review can be defined as a set of six variables (sextuple):

review(i) = {*name*: string, *rate*: [1–5], *when*: date, *helpful*: integer, *short-review*: string, *full-review*: string}, where:

- *name* is the name of a user (reviewer), which may consist of first name, surname or any other string of characters (e.g. John, John Kowalski, JK);
- *rate* is the numerical evaluation of the mobile application in the range of 1 to 5, given by a user,
- *when* is the date of the rate, written in a short format (e.g. February 12, 2019),
- *helpful* is the number of thumbs-ups given by users for the review,
- *short-review* is a verbal evaluation of the mobile app,
- *full-review* is also a verbal evaluation of the mobile application, with a higher number of characters allowed.

It is worth noting that a user can add a review to a particular app if it has been downloaded and installed.

The sentiment analysis was conducted using the ProSuite commercial software [32], being an integrated collection of Provalis Research Text Analytics Tools that allow one to explore, analyse and relate both structured and unstructured data. The computing platform includes three major tools:

- QDA Miner for qualitative data analysis, including coding, annotating, retrieving and analyzing small and large collections of documents and images;
- WordStat for the content analysis of open-ended responses, interview or focus group transcripts, for information extraction and knowledge discovery from incident reports and customer complaints, and for the automatic tagging and classification of documents;
- SimStat for statistical analysis, supporting both numerical and categorical data, dates and short alpha-numeric variables, as well as memo and document variables.

These tools have also been used in other studies for content analysis and text mining [33,34,35], allowing researchers to integrate numerical and textual data into a single project.

V. Results

The research material constituting reviews by WhatsApp mobile application users created a so-called bag-of-words (BOW). After transforming the text into a BOW, we can calculate various measures to characterize the text. In our study, the BOW model consists of 4 245 words (tokens). The most common words are shown below (Fig. 2).

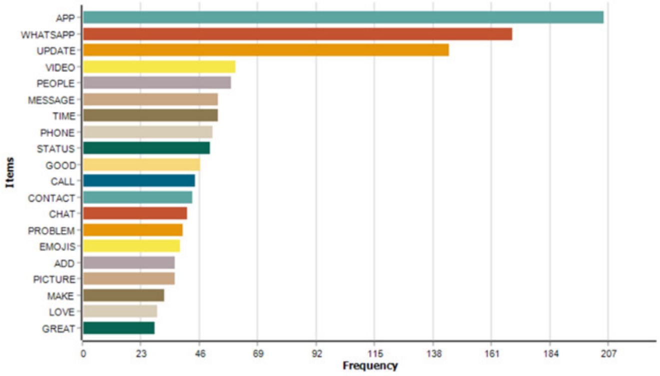

Fig. 2 The distribution of keywords by frequency

In the first step, the sentiment analysis was performed on the users' opinions. The sentiment analysis, conducted according to the stages shown in Figure 1, contained 904 negative words (21.30%) and 1217 positive items (28.67%). However, neutral words identified in the study (50.03%) can be ignored because they do not add value to the study. The obtained results are given below (Fig. 3).

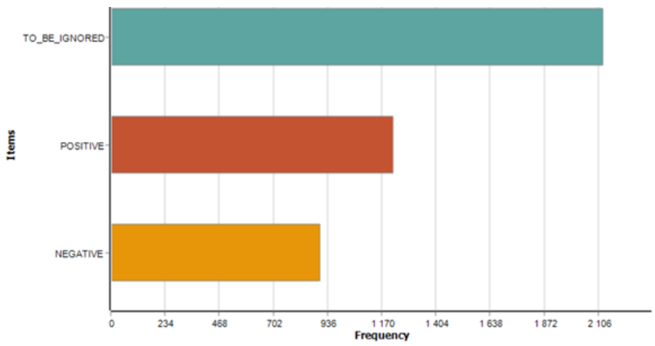

Fig. 3 The distribution of words after the process of sentiment analysis

In the WhatsApp users' ratings, the advantage of positive sentiment is clearly visible. The set of bigrams extracted from the users' reviews also show this trend (e.g. *great app*, *excellent app*, *good app*, *love WhatsApp*).

