

DESIGNING AND IMPLEMENTING A MULTI-CRITERIA INTELLIGENT FRAMEWORK TO ENSURE THE RELEVANCE OF REQUIREMENTS SOURCED FROM SOCIAL NETWORK SITES

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ABSTRACT

The proliferation of social networking sites (SNS) and software failures primarily arising from the requirements elicitation phase, motivated researchers to develop methods, that incorporate SNS-based users' needs into the requirements engineering stage, crucial for developing reliable software. This approach improves user-centric needs and identifies innovative features, but relevance verification has not been thoroughly examined, leading to challenges in filtering and prioritizing relevant information emanated from jargon, informal language, and diverse expressions detected in user comments. This research proposes a novel intelligent framework for relevance verification of SNS-sourced requirements, combining multiple criteria like organizational goals, business rules, related service datasets, and user comments. The proposed framework balances user, organization, and developer needs by simplifying the process of determining relevant requirements and enhancing their validity. The framework learns and utilizes consolidated criteria features as regulation mechanisms, addressing challenges in isolating relevant users' needs and minimizing traditional method limitations. The study uses qualitative methods for framework development and empirical research methods for sentiment and trend analysis, combining customized word embedding models and natural language processing. A case study of digital healthcare systems in developing nations explores three evaluation categories: business rules, related service datasets, and a blend of both. The dataset includes 2400 key phrases from 800 user needs, 540 business goals, and 900 from service datasets. The proposed method achieved a relevance rate of 88%, surpassing individual methods. The study contributes to IT and software engineering fields by providing a novel framework for relevance verification of SNS-based requirements, ensuring their alignment with actual user needs and improving their completeness and prioritization, leading to significant enhancements in system design and development.

Keywords: *Requirements relevance, Users' need, Intelligent model, Word embedding and NLP, SNS*

1. INTRODUCTION

In today's digital environment, the rise of SNS has significantly impacted the way people convey and share information, particularly in software development [1]. These platforms have become an abundant source of user-generated content, reflecting present trends, sentiments, and key specifications through diverse fields, such as software requirements engineering (RE), crucial for the development of effective software [2].

Researchers are now focusing on and leaning towards data-driven practices to overcome system failures detected primarily due to defects in the RE stage [3]. This shift is essential as 65% of software's face ambivalent success mainly due to malfunctioning RE [4-5], and researchers have attempted to address these challenges by integrating SNS-based user requirements. Properly managed user requirements and involvement in the specified platforms are vital for facilitating software RE, aligning software products and services with user

needs, generating valuable ingredients for software product success [6]. Research has also revealed that SNS-based requirements contain vital software development perception and can boost requirements characteristics like completeness [7]. In addition, studies have demonstrated the use of SNS in the RE process, highlighting how the SNS-based method complements the traditional requirement-gathering methods [8-11].

As researchers and organizations inclined towards SNS platforms for insights into user needs and expectations, the dynamic verification of requirements relevance from these platforms has emerged as a critical problem [12]. Specifically, prior researches lack a comprehensive exploration of the process of relevance verification for SNS-sourced requirements from various dimensions, including organizational goals, initial specifications from the intended application's terms of reference (TOR) documents, related service datasets, and users' needs fetched from SNS.

Particularly, though the vast amount of data generated on SNS imparts an opportunity for organizations in an effort to gather sufficient user requirements, firms face difficulties in filtering and prioritizing relevant information [10-11]. Compounding these challenges is the usage of informal language, slang, and varied expressions by users' that complicates the extraction of essential insights. Chen et al. [13] have denoted that due to noisy and contradictory opinions, only 35% of users' requirements encompass information that can aid developers in constructing and improving their software products.

Unable to comprehend the relevance verification process causes a difficulty that lies in accurately verifying and integrating users' needs into the RE process, crucial for designing software that effectively aligns with their preferences. Specifically, when relevance verification of requirements is not properly carried out, it can lead to issues for system analysts and decision-makers in enhancing the quality and relevance of software products [14]. System analysts may struggle to balance user needs and organizational business rules, whereas end users may have incomplete understanding of their needs and post-unrelated issues, affecting the verification process performance [15]. Additionally, the relevance verification process is influenced by unrealistic user needs and overlooking semantic relationships, negatively impacting the quality of a software [16].

In light of these challenges, this research looks into a novel intelligent multi-criteria framework to ensure the relevance of SNS-sourced requirements.

Specially, to mitigate potential issues, the relevance verification process need to be considered from multiple perspectives, including organizational goals, related service datasets, and user needs. Hence, the study aims to design and develop a novel framework by exploring the feasibility of using diverse criteria to enhance relevance verification processes for SNS-sourced requirements. Proper analysis and measurement of the relevance verification of requirements with this approach can significantly impact the software development process by addressing stakeholders' needs.

Accordingly, the research questions focus on harnessing multiple criteria to distinguish effective verification techniques and assess their influence on the software RE process. Thus, the study addresses four research questions:

1. What is the potential correlation between the components of the proposed framework for verifying the relevance of requirements, sourced from SNS platforms?

2. In verifying user needs relevance, is the role of exploiting a novel multi-criteria approach better than harnessing the criteria separately?

3. How can the proposed framework be evaluated using quantitative and qualitative methods?

4. Does the proposed framework help to retrieve and verify the relevance of desired SNS-sourced requirements, for a case study?

Though the specified research questions outline the study's purpose and broad topic, hypotheses have been declared as they assist in providing a comprehensive framework for a focused exploration. They also help comprehend testable predictions, aid in interpretation of results, and guide the process of selecting appropriate methods, data collection techniques, empirical and statistical analysis. Based on the study's objective, problem statement, and research questions, two hypotheses have been established, ensuring the study is fitting to address the research problem.

1. The study hypothesized that using multiple criteria would be associated with enhancement of the relevance rate of uses' needs sourced from SNS, thereby simplifying the relevance verification process.

2. The study hypothesized that execution of the proposed framework would be involved with producing a valuable verification method for assessing relevance of SNS-sourced requirements in a case study.

The driving force behind incorporating multi-criteria based relevance verification feature as part

of the proposed framework is, to utilize various stakeholders' parameters like organizational goal, related service datasets, and users input from the SNS platform, which will be used in the evaluation algorithms for the framework's implementation.

Concerning organizational goals, the framework utilizes business objectives, rules, and the application's TOR as initial requirements to focus on relevant data, serving as a controlling mechanism to verify and align users' needs from SNS with those of organizational goals. Besides, such goals are assigned to software agents to analyze the frequency of user interactions, providing a comprehensive understanding of user preferences [17].

As for related services, the framework considers the reusability of existing proven service requirements and corresponding datasets to validate user requirements and confirm that they meet stakeholder needs. Moreover, existing service features help to filter contextually related requirements from SNS platforms. Service Oriented Architecture based features expedite better alignment between software systems and business processes and can support software development processes in dealing with limitations of traditional relevance verification of requirements [18].

Such service features enable the integration of new requirement features into the run time of the users' need accumulator interfaces. This causes the initial requirements on the application's terms of reference (TOR) to vary during the fetching of user needs from SNS, necessitating continuous verification of specified requirements to account for these variations. Additionally, a web service can be employed to aggregate user requirements from diverse sources like surveys, instant messages, and SNS interactions, allowing for a comprehensive perspective of the user requirements relevance verification process.

Hence, the study investigates the importance of assessing requirements relevance across various dimensions to ensure analysts deliver solutions that meet user needs and enterprise demands, alleviating stakeholder disappointment and project failure. Therefore, the proposed conceptual framework strives to measure the relevance of user requirements' sourced from SNS using specified varied parameters. Accordingly, as part of the framework's evaluation process, the research examines a hybrid text representation and data filtering methods comprising natural language processing (NLP), machine learning, data analytics, and clustering algorithms.

Such learning and analytical models are required, as exploitation of traditional methods for addressing issues in requirements sourced from SNS is challenging due to the vast features of users' needs [18]. NLP techniques reduce verification effort by preprocessing user needs and measuring sentiment. A machine learning model will be trained on a corpus to create word embeddings and detect semantic concepts. A clustering algorithm is used to group related requirements together for categorization. Works by Sonbol et al. [19] demonstrated clustering algorithms and NLP techniques in supporting RE verification processes, while text mining and usage mining techniques detect user attitudes [20]. A. Perini, et al. [21] have discussed how machine learning algorithms aid in analyzing the relevance of users' needs.

The study's boundaries are evident in various facets. In terms of content analysis, the study analyzes text content shared by users on SNS to identify themes and recurring issues. It compares user needs across different groups on one platform to identify common themes. Regarding verification through multiple criteria, cross-referencing SNS data with other sources like organizational goals, related service dataset and feedback forms helps verify the relevance of identified needs. The study ranks user needs based on frequency, harmonization with app features, and potential business impact.

The main contributions of this study include providing a multi-criteria intelligent framework for validating the relevance of SNS-sourced requirements, offering an algorithm for examining relevance of SNS-sourced requirements, delivering information on a case study that complies with stakeholders' needs and expectations, assisting system analysts to detect problems early in the development life-cycle, and facilitating the creation of reliable software products. The research also streamlines and aids in addressing the issues of context dependency that arise during fetching and analyzing essential insights regarding users' needs.

