

Mining User Experience Dimensions from Mental Illness Apps

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Abstract. Mental illness is prevalent, the primary cause of disability worldwide, and regardless of the extensive treatment choices. Mobile apps provide greater support for depression treatment that eliminates the communication barriers. This perspective can be dropped with poor application design. Our goal is to mining the user experience (UX) dimensions from top-n mental illness apps reviews that will help to design the better application for persons with severe mental illness (SMI) and cognitive deficits. In this paper, we extracted the key UX dimension from a huge corpus of mental illness apps reviews using unsupervised Latent Dirichlet Analysis (LDA). Finally, LDA uncovered 20 UX dimensions that need to consider for mental illness app design in order to promote the positive UX by reducing the cognitive load of app end users.

Keywords: Mobile application · Cognitive impairment · mHealth · mHealth design · Severe mental illness · User experience · Usability

1 Introduction

Mental illness, the major contributor in disability worldwide. Mental illness is the fifth greatest contributor to the global burden of disease. It disrupts the individual's mood, cognitive and language styles, ability to work and routine activities. Some individuals might not even know what's going on, especially in the initial episode of psychosis [1]. Globally, medical resources are utilized to overcome the consequences of mental illness by strengthening health system, including mobile health (mHealth) applications. mHealth can offer different services such as self-assessment, self-help support, notification to promote positive behavior, symptoms monitoring, therapy, education how to cope with SMI, skills training, gamification for user engagement, and much more [2, 3].

However, these features benefits may be drop with poor app design. Research shows [4] that the usability of website application heavily depends on the user ability, so called mental model. Mental model is a cognitive representation of ideas, beliefs, image, and verbal that leads to form user experience [5]. These representations of user perception explain cause and effect and conduct us to expect certain results, and move us to act in certain ways. Cognitive abilities strongly bound by the application usage, such as researching, reading and task completion. The study found that person with depressive disorder have neurocognitive deficits such as lack of perception and attention, which

deals with object relationship, and episodic memory, which deals with the learning process, and recall from learning experience [6].

A standard website design model is already published [7, 8] that focus on website design such as content organization, hypermedia, links organization and its deep level, and pages distribution and its styling. Few studies focus on accessibility issues for the persons with cognitive deficits [5, 9, 10]. However, we need design model for mHealth that cover the all aspects of user's having depressive disorder.

There are thousands of mental illness apps having user reviews are available at distribution platforms such as iTune and google play store. User reviews contain useful information related to usability and user experience, which is freely available at anywhere, anytime [11].

In this study, we attempted to extract important information of user experience design from mental illness apps reviews that influence the positive user experience of mental illness apps for the persons with SMI problem.

The rest of the paper is structured as follows. In Sect. 2, the proposed framework is described. Section 3 is about the implementation, results and validation of study. Finally, Sect. 4 concluded the study.

2 Method

We use the following framework to extract the UX dimension from the mental illness apps as shown in Fig. 1, which described the overall process used in the study.

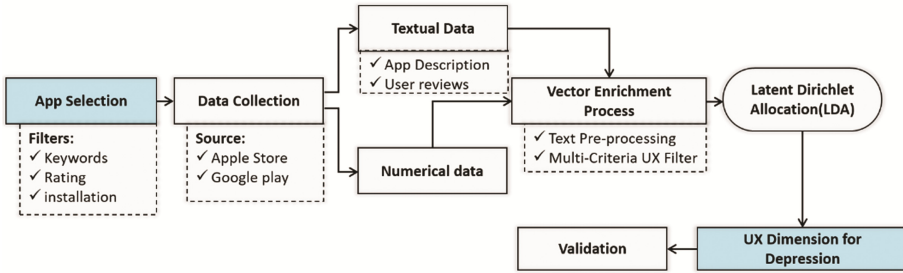


Fig. 1. Framework of UX dimension extraction from depression apps for depression application design

2.1 Apps Selection

For mining the user experience (UX) dimension, we made the selection of applications in 4 steps using systematic review [12]. First, downloaded the mHealth application repository [13] having comprehensive details of health and fitness apps collected from iTune and google play store. Second, exclusion using keywords (mental illness, depression, and stress) filters. Third, for top n apps selection, other filters such as average rating, user rating, and number of installing/download used. Forth, 5 coders manually review the description of filtered apps and apply further inclusion criteria using the MARS scale

[14], which having four dimensions: engagement, functionality, aesthetic and information quality. Apps are included that's related to mental illness, depression, stress, anxiety, and bipolar disorder for future study. The selection process is shown in Fig. 2.