In the next step, we assumed, as already indicated above, that in textual analysis research, a higher negative (positive) word frequency indicates a more pessimistic (optimistic) sentiment. Therefore, we extracted the crucial negative and positive words with the highest frequency of occurrence (Table 1).

TABLE I.
LIST OF THE MOST FREQUENT KEYWORDS

Negative		Positive	
Word	**Frequency**	**Word**	**Frequency**
fix	46	call	58
problem	39	contact	57
issue	36	good	46
number	19	friend	34
annoying	18	make	32
remove	18	feature	32
bug	17	share	31
hate	13	love	29
unable	11	work	29
stop	11	great	28
bad	11	open	15
delete	10	fine	14
sucks	9	easy	12
horrible	9	quality	12
reduce	8	make	11
lost	8	nice	11
error	8	free	10
limit	7	happy	9
wrong	6	awesome	9
miss	6	excellent	8

Keywords frequently appearing with negative reviews are likely to describe the issues or features of apps that cause a negative user experience, i.e. making users unsatisfied. Thus, such keywords would be of interest to app developers because they can help to identify the bad aspects of an app and user opinions about such aspects (e.g. bigrams: *fix this issue*, *Feb update*, *app lock*, *dark mode*). And similarly, with positive words that point to the aspects that satisfy the user (e.g. bigrams: *good work*, *excellent app*, *good app*).

Based on selected keywords from the sentiment analysis, we searched for the actual user reviews that are the most relevant to those keywords. On this basis, we were able to assign usability attributes and user experience dimensions. An example of our work is included in Table 5 and Table 6 (see Appendix). The mappings between keywords and usability (Fig. 4) and UX dimensions (Fig. 5) are shown below.

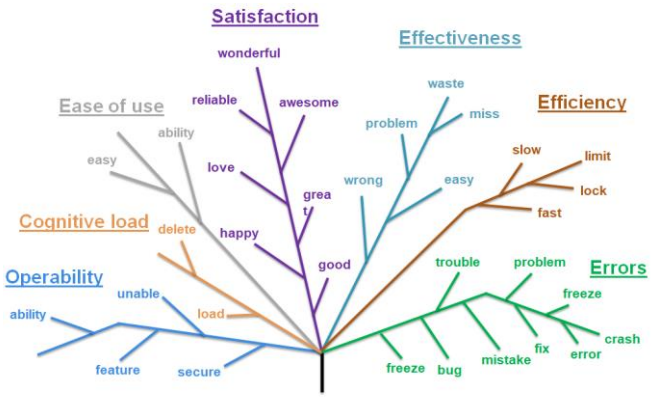

Fig. 4. The mapping between keywords and usability attributes

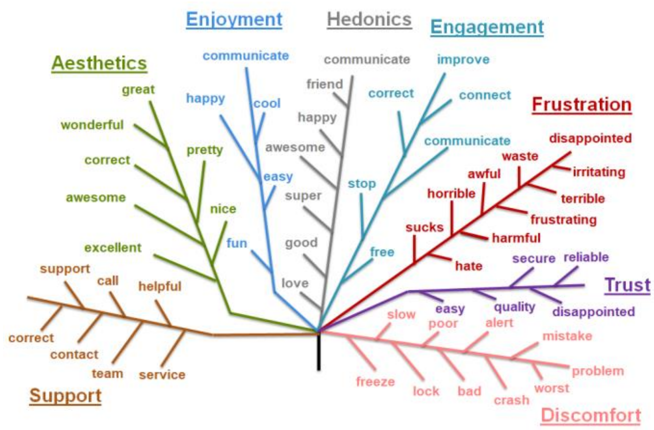

Fig. 5. The mapping between keywords and UX dimensions

The same keywords (e.g. *easy, awesome, problem* and *communicate*) can be used to describe different UUX attributes and dimensions. In addition, the negative words describe a larger number of dimensions and attributes than the positive ones. Similar conclusions were drawn by Provost and Robert [36].

Next, the bag of words was divided into seven clusters by applying the hierarchical grouping method (Table 2), where a cluster is a group (or class) of similar objects created as a result of data grouping. On further analysis, these clusters can be compared to the classes developed by grouping original user reviews, which have an absolute meaning and should not be standardized.