The study is also designed to contribute to related academic researches by presenting a scalable method to recognize user needs in a dynamic environment. Furthermore, the experimental case study validates the conceptual framework, motivating other researchers to apply the model to another case study. Moreover, the study can be extended to verify the relevance of requirements for groups of software products that share a set of features, such as software product lines. Enhancements of the study also suit systems

designed based on dynamic policies for software requirements and predicting software shortcomings.

The rest of the study is structured as follows. Section 2 discusses related works in brief. The proposed method will be described in Section 3. Results and findings are then presented in Section 4. Discussion, recommendation and limitations will be specified in Section 5. Finally, conclusion and future outlooks will be stated in Section 6.

2. RELATED WORKS

This section investigates related works on the topics of verifying relevance of requirements sourced from SNS using performance indicators, business goals, business rules, related service datasets, pre-processing, and text representation methods. To the best of our knowledge, previous studies have not utilized a multi-criteria approach to assess the relevance verification of requirements derived from SNS.

In terms of organizational objectives and application's TOR, the study by Hafiz M et al. [22] highlights the importance of understanding user needs from customer feedback and aligning them with performance indicators for organizational success. This approach leads to higher product adoption and improved customer satisfaction. The authors used a factor-wise reliability approach for validating feedback, but the study has limitations, including data being gathered from a single Pakistani zone rather than multiple zones, and usage of only one verification method without comparing it with other verification methods.

Liming et al. [23] underlined the importance of confirming users' needs in SNS and their alignment with business requirements. The researchers conducted a survey by incorporating system analysts to identify requirements regarding knowledge sharing. They have utilized partial least squares method for model verification. Their findings showed a positive relationship between functional requirements and perceived social media, but a weak association between non functional requirements and perceived social media to assist knowledge sharing.

Seyff et al. [24] analyzed 2215 user comments from SNS and found that 61.5% of user comments were relevant to enterprise business requirements, emphasizing the potential of analyzing business goals and rules for validating users' needs in SNS. The authors conducted three experiments to explore the impact of SNS on requirements analysis processes. Their findings showed that popular platforms like Twitter and Face-book may support

these processes. However, the survey is restricted to college students, potentially excluding other prospective users.

M. Krisperre et al. [25] emphasizes the significance of considering the "what" and "why" of a system in initial requirements, along with business goals and objectives, to comprehend its purpose and gain a comprehensive understanding of a user's perspective. The authors discussed that aligning this approach during SNS-based requirement gathering helps verify the relevance of users' needs. Moreover, the researchers have utilized the proposed method to identify requirements for an organizational information system, with a tool support which is suitable for the model but has not been thoroughly tested on multiple case studies.

Veerendra [26] discusses the importance of initial requirements for project success, creating a structural model using business actors and generating high-level rules based on scenarios and use cases. The study is augmented by a mini prototype to verify the relevance of users' comments and assist in knowledge acquisition. The study explores the use of mobile app store reviews to verify requirements sourced from SNS platforms and examines the correlation between summary of product descriptions and software requirements specifications in eliciting SNS-sourced user requirements. Despite receiving ample app review input, the study didn't prioritize user requirements based on the app review description.

In relation to the role of SNS in the extraction and verification of users' needs, Guzman et al. [27] conducted an investigation on categorizing and ranking tweets for software evolution using Twitter as a platform and customized classification algorithms for model verification. The specified method is identified as capable of categorizing tweets automatically into improvement request and new feature request. However, the research did not reflect on the effect of utilizing multiple criteria, additional case studies, and multiple platforms to heighten the findings.

Eduard et al. [28] discussed the impact of crowd-sourcing on stakeholder discovery and the difficulty in identifying relevant users' needs in complex systems. The study recommends a participatory approach to identify relevant stakeholders and suggests solutions to overcome challenges in verifying the relevance of requirements in SNS. The authors have also detailed the challenges of validating software in a dynamic context, highlighting the unpredictable nature of software requirements.

In relation to inadequate verification of users' needs sourced from SNS, WaiShiang et al. [29] discuss the challenges of rapid prototyping without verification of users' comments and domain understanding due to the rapid expansion of mobile devices and SNS. They propose a modeling approach that leverages business objectives to overcome the lack of domain knowledge and recommend it as future work for verifying the relevance of users' needs fetched from SNS. The authors have also advised developers to utilize SNS, such as Twitter, to stay informed about industrial and technological changes, and to remain aware of the relevance verification process of SNS-sourced requirements.

With regard to the influence of related services in filtering contextually correlated users' needs, Bano and Ikram [30] explore dynamic service discovery, paying attention to its impact on understanding new systems, verifying user needs, and correlating with available services. Muneera and Naveed [31] emphasize the challenges of identifying suitable services and suggest that the integration of a knowledge management concept in the service discovery process enhances the effectiveness of verification of system requirements. Pablo Marti et al. [32] discuss the challenges and opportunities of SNS in urban studies, emphasizing the lack of consistency in data specification and potential bias of requirement information due to social, economic status, and education.

Cody Butain et al. [33] compared traditional survey and social media-based approaches to understand users' need analysis issues, assessing their respective roles in determining the relevance of requirements and comparing their similarities and differences. The authors discovered that despite SNS-based data being a significant source of user-generated content and sentiments, it suffers from quality issues due to unrelated user responses. They applied NLP algorithms to clean the data and performed sentiment analysis and topic modeling to identify frequently discussed issues. Nada Sherief et al. [34] highlighted the challenges of precision and ambiguity in SNS-sourced user needs due to informal natural language use. They proposed NLP algorithms to overcome these issues and show that a knowledge base aids in maintaining the correctness feature of requirements based on users' need analysis. Joni Salmin et al. [35] designed a method to detect fake reviews from users' needs relating to online products using a universal language model, classifier algorithm, and Amazon e-commerce dataset. They have suggested that

implementing a prototype testing method ensures the relevance of user needs and facilitates the integration of resulting specifications in future product versions.

Therefore on one hand the specified researches indicate that integrating existing related service features can enhance alignment between business requirements and software systems, ensuring relevance and compliance with related service functionalities. On the other hand, using business goals as a performance indicator aids in detecting relevant requirements within an organization. Hence, the proposed research aims to develop a model that balances business goals, rules, and related service datasets to verify the relevance of requirements sourced from SNS. In doing so, it examines the impact of multi-attribute dynamic verification of requirements in SNS compared to traditional approaches, as no research has focused on dynamic relevance verification of requirements with multiple criteria.

3. RESEARCH METHODOLOGY

The research methodology for this study employs a research strategy, discussion of related works, data collection and analysis, and the establishment of a conceptual framework. It also creates an experimental case study and customizes word embedding models for practical suitability and evaluation of the conceptual framework.

3.1 Research Strategy

The study investigates relevance verification of requirements derived from SNS using multi-criteria parameters, including organizational goals, business rules, and related service datasets. It evaluates how this approach optimizes the relevance verification of requirements by utilizing individual criteria. Consequently, after assessing the research intention and the problem nature, an empirical research methodology for software engineering is proposed [36]. This methodology is regarded for its ability to establish a convenient framework for implementing interaction-focused methods, intended for verifying the relevance of requirements [37].

The proposed methodology combines qualitative and quantitative methods, using a qualitative method for evidence collection, analysis, and formation of a conceptual framework. Furthermore, a quantitative method is utilized for framework evaluation. Accordingly, the methodology flowchart for the study is illustrated in Figure 1.

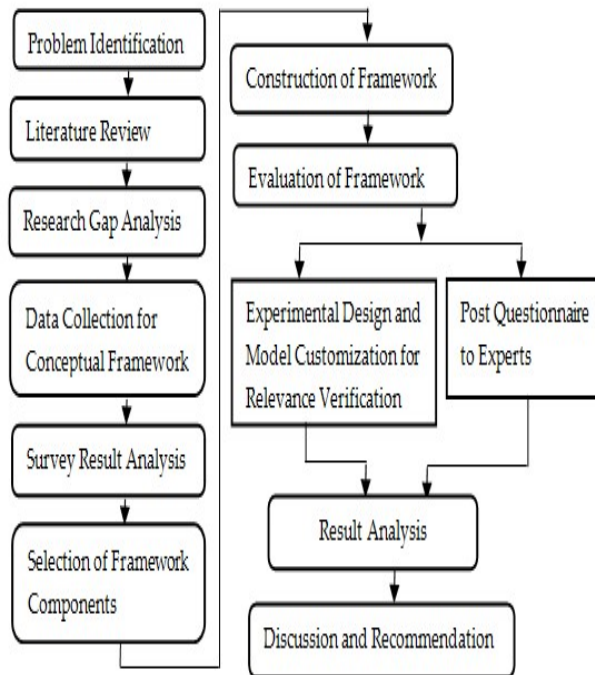


Figure 1: Methodology Flowchart for the Study

3.2 Expert Survey to Get Insight on the conceptual Framework

The study aims to fill a research gap in verifying the relevance of requirements sourced from SNS. In order to gather insights about the development of a conceptual framework, an expert survey that aligns with research questions and objectives is used, involving participants from universities and software development companies selected for pertinent input. The survey, created using the Survey Legend Form Generator [38], consists of 20 multiple-choice questions on a 5-point Likert scale (Table 8, Appendix A). The survey was distributed to 72 experts from five software development companies and three universities in “Addis Ababa”, Ethiopia. The educational status of respondents is 40% first-degree, 35% master's level, and 25% PhD level. The majority of respondents were over 37 years old, with extensive experience in industry and institutions. Nearly 60% of the respondents had worked for more than 7 years, indicating a broad knowledge of software development in industry and academic environments. Both online and in-person survey types were used to accommodate participants' adaptability.