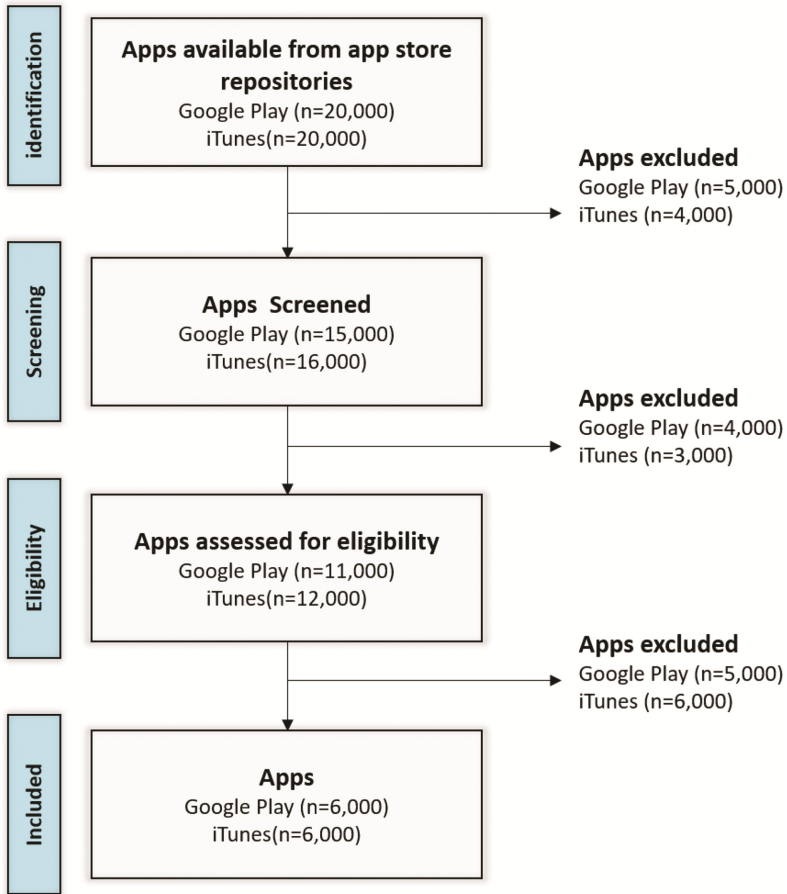


Fig. 2. Selection criteria process flow chart

2.2 Data Collection

We developed the crawler program that's collected user reviews from selected applications. We used Breadth-First search starts from the first app in the selected list, and crawled all app page by paring the HTML tag to extract the app's information such as app description, rating. Next at each app description page, we collected all user reviews against that app. Finally, the collected data are stored as dataset for text analysis.

2.3 Vector Enrichment Process

- **Text Pre-processing:** text pre-processing includes English word filter, spell checker and auto correction, tokenization, stop words removal, stemming, and Part-of-speech (POS) tagging. For example, the output of review after prepressing as:

Review text	Pre-processing
“An interesting, helpful app for those who have children or other family members with depression”	“interesting helpful app child family member depression”
“Great app It was very helpful to me at time when I was depressed and need help. Dr. Robert is a very helpful person and extend me a great help”	“app helpful time depressed help robert helpful person extend help”

- **Multi-criteria UX Filter:** It includes richness, which check the reviews subjectivity [15]; coverage & diversity, check the coverage of different UX facets such as user cognitive, situation, and product facets [16].

2.4 Mining UX Dimension Process Using Latent Dirichlet Allocation (LDA)

Mining UX dimension from large sample of user generated Content (UGC) is the main contribution of this study that influence the positive UX in domain of mental illness app design. We used the topic modeling [17] for the extraction of UX constructs from huge corpus of textual data. Topic modeling is probabilistic model for finding the abstract topics discussed in the collection of corpus. Latent Dirichlet Allocation (LDA) [18] is most common method for unsupervised topic modeling that automatically discovers hidden topics from the huge volume of textual data called big-data. It discovers the number of topics from the set of documents, each documents contains several topics, and topic consists of several words.

3 Results

In this section we described the extracted dimensions of UX for mental illness application. We validated the extracted dimensions by comparative analysis with prior studies on depression application. Topic modeling is performed using KNIME, which provide the open source analytics platform [19]. The workflow created based on proposed framework, includes corpus reading, text preprocessing, multi-criteria UX filters, and topic extractor (LDA) components as shown in Fig. 3.