TABLE II.
KEYWORD CLUSTERS

No	Keywords
1	problem, contact, message, send, people, time, fix, good, profile, chat, option, video, phone
2	unable, user, text, notification, nice, long, full, check, call, bug, communication, feature, easy, support, data, bad, delete, issue, quality, post, friend
3	view, team, set, screen, message, card, conversation
4	work, update, online, chat, fine, hate, voice, annoying, video, app, feature, photo
5	call, thing, change, friend, person, issue, great, version, group, picture, love
6	download, free
7	update, WhatsApp

The steps completed so far have provided a basis for the mapping of frequent keywords to usability attributes and user experience dimensions (Table 3 and Table 4).

TABLE III.
THE MAPPING BETWEEN FREQUENT KEYWORDS AND USABILITY ATTRIBUTES

Attribute	Keywords
efficiency	limit, slow, lock, fast
satisfaction	good, love, great, awesome, happy, reliable, wonderful
effectiveness	wrong, miss, problem, easy, waste
learnability	–
memorability	–
cognitive load	delete, load
errors	bug, error, fix, freeze, crash, problem, trouble, mistake
ease of use	ability, easy
operability	ability, unable, secure, feature

TABLE IV.
THE MAPPING BETWEEN FREQUENT KEYWORDS AND UX DIMENSIONS

Dimension	Keywords
aesthetics	correct, great, nice, awesome, excellent, pretty, wonderful
enjoyment	happy, fun, cool, easy, communicate
hedonics	friend, communicate, awesome, love, happy, super, good,
trust	quality, secure, reliable, easy
support	service, contact, call, support, team, helpful, correct
engagement	correct, stop, communicate, connect, improve, free
discomfort	alert, problem, bad, slow, poor, lock, freeze, crash, worst, mistake, disappointed
frustration	irritating, sucks, horrible, waste, disappointed, terrible, hate, irritating, frustrating, awful, harmful

Interestingly, two usability attributes are empty sets. In other words, none of the keywords were assigned, which indicates that users neither report on the ability to learn nor to remember. Moreover, one can classify UX dimensions as positive (aesthetics, enjoyment, hedonics, trust, support), neutral (engagement) and negative (discomfort, frustration). In Fig. 5 specific dimensions were marked off by labelling sets of the keywords with different colors, ranging from green and blue to red, respectively.

On the other hand, the words included in the above two tables indicate the importance of the reported UUX issues by the users. As a matter of fact, eWOM data are meaningful for app vendors not only because users often rely on this resource when making decisions, but more importantly, online reviews might leverage app design and quality.

VI. DISCUSSION

There is no doubt that the ability provided to users to tell their stories about mobile applications in any way, has brought popularity as well as obstacles for apps. However, there are many examples of those who have taken an unfair advantage this ability. For example, in December 2018, as a response, Google announced a crackdown on app developers who buy ratings and reviews to deceive users or ruin their competitors' reputations [37].

Moreover, in the Notes section of the store, one can read that reviews are automatically processed to find inappropriate content (such as obscene, offensive, or meaningless language). Online reviews are also automatically scanned for spam (like messages sent by bots or repeated content posted multiple times or from multiple accounts). The company has no tolerance for fake reviews, which will be taken down if they are flagged as fake or are in violation of review policies. Therefore, in our opinion, the Google online store of mobile applications is a reliable source of information.

Although 50.03% of identified words were discovered to be valueless, we found the other half of great value. Indeed, eWOM involves positive and negative statements made by users about WhatsApp. This real user-created information has brought insight into users' direct experiences as well as application performance and properties. On the other hand, since software testers are not able to detect all bugs, defects and errors, the users act on their behalf unintentionally but competently.

Like any other similar research, this study has both its limitations as well as strengths. Firstly, only one app, as the source of the reviews, was explored in order to gather the necessary evidence to formulate an answer to the research question. Secondly, there is no mechanism implemented which could automatically process a relatively large volume of data, and set up keyword clusters in a non-supervised mode. Future research will address broadening the sample and implementing a relevant method. Additionally, while the present approach assumed off-line processing, online processing will also be considered. Lastly, multiple experiments with different apps are being investigated and validated in order to elaborate the unified UUX model.