3.3 Expert Survey Results

A survey, conducted to assess the design of a framework for verifying the relevance of user needs

from SNS, revealed that 58% of respondents strongly agreed and 31% agreed that integrating organizational business objectives in the framework would facilitate relevance verification. 85% agreed that using concepts from related service datasets would also facilitate the relevance verification process. 87% of respondents believed that the relevance check process would ensure consistency of extracted requirements. Only 3% agreed that introducing multi-criteria-based verification would create difficulty in the relevance verification process. Most respondents (88%) recommended that comparison with related research helps to ensure certainty. Overall, the survey results highlight the importance of incorporating organizational business objectives, rules, and related service datasets in the relevance verification process.

3.4 Conceptual Framework

This section details the creation of a novel conceptual model based on survey results from Section 3.3 and informal meetings with professionals. Key features like research objectives, scope, input, output, research questions, and literature review assessment were investigated. These components were then integrated into a draft logical model, thus creating a high-level framework as shown in Figure 2.

3.5 Explanation of the High-Level Framework

The framework, based on business goals, rules, and related service datasets, aims to provide an understanding of the relevance verification of users' needs sourced from SNS. Key parts of the framework are illustrated in Figure 2, with further clarifications provided in subsequent discussions.

3.5.1 Data collection component

The data collection component of the framework retrieves user comments from a GUI integrated with the SNS platform and creates datasets containing requirements-related features from related services and organizational business goals. It then employs preprocessing and keyword extraction methods for further analysis.

3.5.2 Text preprocessing function

The text preprocessing function removes connectors and normalizes input data by turning it into lower cases and capitalizes texts using lemmatization. This reduces ambiguity, improving user requirements clarity by transforming words like 'validate', 'validating', and 'validated' into their root form [39].

3.5.3 Hybrid text representation method

This component constitutes a model that uses preprocessed business goals and related service corpus, in order to construct word embeddings and detect semantic relationships with adjacent texts. This model is necessary, as utilizing only text representation models favors semantic relationships and lacks a feature for recommending the most relevant key phrases to a document. By combining both key phrase extraction and semantic correlation outcomes, the model facilitates the relevance verification process.

3.5.4 Relevance verification component

This part of the framework verifies the relevance of requirements from SNS by analyzing their relationship with user needs. Three test cases are prepared to ensure that these requirements meet both users' and organizational needs.

The first case analyzes the relevance between initial requirements (business goals and rules) and user needs. The second case examines the relevance of reused service features and user comments. With the intention of optimizing the relevance rate, the third case combines datasets utilized in test cases 1 and 2 and explores their relevance with user needs.

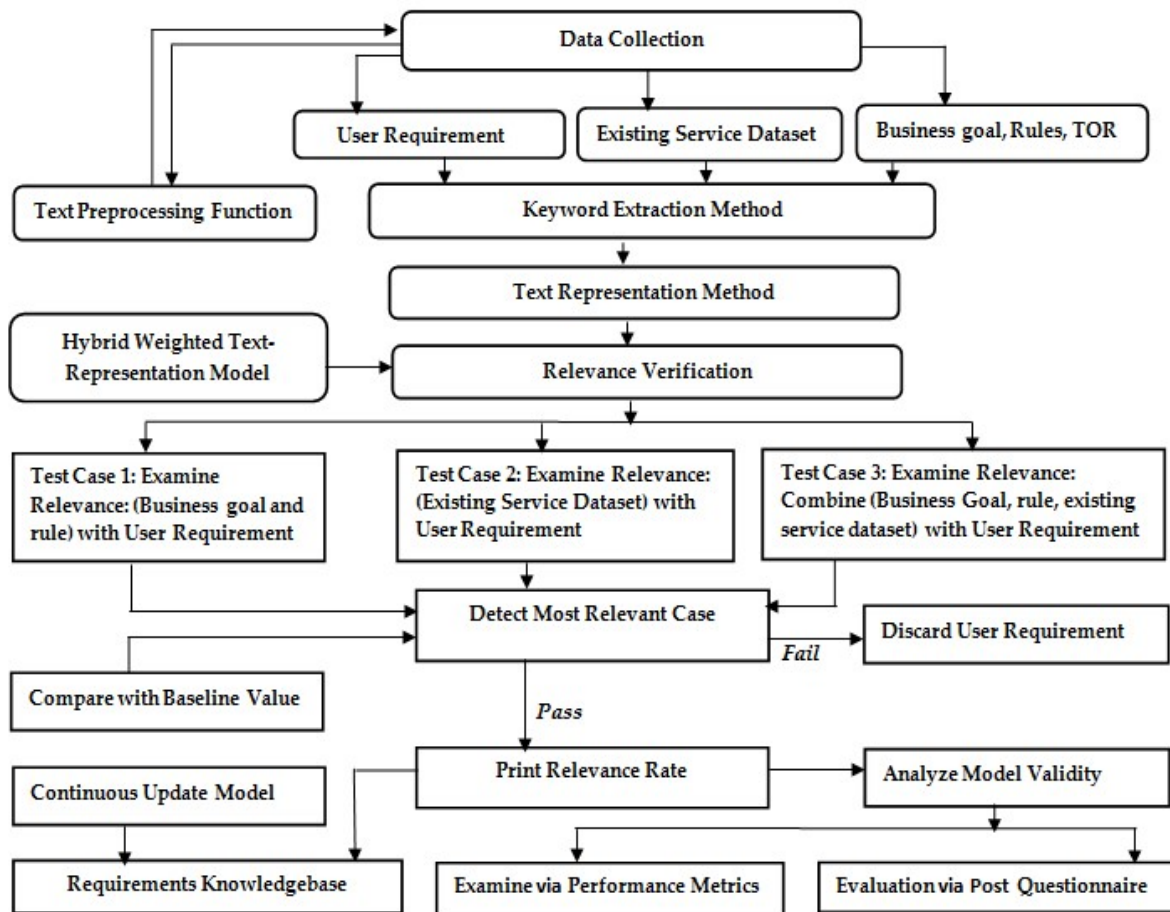


Figure 2: High-level Framework for the Proposed Research

3.5.5 Detect most relevant case component

The data collection component of the framework retrieves user comments from a GUI integrated with the SNS platform and creates datasets containing requirements-related features from related services and organizational business goals. It then employs preprocessing and keyword extraction methods for further analysis.

3.5.6 Print relevance rate component

This component is responsible for displaying the relevance rate information. Moreover, it consists of the requirement knowledge base sub-component and analyze model validity sub-component.

3.5.7 Continuous update model

This part of the framework is dedicated to accomplishing a dynamic feedback mechanism to

allow continuous learning from new user inputs. To this effect, the model will stay updated and adapt to changing user needs, business goals, and related service datasets.

4. MODEL EVALUATION, EXPERIMENTS AND RESULTS

This section presents an approach tailored for the evaluation of the proposed framework, focusing on addressing significant key phrases and semantic relationships between words in a corpus. It uses a correlation and verification procedure to assess users’ requirements sourced from SNS, with regard to organizational goals and related service datasets.

An algorithm design is presented for further understanding of the framework's logic and facilitating experimental analysis. An experimental case study is covered, followed by data analysis, results, and findings. Moreover, a post-questionnaire to experts is conducted for triangulation. Additional experimental analysis is also performed relative to an algorithm for categorizing requirements.

4.1 Text Representation Method

The conceptual framework discussed in Section 3.4 requires implementation and validation using a customized word embedding model for addressing significant words and semantic relationships in a corpus, and an algorithm design for prototype implementation. The customized model combines Tf-Idf and word2Vec to create a weighted Word2Vec. This model is examined for various reasons, including emphasizing vital terms in the business goals and related service datasets, identifying semantic concepts from users’ comments, assessing corpus size, and blending methods to achieve the best possible outcome.