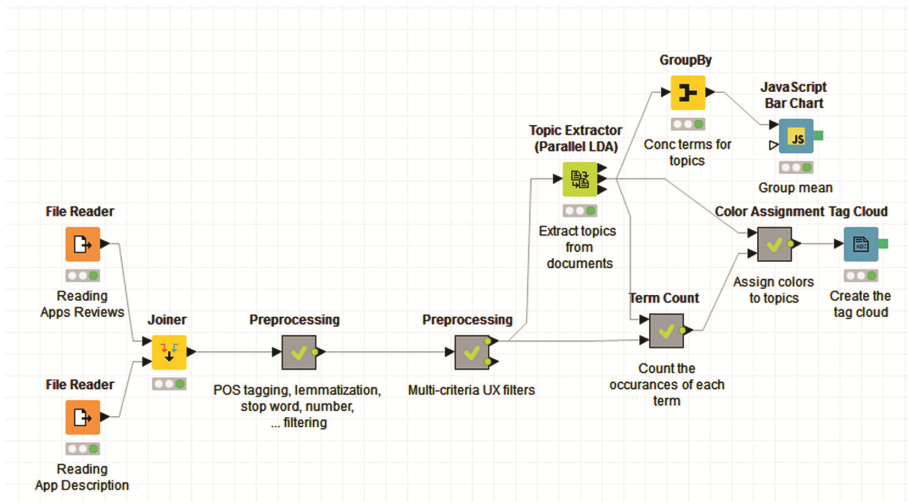


Fig. 3. KnimeLDA workflow

3.1 Dimension of UX for Mental Illness Application

We apply the LDA for the extraction of effective UX dimension from the collected mental illness apps description and user reviews. The LDA extract 20 topics and each topic having 30 words with the relative weight. The word cloud of extracted words is shown in Fig. 4.



Fig. 4. Word cloud of apps description and user reviews

For Topic labeling (naming), peer reviews was conducted by using the word connection among the topic words. Labels are barrows from our prior work, developed UX

Table 1. An example of topic naming/labeling

Topic	Relative weight		Relative weight
User interface		Pro version	
button	30702.62	money	22219.07
click	9930.66	gold	13710.02
press	8373.58	star	12487.22 3
screen	8115.33	buy	8254.09
touch	5881.83	time	5988.69
error	5356.02	upgrade	5766.55
download	5050.8	waste	5337.27

models from existing UX models literature [20]. For example the Topic name “User Interface” is based on the top three words connection shown in Table 1. After identification of topic name, again check with top 20 words. If the logical connection there, the name retained, otherwise recheck for naming.

Table 2. A comparison of dimensions between LDA analysis and prior studies.

Dimensions/Constructs	LDA Analysis	Prior studies
Accessibility	✓	✗
Attachment	✓	✗
Competence	✓	✗
Complexity	✓	✓
Comprehensibility	✗	✓
Context	✓	✗
Dependability	✓	✗
Disorientation	✓	✓
Ease of use	✗	✓
Efficiency	✓	✓
Engagement	✓	✗
Flexibility	✓	✓
Flow	✓	✓
Informativeness	✓	✗
Learnability	✓	✓
Perspicuity	✗	✗
Rewarding	✓	✓
Satisfaction	✓	✓
Simplicity	✓	✓
Stimulation	✓	✗

Notes: ✓ = included; ✗ = not included. Jaccard coefficient: 0.45. We compared the dimensions derived from LDA with the FEDM [2, 5].

3.2 Validation

We compared the extracted dimension using LDA analysis with existing studies on mHealth application UX dimension. We used the Jaccard coefficient similarity [21] to check the degree of dimension overlapping. The Jaccard coefficient is calculated as

$$JC = \frac{|D_{LDA} \cap D_{Ex}|}{|D_{LDA} \cup D_{Ex}|} \quad (1)$$

Where D_{LDA} dimension is extracted using automatic LDA analysis and D_{Ex} is dimension mentioned on existing studies.

The higher the Jaccard coefficient's value, the higher the degree of overlap between the two sets of dimensions. The Jaccard coefficient of our study is 0.45 as shown in Table 2.

This concludes that our study inferred new latent variables or dimensions from the app description and reviews that have been ignored by earlier studies. We claim that our study outcomes are more reliable for generalization due to a large corpus textual data.

4 Conclusion

In this paper, we propose a framework for the extraction of UX dimension for mental illness app in mHealth domain. For Latent dimension extraction, our proposed LDA identifies important dimensions that are not found using traditional methods such as interviews and questionnaires in mHealth domain. Our work has some limitations such as, our model ignores infrequent words, that might be very important in mHealth apps, and need large corpus of textual data for better results.

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