VII. Conclusions

In the case of WhatsApp, in this paper we were able to evidence a positive answer to the given research question. eWOM provides a new venue for software vendors to reach users and to influence their opinions. With zero cost for accessing and exchanging information, eWOM creates a new opportunity to better understand users' genuine concerns formulated toward the features and properties of apps, covered by UUX theory and practice. In light of the evidenced results, it seems likely that users in increasingly larger numbers will either read and/or write reviews, expecting afterwards to have a better app in the next release.

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APPENDIX 1

TABLE V.
EXTRACTED NEGATIVE UUX ATTRIBUTES AND DIMENSIONS FROM ONLINE USERS' REVIEWS

Word	Review	attribute/ dimension
fix	"I am not even getting any notifications from Whatsapp on the status bar nowadays and am very disappointed to say that even though I've double checked the settings for both message and group notifications, there's still no changes. Please **fix** this problem ASAP."	errors
	"I can't see any status updates from my contacts. The status feature just stops for a while and then returns and stops again. Can you please **fix** this bug."	errors
	"Useful little app but does come with frustrations. I want to view images and when I click on an image to load it downloads onto my phone which is annoying. Want to view the image not save it and clog up my phone. Same goes for gifs and videos. Please **fix** it, if you do I'd probably use this more than fb messenger."	errors
	"**fix** the change! I have contact photos in my phone and people that do not have profile photos would show up with the contact photo now it does not do that after this new update. change it back it was better before"	errors
	"I really like whatsapp messenger but one thing that annoys me is that I cannot forward message to more than (limit set by Whatsapp) five people i guess. Please **fix** this."	errors
	"do like this app, but the recent update keeps causing it to freeze and crash. Effecting my whole phone. Please **fix** bugs or whatever is causing it to freeze."	errors
	"Why are whatsapp emojis are looking sooooooooo badd. like after installing new update, emojis got worse, please **fix** this in next update."	satisfaction
	"Great App, but there is a bug I am not able to call or video call 3 people at once from the group chat video call option. The call don't respond and automatically disconnect without ringing. Please fix this issue and one more thing when we are getting feature for group video call more then 4 members..."	errors
	"Please **Fix** bugs . when I Video call , I can't touch anything and can't turn back to the Conversation and can't typing anything . my friend told me either ... please FIX the bugs soon"	errors
	"A great way to communicate, but since the last update, my contact's pictures aren't showing. Even though when I go into edit contact and there's a picture there, it's not showing on the main screen. Please **fix** this!"	errors
problem	"Plz do something the app has become slow on the two devices I own, one is the huawei p20 and the other is oneplus 6t.I checked my devices but others are all facing the same **problem**."	efficiency
	"My WhatsApp crash twice in less than 2 months' time ... All my chats are gone. **Problem** is I didn't do anything. An error message just pop up and say there's something wrong with my chats history. I lost all my important work chats. This is bad. You can't expect me to do backup every single day."	errors
	"I have a **problem** sending videos to my contacts, each time I try to send videos that are five minutes long, it is reduced to a lesser minute of 3 minutes of streaming before it can be sent to my contacts. please how do I go about this?"	efficiency
	"I'm using WhatsApp, but I don't see blue coloured double tick after my messages are read. And my friend didn't change the setting on mobile. This not the first time of **problem**."	satisfaction
	"Last three weeks I have a **problem** for message sending. I didn't send any message more than five people. Before 20 people but now 5. I don't know why whatsapp management reduce the contects for sending messages."	effectiveness
	"I can't sent Voice Messages .... Same problem with both my Whatsapp accounts."	errors
bug	"Everything was fine but since last month's my old chat messages are being deleted by WhatsApp without my knowledge and I am shocked with this new **bug**."	errors
	"I can't see any status updates from my contacts.. The status feature just stops for a while and then returns and stops again. Can you please fix this **bug**."	satisfaction
	"After make video call, it's not getting minimized. Its hanged. New update killing it badly. My mobile note 5 pro.. please solve this **bug**."	errors
hate	"I **hate** the new update. I lost contact photos to over half my contacts. I can't figure out how to restore contact pics. Also....as popular as this app has been throughout the years, you'd figure that they'd come up with different themes. Instead, same old boring green theme."	satisfaction
	"I **hate** the new update. I lost contact photos to over half my contacts. I can't figure out how to restore contact pics."	satisfaction
	"I **hate** the new version. The emojis are old , some are nice , but I would like if the emojis looked more realistic and not fake or something. I recommend this app, although the emojis are not cool. But I would and its useful."	satisfaction
	"I **HATE** THE NEW UPDATE. ... The previous version was way better. Please restore it."	satisfaction