4.1.1 Tf-Idf weighted Word2Vec

Tf-Idf (term frequency-inverse document frequency) is a statistical computation that measures the relevance of a word to a document in a set of documents [40]. The computation involves multiplying a local component (Tf) with a global component (idf), where Tf represents the word's frequency in the document and idf scales the value by its rarity in the corpus. Tf-idf is calculated as follows:

$$Tf = \frac{NTTD}{TNTD} \tag{1}$$

Where, NTTD=Number of times a term appear in a document, TNTD=Total number of terms in a document.

$$Idf = \log \left(\frac{NDC}{NDCT + 1} \right) \tag{2}$$

Where, NDC=number of documents in the corpus, NDCT=number of documents in the corpus containing the term.

$$\text{Then, } Tf\text{-}Idf = Tf * Idf \tag{3}$$

Word2Vec [41] converts words into vectors and generates word embeddings, detecting semantic relationships with nearby texts. The meaning of a word is based on its context, including words before and after it. In Word2Vec representation, a dictionary comprises a list of words in the corpus, such that, D: {W1, W2, W3 ... Wn}. Then, a vector representation of a word is given in a way that 1 denotes the position where the word exists and 0 anywhere else. So, the vector representations of all the words in the dictionary are:

$$W_1: [1, 0, 0, 0 \dots 0, 0, 0], W_2: [0, 1, 0, 0 \dots 0, 0, 0], \\ W_3: [0, 0, 1, 0 \dots 0, 0, 0] \dots W_n: [0, 0, 0, 0 \dots 0, 0, 1]$$

So, the actual word representation is emanated from the matrix used in the model. The dimension of the matrix eventually is established in such a way that its dimensions will be VxY, where V is the number of words in the corpus, and Y indicates the dimension of the vector for each word Wi. The Tf-Idf model, which lacks a semantic relationship between words, is used along with word2Vec, which addresses semantics but cannot fully differentiate between significant words in a corpus. Tf-Idf value is used to weight the vector after the word2Vec model is adopted. Researchers also suggest as a future work that, a word representation blending word2Vec and Tf-Idf could yield more effective output than individual vector representations in NLP operations [42]. The vector of text Ti, realized by the Tf-Idf weighted word2Vec model, is illustrated in formula 4 as shown below:

$$Weight_R(T_j) = \sum_{i=1}^n word2Vec(w_i) \times (Tf - Idf_{ij}) \tag{4}$$

Where n is the total number of words in the text Tj. The word2Vec values are multiplied by the correlated Tf-Idf values, and sum up in order to acquire the weighted word2Vec values of the specified text. R is a weighted sum function for vector values in R programming [43].

4.2 Algorithm Design

The algorithm, based on the conceptual framework notion and the discussion regarding weighted word2Vec is detailed in Algorithm 1 (Appendix B), and is designed to facilitate experimental analysis and associated mini

prototype for conducting the experiment. The procedure for analyzing user needs in the case of individual criteria involves adjusting the number of parameters in Algorithm 1 (Appendix B). That is, the specified algorithm is customized to check the relevance between users' comments and business goals, as well as between users' comments and related service datasets. Similarly, algorithms for requirements categorization and continuous update model are detailed in Algorithm2 (Appendix C) and Algorithm3 (Appendix D), respectively.

4.3 Experimental Design

This section details the datasets and features for the proposed text representation model and the algorithm used in the experiment. Then, data pre-processing procedures are presented, and a demo mini prototype is designed for evaluation. Hence, comparisons are made to evaluate the conceptual model and analyze experimental results. The experimental case study has been conducted on digital healthcare systems in developing nations, specifically, the "CMC General Hospital" in Ethiopia, a private hospital aiming to enhance patient care and healthcare efficiency. The hospital currently uses a partially automated system for routine duties and plans to deploy integrated software to handle several tasks. The hospital outsources a software development company, "Make Enterprise", to provide an "Online Digital HealthCare System".

To this end, the company plans to gather user requirements through the SNS platform and verify their relevance, indicating that the proposed framework is found suitable for the specified case study in facilitating the process of verifying the relevance of SNS-sourced needs. Data for the experiment was collected from documents such as organizational business rules, objectives, TOR, and service datasets related to online digital health care systems. After pre-processing, the files were sent to a comma separated values (CSV) file for further processing.

4.3.1 Data pre-processing

The research focuses on data pre-processing for cases, such as organizational business goals, rules, application's TOR, related service datasets, and user needs from the prototype's GUI. Split (), lemmatize (), and to lower () operations are used in the pre-processing. Additionally, core feature selection is performed using NLP methods like "RAKE_NLTK", and "Text Rank API", along with string operations like read (), compare (), and intersection().

Detailed code implementation is available at: https://github.com/mekugit/digital_healthcare_code. The study also focuses on pre-processing user needs for the prototype of the specified hospital. Users have been given information about the local hospital, "CMC General Hospital", and comments were gathered from participants working in various hospitals. Following a brief brainstorming session and discussion forum invitation, respondents were invited to participate for a period of three weeks. Then, users' needs were exported to a CSV file after they had been fetched from the GUI, as shown in Figure 3 (Appendix E). The Tf-Idf is computed to determine user intention and assign more weight to texts stored in the CSV file. Consequently, the word2Vec model is trained with business goals and related service datasets, and the Word2Vec values are multiplied by the correlated Tf-Idf values to obtain weighted Word2Vec values of texts. This helps identify the most relevant words to the document and understand the semantic relationship between words in the document.

4.3.2 Prototype demonstration

The pseudo-code in Algorithm 1 (Appendix B) was tested in a demo prototype for a case study, performing tasks like fetching, preprocessing, and analyzing user needs. The prototype verified the relevance of user needs with initial requirements, existing service datasets, and a combined feature dataset. The web-based GUI (Appendix E) was integrated with Twitter [44], gathering comments from a group of medical professionals in "Addis Ababa", Ethiopia.

4.3.3 Data analysis

In order to undertake a data analysis, an experimental demonstration has been conducted to gather 800 users' needs from a GUI, Figure 3 (Appendix E). Moreover, 540 and 900 key phrases have been extracted from initial requirements (business goal and TOR) and related service datasets, respectively. Then, the demo mini prototype was tested using algorithm1 (Appendix B) to verify the relevance of requirements.

Accordingly, three categories of data analysis were conducted, focusing on the effect of business goals on detecting relevant users' needs, the impact of related service datasets on extracting relevant users' needs, and the concatenation of business goals and related service datasets in comprehending relevant users' requirements. The results and findings of the data analysis are demonstrated in Section 4.4.

4.4 Results

The study emphasizes the importance of verifying the relevance of requirements, in order to assess users’ needs derived from SNS platforms. A practical demonstration indicates that it is possible to achieve relevance between users’ needs, existing related service datasets, and initial requirements (business goals and TOR). Table 1 reveals a 76% relevance rate when comparing existing service datasets with users’ needs, 81% when analyzing business goals and TOR with users’ needs, and 88% when combining business goals, TOR, and existing service datasets with users’ needs, indicating that a combined approach offers the highest relevance verification rate.

Table 1: Relevance verification of requirements for the three comparison types

S. N	Comparison Type	Model	Requirements Relevance Rate
1	Related services dataset, with users’ need	ww2Vec	76%
2	Business goal, with users’ need	ww2Vec	81%
3	Concatenation of business goal and related service datasets, with users’ need	ww2Vec	88%

Figure 4: shows that the combined approach outperforms individual cases in relevance verification analysis, with a higher relevance rate.

This outcome is achieved because the novel consolidated approach balances the relevance of SNS-sourced requirements with organizational interest and related service datasets, compared to individual approaches. Moreover, the weighted word2Vec, which uses word importance and semantic meaning, detects relevance between SNS-sourced requirements and the specified test cases.

As the number of users’ needs increases, the number of common key phrases tends to increase as well, even when respondents send their suggestions in divergent ways.

4.4.1 Relevance verification of users’ need by exploiting related service datasets

To verify and enhance the pertinence of users’ needs sourced from SNS, the existing service dataset is considered as part of the test cases in the relevance verification process. A partial dataset from Azizi et.al [45] and IDS Online [46] is harnessed. A study of 800 users’ needs relating to

900 requirements in the related service dataset corpus is performed.

Consequently, the corresponding association is evaluated, and based on the experiment, 76% relevance of users’ needs with the existing service dataset is obtained.

4.4.2 Relevance verification of users’ need by using initial requirements (business goal, rule)

In this category, the study evaluates the relevance of SNS-sourced users’ needs concerning initial requirements. Such requirements are formulated from features, extracted from business rules and objectives. An analysis of 800 users’ needs relating to 540 initial requirements was conducted, and 81% relevance was achieved, depicted in Table 1. The relevance verification process, utilizing enterprise goals and objectives, is better than leveraging related service features as it ensures that business rules are influential in originating expectations and aligning with business specifications.

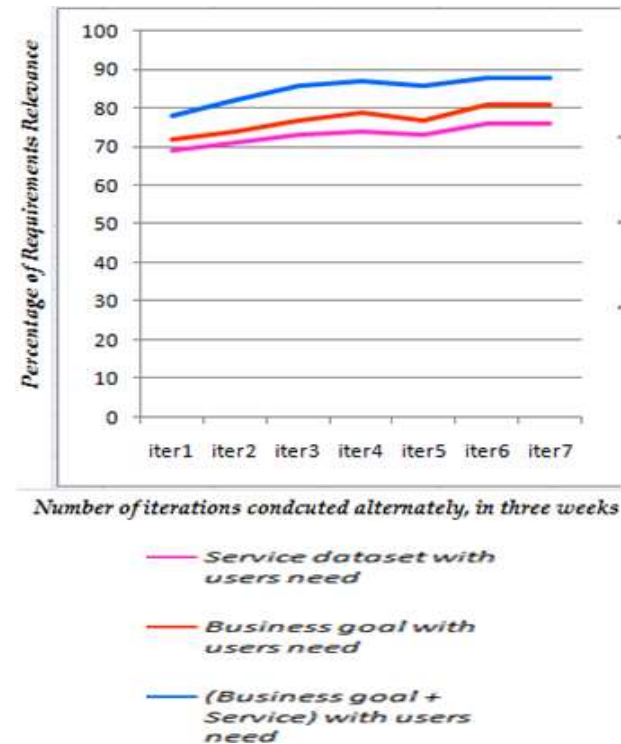


Figure 4: Relevance rate between the three test cases.

4.4.3 Relevance verification of users’ need by combining service datasets and business goal

In this category, the study employs a combined approach of initial requirements (organizational goal and TOR) and related service datasets to improve the relevance verification process of users’ needs. After analyzing 800 users’ needs relating to 1440 requirements generated from initial

requirements and related service datasets, the combined approach achieved 88% relevance as shown in Table 1. Figure 5 also illustrates the

average relevance rate for verification of users' needs in utilizing the combined approach. The experiment is tested and presented in Python.

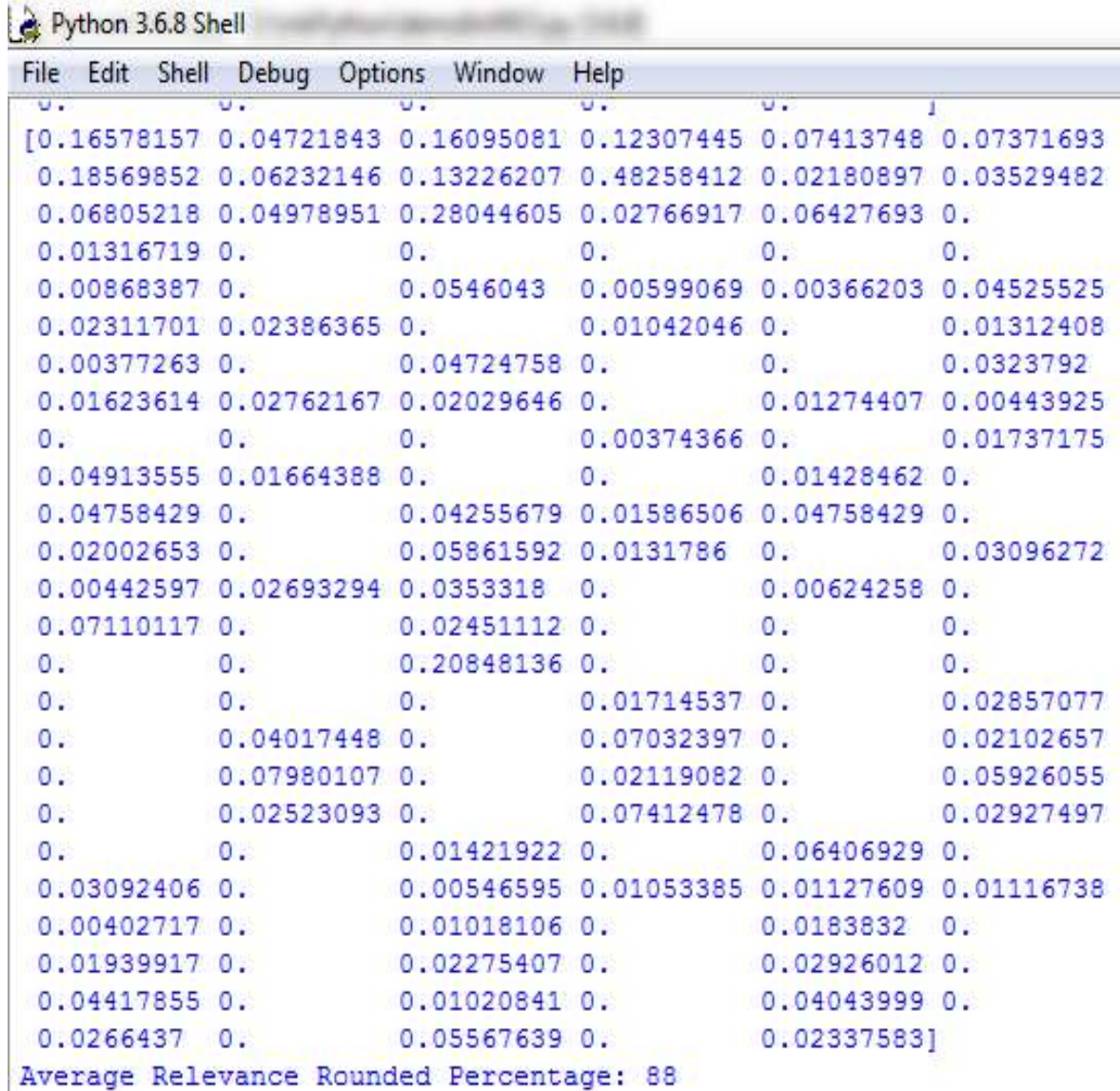


Figure 5: Average relevance score for verifying users' needs by utilizing the combined approach

4.4.4 Some highlights on sample relevance verification of users' needs in the experiment

Table 2 shows that the combined approach performs better than individual approaches in most sample requirements, with a maximum relevance rate of 0.92 for requirement number 8. However, a minimum relevance rate of 0.69 is observed for requirement number 9. Moreover, an average relevance rate of 0.72 is detected for requirements 1, 5, 12, and 15.

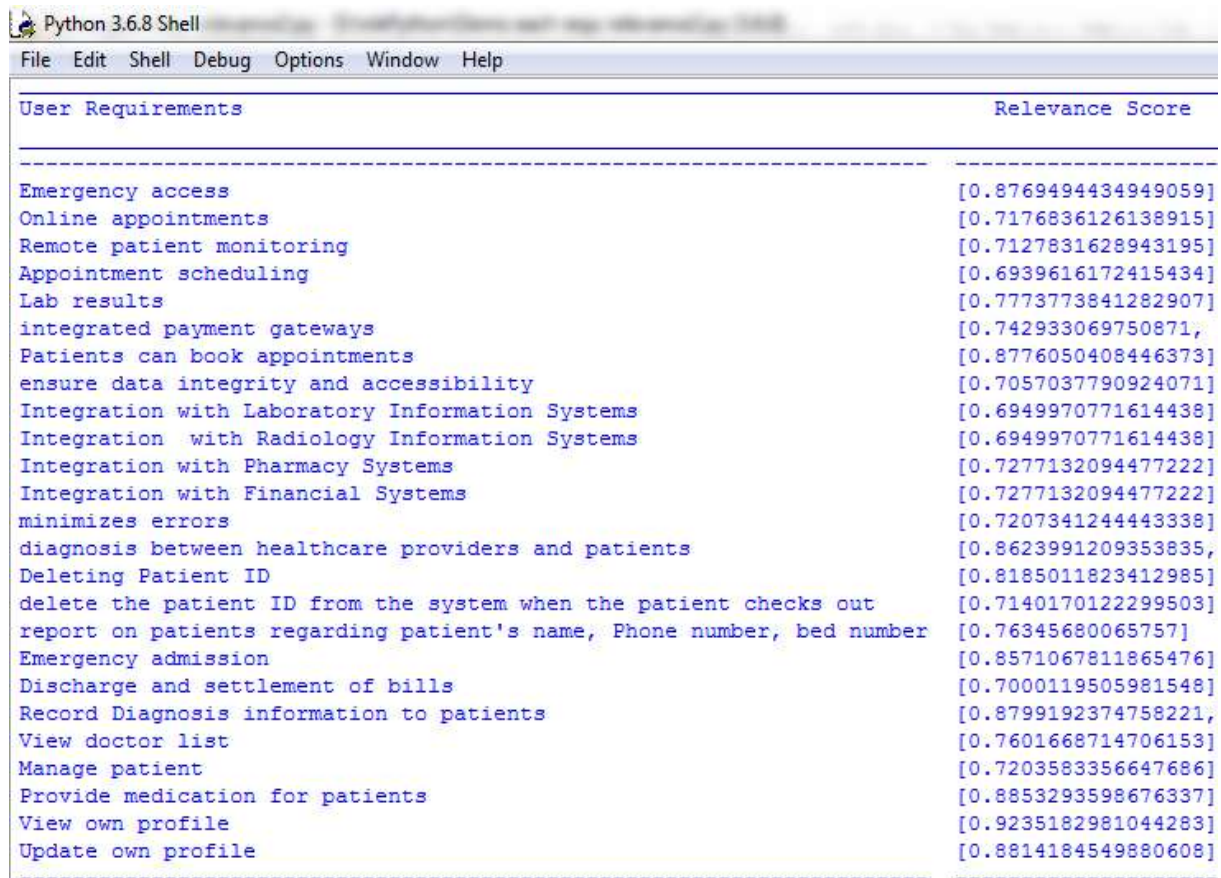
Some user requirements have similar relevance rates in initial requirements and related service

datasets, such as "Easy access to my medical records" with requirement number 6. However, there are discrepancies in the same requirements, such as the difference in relevance rates for requirements 1 and 12 in the business goal column, suggesting that users prefer "book appointment" over "online appointment".