	"I really love this app...however I and all of my friends **hate** the new emojis for android... They are awful. Please change the emojis so that they look like IOS emojis ... please"	aesthetics
	"Horrible update. **Hate** when the update makes the app worse, not better!"	frustration
	"I **hate** the new update. Pls get back the previous version."	frustration
	"It's still great for communication but I **hate** the new "upgraded" emojis. As if it wasn't enough that you ruined my favourite emojis, the moons, you've ruined the rolling eyes emoji for me as well. Please fix them and make them look like their past selves."	frustration
bad	"Recent whatsapp update is so **bad**, I only use it because I have contacts on it. All new icons have gone. Profile icons picked up from phone contacts for those who haven't loaded profile pics, is gone, so there are gaping holes where there should be a contact icon."	discomfort
	"New update is very **bad**. You can't send msg to more than 5 people, please give us new update and solve this."	satisfaction
error	"When sending a video from your gallery, it comes up with an **error** message ... fix this too."	errors
	"Unable to send pdf files. **Error** shows it's not a document what the hell is this.. I think I need to switch messenger."	satisfaction
	"Latest update has a few **error**s but the one that's bugging me is I had pictures assigned to my phone contacts that used to show as the profile picture on WhatsApp if the person didn't have a profile picture and after the update it's not showing."	errors

TABLE VI.
EXTRACTED POSITIVE UUX ATTRIBUTES AND DIMENSIONS FROM ONLINE USERS' REVIEWS

good	"My experience is too **good** with whatsapp. I am happy to make a group and chat within it. It is very helpful and good for school work ... thank you so much."	satisfaction
	"Pros: Its free. Clarity pretty **good**. Not many adds."	satisfaction
	"It's just so **good** we can call free, video - chat, share safely, it's one of the necessities in life now. I'm impressed."	satisfaction
feature	"Great! It still remains the most used app in the world. But a **feature** that can allow us to save what we want needs to be added please."	operate
	"Getting better with each update. The swiping right to reply **feature** is something I really like."	pleasure
	"… indeed your new **features** are just amazing. Keep up the good work."	enchantment
	"Neat customization tools, group chat **features**, and easy location, and now money transfer payments sending & receiving money adding are all cool additions."	comfort
easy	"Fast (especially for sending images), more reliable than SMS, and everyone has it, so it's **easy** to connect with people."	enjoyment
	"awesome app in social world **easy** to use fantastic"	easy to use
	"This is the best messaging app ever! I love how it is laid out and how **easy** it us to use."	easy to use
	"It's quite simply, brilliant. User interface is a tad lame and boring but the app is efficient and **easy** to use."	efficiency, easy to use
	"Very **easy** and reliable app for communication. Thanks."	trust
awesome	"It is **awesome**. I love it. Whatsapp is my favorite app."	satisfaction
	"It's always **awesome**. It deserves full rating ..."	hedonics
	"You have it because everyone has it. A 'smartphone' is defined by its capability to run this app! **Awesome**. Saved me a whole lot of money undoubtedly."	satisfaction
communicate	"Great app to **communicate** quickly and easily …"	enjoyment,
	"A great way to **communicate** with friends and family. So clear without a hitch."	enjoyment
	"It's very practical. Great audio in the calls. Simply the most consistent form of **communicate** on the internet."	enjoyment
super	"This App has made my texting so much quicker and is **super**-fast sending pics and video's. My wife and I love it and text each other only on WhatsApp! Get it and you won't be sorry!"	hedonics
	"**Super**b application...user friendly ... just there should be some kind of indications of those who are online like we have in Facebook ... a green signal or something like that should be there so that we don't have to check that who are online. Other than that it's perfect."	hedonics