Such related requirements will be clustered and categorized in Section 4.9, to facilitate better management and prioritization.

Table 2: Sample relevance verification result of users' needs in the three approaches

R.No	Users' requirements	Business goal and rules	Related Service Dataset	Business goal, rule and Service dataset
1	Online appointment capability	0.54	0.48	0.72
2	Ensure data integrity	0.55	0.47	0.70
3	Diagnosis among healthcare providers and patients	0.56	0.52	0.86
4	Display lab results and profile information	0.57	0.53	0.77
5	Verify insurance for payment	0.49	0.44	0.72
6	Easy access to my medical records	0.47	0.47	0.87
7	Tele-health to speak with my doctor	0.56	0.49	0.71
8	The system should help me track my medications	0.48	0.46	0.92
9	Notifications for my upcoming appointments	0.46	0.44	0.69
10	Integration with wearable devices for health tracking	0.52	0.48	0.70
11	Want to see list of doctors working in the hospital	0.54	0.51	0.76
12	I want to book appointments	0.49	0.48	0.72
13	Tools to access services, monitor and assist myself	0.58	0.52	0.84
14	Easy to understand reporting features	0.56	0.50	0.76
15	Integrate payment with bank and insurance	0.58	0.48	0.72



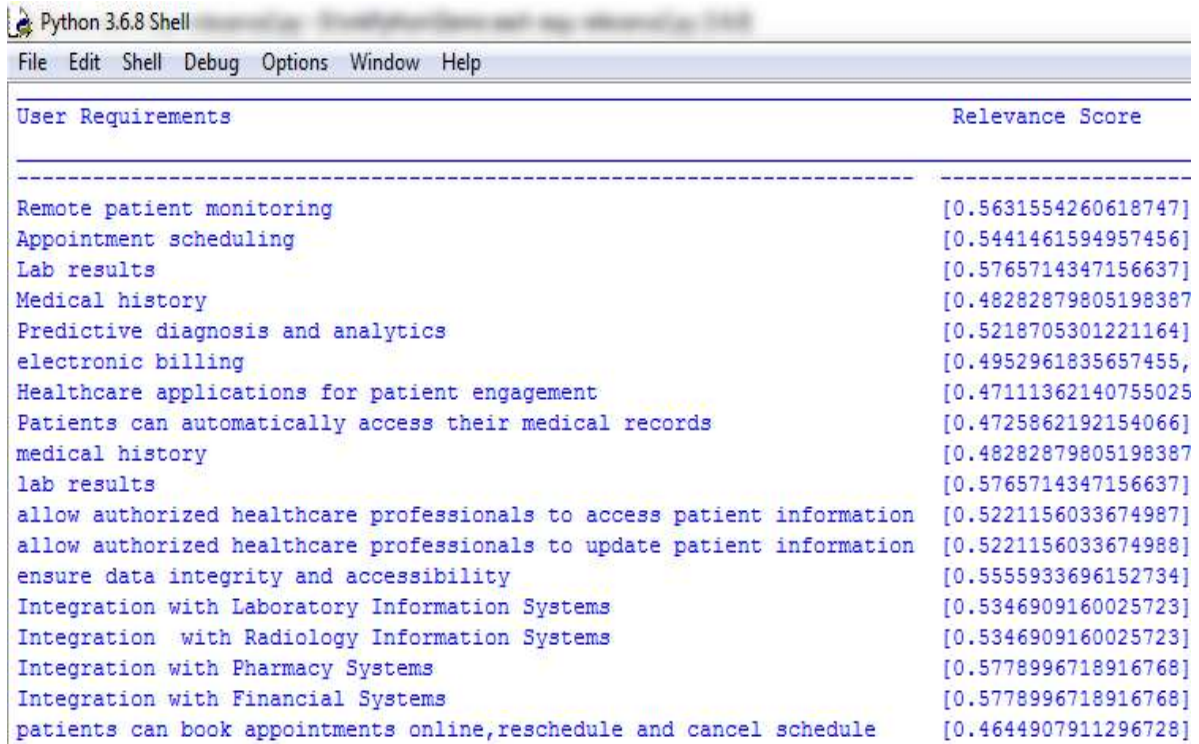
```

Python 3.6.8 Shell
File Edit Shell Debug Options Window Help
User Requirements                                     Relevance Score
-----
Emergency access                                     [0.8769494434949059]
Online appointments                                  [0.7176836126138915]
Remote patient monitoring                            [0.7127831628943195]
Appointment scheduling                               [0.6939616172415434]
Lab results                                          [0.7773773841282907]
integrated payment gateways                         [0.742933069750871,
Patients can book appointments                       [0.8776050408446373]
ensure data integrity and accessibility              [0.7057037790924071]
Integration with Laboratory Information Systems      [0.6949970771614438]
Integration with Radiology Information Systems      [0.6949970771614438]
Integration with Pharmacy Systems                  [0.7277132094477222]
Integration with Financial Systems                  [0.7277132094477222]
minimizes errors                                    [0.7207341244443338]
diagnosis between healthcare providers and patients [0.8623991209353835,
Deleting Patient ID                                 [0.8185011823412985]
delete the patient ID from the system when the patient checks out [0.7140170122299503]
report on patients regarding patient's name, Phone number, bed number [0.76345680065757]
Emergency admission                                 [0.8571067811865476]
Discharge and settlement of bills                   [0.7000119505981548]
Record Diagnosis information to patients            [0.8799192374758221,
View doctor list                                    [0.7601668714706153]
Manage patient                                      [0.7203583356647686]
Provide medication for patients                    [0.8853293598676337]
View own profile                                    [0.9235182981044283]
Update own profile                                  [0.8814184549880608]
    
```

Figure 6: Sample users' needs with relevance rate for the combined approach

Figure 6 and Figure 7 show the relevance of users' requirements using combined and individual criteria, respectively. For instance, emergency access is not considered a vital requirement concerning the utilization of individual approach as criteria, but it is important regarding combined approach, with a relevance rate of 0.87. Integration with various organizational sections, such as

finance, laboratory, pharmacy, and radiology, is indicated in the combined approach, whereas it is not detected in the relevance requirements analysis employing individual criteria. Online appointment-related requirements are found in the combined approach, with a relevance rate of 0.72, compared to 0.54 in the business rules base relevance analysis.



User Requirements	Relevance Score
Remote patient monitoring	[0.5631554260618747]
Appointment scheduling	[0.5441461594957456]
Lab results	[0.5765714347156637]
Medical history	[0.48282879805198387]
Predictive diagnosis and analytics	[0.5218705301221164]
electronic billing	[0.4952961835657455,
Healthcare applications for patient engagement	[0.47111362140755025]
Patients can automatically access their medical records	[0.4725862192154066]
medical history	[0.48282879805198387]
lab results	[0.5765714347156637]
allow authorized healthcare professionals to access patient information	[0.5221156033674987]
allow authorized healthcare professionals to update patient information	[0.5221156033674988]
ensure data integrity and accessibility	[0.5555933696152734]
Integration with Laboratory Information Systems	[0.5346909160025723]
Integration with Radiology Information Systems	[0.5346909160025723]
Integration with Pharmacy Systems	[0.5778996718916768]
Integration with Financial Systems	[0.5778996718916768]
patients can book appointments online, reschedule and cancel schedule	[0.4644907911296728]

Figure 7: Sample users' needs with relevance rate for the individual approach

4.4.5 Irrelevant words detected in each iteration and associated irrelevance rate

In addition to undertaking a practical demonstration to show how the combined approach outperforms the individual criteria approach, the study aims to conduct a performance using precision, recall, and F-measure metrics. It has been conducted in seven iterations within three weeks, learning and verifying correct and incorrect phrases. The process of detecting irrelevant key phrases from 2400 emerging key phrases is detailed in Table 3.

In the process of undertaking data analysis, irrelevant words in the initial level are high, but as iteration increases, the amount decreases due to declining users comment and the model also learns from previous iterations. The combined approach detects fewer irrelevant words due to its high relevance rate, and in the last iteration, irrelevant words become insignificant as the possibility of obtaining new emerging keywords diminishes, indicating a constant growth. The total irrelevant words on the "ith iteration" are computed using the following formula.

$$Total_irrelevant_words(i) = [\sum_{k=1}^i Total_words(k)] \times (100 - relevance_rate(i)) / 100$$

(5)

where, i=iterations: 1, 2, 3,.....7, and K=1,2, ... i

Table 3 shows that the detection of new irrelevant keywords decreased in the last two iterations, due to a decrease in the size of newly emerging key phrases. This decrement is proportional to the size of new key phrases in users' need, indicating a decrease in the introduction of new key phrases compared to the first and second iterations. In addition, an analysis of average irrelevant key phrases is presented in Table 3 for

the three cases: related service datasets, business goals, and a combination of related service and business goals. The average irrelevant key phrases in each case are (452, 379, 239), resulting in a 19%, 16%, and 10% irrelevance rate over seven iterations, respectively. Thus, the proposed approach improves verification of SNS-sourced users' needs by reducing irrelevant key phrases to 10%.

Table 3: Irrelevant key phrases detected in each iteration for the 3 cases (service=s, business goals and rules=b, (s+b))

	Iterations						
	Iter 1	Iter 2	Iter 3	Iter 4	Iter 5	Iter 6	Iter 7
Emerging key phrases per iteration	590	495	430	375	290	160	60
Relevance rate per iteration	(s,b,s+b)	(s,b,s+b)	(s,b,s+b)	(s,b,s+b)	(s,b,s+b)	(s,b,s+b)	(s,b,s+b)
	(69,72,78)	(71,74,82)	(73,77,86)	(74,79,87)	(73,77,86)	(76,81,88)	(76,81,88)
<i>Irrelevant phrases (Service dataset with users need)</i>	183	142	84	81	83	80	79
<i>Irrelevant phrases (Business goal with users need)</i>	165	117	68	47	51	45	44
<i>Irrelevant phrases ((service dataset + business goal) with users need)</i>	130	65	18	15	17	14	12

Figure 8 shows that the irrelevant key phrases rate per iteration decreases for all three cases, but the combined approach has a notably lower irrelevant rate due to its high relevance pace. The irrelevance rate of business goals is also lower than that of existing service datasets, as the test case

capitalizes key performance indicators of the target organization. Though the value is insignificant, there is an unusual relative rise in iteration 5 relative to previous iterations. The reason might be that relatively more contrasting issues have been reflected on that day by respondents.

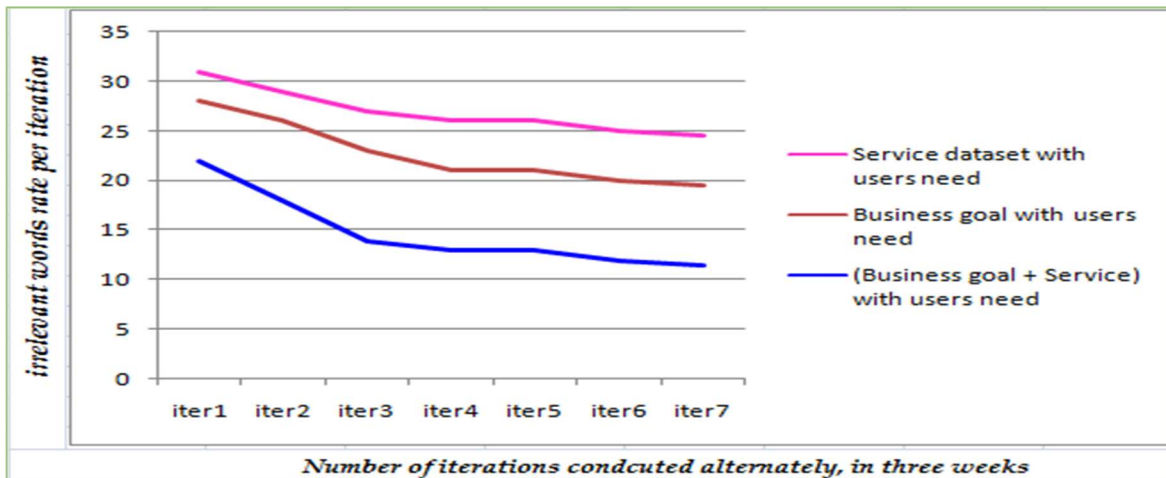


Figure 8: Illustration of irrelevant keywords rate in each iteration.

4.5 Performance Measures for the Model

In addition to demonstrating the effectiveness of the proposed combined approach compared to individual approaches (Section 4.4), the performance of the proposed method is also evaluated using precision, recall, and F-measure metrics. As detailed in Table 3, the model uses 2400 emerging key phrases from participants' comments in seven iterations, learning and verifying 2112 correct and 288 incorrect key phrases by correlating with the 4320 key phrases in the combined dataset, including organizational objectives, rules, and related services.

Correctly predicted keywords are deviated by 48 from half of the combined dataset (that is, 2160). A 1:2 minority-to-majority ratio was considered, with 2160 minority and 4320 majority samples. Subsequently, the true positive value was 2112, the false positive was 288, and the false negative was 48. Consequently, the model's performance was evaluated follows. The variables: True-positive, False-positive, False-Negative, Precision, and Recall are represented as TP, FP, FN, P, and R respectively.

The Precision metrics evaluate the fraction of correctly predicted positive keywords divided by the total number of positive keywords.

$$P = TP / (TP + FP) \tag{6}$$

Therefore, Precision=2112 / (2112+288) = 0.88

The Recall metrics evaluate the fraction of the number of true positives divided by the total number of true positives and false negatives.

$$R = TP / (TP + FN) \tag{7}$$

Therefore, Recall=2112 / (2112+48) = 0.97

The F-Measure metrics are a way to articulate and merge both precision and recall into a single score that exhibits both properties.

$$F1\ Score = (2 * P * R) / (P + R) \tag{8}$$

Thus, F1 Score = (2 * 0.88 * 0.97) / (0.88 + 0.97) = 0.91

Hence, the proposed model demonstrated good precision (0.88), outstanding recall (0.97), and a reasonable and inspiring F1-Score (0.91) in performance metrics analysis.

4.6 Performance Measure of the Proposed Method with Other Classic Metrics

In addition to previous performance measures, the proposed method's effectiveness was assessed through an experimental demonstration with cosine similarity metrics by utilizing users' comments and

the combined corpus. The evaluation using the specified metrics revealed that the proposed method performed better, as shown in Table 4.

Table 4: Comparison of customized weighted word2Vec (ww2Vec) with Cosine Similarity metrics

S. No	Metrics	Comparison Type	Relevance Index
1	Cosine Similarity	Users need with Combined Corpus	0.81
2	Weighted word2Vec	Users need with Combined Corpus	0.88

4.7 Comparison with Previous Approach

To our understanding, an integrated multi-criteria approach has not been developed for relevance verification of SNS-sourced needs; but, a related work without applying a combined approach demonstrated a 68.2% degree of relevance, as discussed by Nazakatet al [47]. Thus, the proposed model surpassed the related work in all three test cases, with a relevance rate of 76%, 81%, and 88%, as shown in Table 1. Though there are other few related studies about relevance verification of SNS-sourced requirements, they lack numerical descriptions and quantitative reporting. Nevertheless, the proposed study performed a comparative analysis using different assessment criteria, detailed in Section 4.8.

4.8 Comparative Examination with Published Research Works

This section aims to compare the proposed study with published related works based on criteria from Table 5 to assess their strengths and weaknesses, as few related works are available. The selected journals include Journal 1 (JNL 1), Journal 2 (JNL 2), Journal 3 (JNL 3) and Journal 4 (JNL 4), which covers topics such as "Exploring critical benefits and challenges of SNS-based RE in Saudi Arabia" [48], "Multi-Agent based social CRM Framework for extracting and analyzing opinions," [49] and "Analysis of Requirements-Related Arguments in Users Forum" [50], and "The proposed study" respectively.

The correlation process indicates FS, PS and NS which represents fully supported, partially supported, and not supported, respectively, according to the set criteria.

Table 5: Comparative analysis of the proposed approach with related published journal articles

Cr. No	Criteria	Description	JNL 1	JNL 2	JNL 3	JNL 4
1	End user involvement	The potential of the model to aid end user engagement	FS	FS	FS	FS
2	Facilitate completeness features	Capability of the model to deliver whole functionality	FS	FS	FS	FS
3	Effective time saving	Model efficiently gathers requirements within a shorter timeframe compared to traditional approaches	FS	FS	FS	FS
4	Effective Detection of relevant requirements	The model is built to effectively discover vital user demands	PS	PS	PS	FS
5	Analyze Ambiguous requirements	Model identifies and analyses unclear requirements	PS	PS	PS	PS
6	Examine irrelevant features	The model ensures the identification of unrelated user needs	PS	PS	PS	FS
7	Prioritize requirements	Model ranks users' needs based on importance	FS	FS	FS	FS
8	Generate innovative features	Model produces emerging users' needs	FS	PS	PS	FS
9	List frequently used phrases	Model records recurrently used keywords and phrases	FS	FS	FS	FS
10	Multi-Criteria relevance verification	Analyze relevance of requirements based on multiple criteria	PS	FS	PS	FS
11	Availability of conceptual framework	Model is prepared for verifying relevance of SNS-sourced requirements	FS	FS	FS	FS
12	Demonstration with prototype	Prototype is prepared for verifying the conceptual framework	FS	FS	FS	FS
13	Algorithm involves NLP and machine learning	Model utilizes Natural NLP and machine learning methods to assess the relevance of user needs	FS	FS	FS	FS
14	Study Provides tool support	The study offers software application for continued exploration	NS	FS	FS	FS
15	Privacy and data security	Data protection concerns in SNS-sourced user needs	PS	NS	PS	PS
16	Identify non-functional requirements	Assist detection of non-functional requirements	PS	PS	NS	PS

The four journal articles have been deemed "fully supported" in various criteria, including end user involvement, time saving, completeness features, prioritize requirements, conceptual framework availability, prototype demonstration, listing frequently used phrases, and utilize NLP and machine learning algorithms.

However, the proposed study outperforms the other articles in assessment criteria, such as, effective detection of relevant requirements, irrelevant features examination, innovative features generation, multi-criteria relevance verification, and providing tool support, showing its novelty.

In evaluation criteria like ambiguous requirements, privacy and data security, and identification of non-functional requirements, the status of the proposed study is "Partially Supported," indicating the need for further exploration.

4.9 Post Questionnaire to Experts for Framework Verification

As previously explained in Section 3.1, the research aimed to evaluate the proposed framework using quantitative and qualitative methods to boost confidence and credibility by assessing its practical applicability. Therefore, alongside quantitative data analysis, a qualitative method was used to verify the prototype output, to reach triangulation. The prototype was demonstrated to hospital administrators, system analysts, and consultants. Hence, a questionnaire (Table F9) was provided to respondents, and 91% acknowledged the requirement relevance verification process. 86% of participants replied that the implementation of the proposed idea improved the quality of requirements sourced from SNS. Additionally, 81% of participants agreed that the research has complemented the task of categorization for the identification of representative key phrases.

4.10 Categorization of Verified Key Phrases

The study uses a clustered approach to select key phrases representing related concepts in the combined corpus, identifying patterns and themes in users' needs. The word embedding model is used to apply appropriate representation and categorization for texts with related meanings as shown in Figure 9 (Appendix G) and Figure 10 (Appendix H). The algorithm then clusters these concepts into smaller fragments, aiding the detection of representative key phrases. For example, key phrases detected from participants' inputs, such as treatment date, diagnosis date, and examination date, are represented by the "Treatment Date" attribute.

4.11 Mostly discussed requirements

Table 6 and Figure 11 (Appendix I) categorize users' requirements and list the most frequently discussed needs.

<i>Table 6: Mostly discussed sample users' needs</i>		
R.N	Phrases	Score
1	Register patient, add patient, assign patient ID, Consult patient	81.7
2	Check beds availability, assign doctor, inform doctor, medical matter management	80.2
3	Manage patient's electronic health record, record medical history	78.2
4	A hospital management system staff adds new patient records	76.5
5	Extract meaningful insights, mandatory patient information for every patient	69.3
6	Easy navigation, a comprehensive search functionality, integrate analytical tool	65.5
7	Surgery information, nursing, materials, pharmaceuticals, radiology	63.6
8	Profile information, allow update of only personal details	61.5
9	Financial report, laboratory, inpatient, outpatient, surgery operation	49.8
10	Book online appointments, integrated billing system	48.5
11	Consultation and prescription management	36.8
12	Send electronic prescription	32.6

Identifying and addressing such needs during the requirements relevance verification phase assists in mitigating risks early in the development process, proactively addressing completeness issues, contradictory requirements, and related challenges.

Furthermore, detecting these matters facilitates requirements prioritization and management activities in the analysis stage.

4.12 Key Findings and Analysis with Plus, Minus, Interesting facts (PMIS)

Table 7 presents a comprehensive analysis of the framework, outlining key findings, observations, challenges and future outlooks using plus, minus, and interesting facts (PMI). Significant enhancement has been detected related to verifying relevance of requirements, facilitating completeness and prioritization features of user requirements, users participation, recommending innovative features and enhancing collaboration between users, developers and managers.

Despite improved user involvement and quality of requirements, access to sensitive SNS content and related service dataset remains challenging. A comprehensive approach is needed to counter potential security and privacy threats, including advanced malware and social engineering tactics.

Moreover, though most discussed requirements are identified, incomplete requirements due to unrealistic expectations, conflicting priorities and scope creep persist.

The framework offers relevant user needs rapidly to new software system and effectively connects users, developers, and managers, but its impact in relation to cultural practices on SNS and software project management activities is not thoroughly examined, necessitating further investigation.

Effective users' interaction with the demo prototype has been observed. However, some users express their requirements using local language but with English characters, demanding further exploration to augment the model with transliteration plug-ins.

Furthermore, the study evaluated the framework and corresponding prototype for General hospital health information system, but also presented them as potential applications in a different case study.

Table 7 : PMI facts regarding the findings of the proposed framework and associated demo prototype

Plus	Minus	Interesting
Better user involvement and improved quality of requirements	Access to some sensitive contents in SNS and related service datasets are challenging	Exploring a comprehensive approach is crucial to combat current and potential security and privacy threats, including advanced malware and social engineering tactics
Bridges gap between users, developers and managers	A platform for stakeholders to share perspectives on users' requirement is provided, but its impact on cultural practice exchange has not been examined	The study provides an opportunity for participants to exchange ideas and cultural practices on SNS, but further examination should be conducted,
Offers rapid and relevant user needs and interface to new software system	Some users express their requirements using local language but with English characters.	Further investigation is needed to explore and augment transliteration plug-ins, this study has not prepared a transliteration plug-in software
The study assessed the framework and prototype on a case study, focusing on General hospital HIS.	The study is primarily focused on a medical case study and has not yet deployed the model in a different domain.	The model and prototype are presented as potential applications in a different case study.
Most discussed users' needs have been identified.	Some user requirements are incomplete	The study requires further investigation and insights to identify the common causes of incomplete requirements.
Intelligent agents recommend innovative idea, new feature request, and improvement request, so time saving for relevance verification tasks	The impact of identifying emerging trends and user behavior on software project management was not examined in detail	Further investigation is needed to understand the impact of the study findings on the effectiveness of software project management tasks.
Execution of the framework focuses on customizing a word embedding model by optimizing and utilizing hybrid features of TfIdf and word2vec in NLP.	The study optimizes efficient word embedding models based on word's importance to a document and its semantic relatedness. Main objective was not to compare all word embedding model variations	The proposed model's impact on other word embedding variations, such as GloVe and BERT, would be intriguing to observe.

5. DISCUSSION

This research presents a framework for relevance verification of requirements, sourced from SNS, to minimize problems detected during the verification analysis of users' needs in the RE processes. It has utilized a consolidated concept from organizational goals, the application's TOR as

initial requirements and related service datasets to balance user needs and organizations' interests.

The framework was evaluated quantitatively through an experimental case study and qualitatively through a post-questionnaire distributed to experts' teams. Thus, discussions and recommendations will be provided through revisiting research questions.

5.1 Explanation of the First Research Question

RQ1: What is the potential correlation between the components of the proposed framework for verifying the relevance of SNS-sourced user needs?

The research identifies target participants from academic institutes, government, and non-government organizations to identify components of the proposed framework. Survey questions explore the research purpose, scope, questions, and related works. Moreover, formal and informal expert discussions are conducted to clarify features.

Major issues are analyzed, including research objectives, input, questions, contribution, survey results, and literature review. Consequently, Section 3.5 discusses the key components and their relationships, integrating them into the proposed logical model for a comprehensive understanding of the framework components.

5.2 Analysis of the Second Research Question

RQ2: In checking the degree of relevance of users' needs, is the role of a combined approach of initial requirements and related service datasets better than exploiting the approaches separately?

This research question is addressed through a discussion and interpretation of the results in Section 4.4.3, highlighting the superiority of the combined approach in analyzing the relevance verification of users' needs, with further discussion provided in Section 5.2.1 as detailed below.

5.2.1 Examination of individual versus combined approach in relevance verification process

The study has investigated the use of multiple parameters with a customized word embedding model, in verifying the relevance of requirements fetched from SNS. The experiment which is conducted in Section 4.4.3, shows that a combined approach with consolidated concepts from organizational goals, business rules, and related service datasets has a higher relevance rate (88) compared to business goals and related service datasets (81 and 76) respectively.

The combined feature of initial requirements and related service datasets is used to balance users' needs and organizations' interests, minimizing issues detected during the fetching of users' needs for the requirements elicitation process. That is, the mutual use of consolidated initial requirements and related service datasets serves as a regulation mechanism in the verification process of users' needs sourced from SNS.

Consequently, the combined approach effectively addresses the verification of SNS-sourced requirements for IT and software

engineering projects by balancing the needs of both users and organizations. The combined approach can be implemented independently or with the traditional relevance verification methods, depending on an organization's size, interest, or current IT status.

5.3 Interpretation of Research Question Three

RQ3: How can the proposed conceptual framework be evaluated using quantitative and qualitative methods?

As elaborated in Section 4.4.3, the real-world applicability of the study has been tested through a quantitative analysis conducted with multiple parameters, natural language processing, and customized word embedding models. The study has been further validated by an expert team comprising medical, administrative, and IT professionals in CMC General Hospital.

That is, a second-round survey was conducted to evaluate the prototype's output (See Appendix B). 91% of participants acknowledged the effectiveness of the relevance verification process, focusing on the combined approach of initial requirements and related service datasets.

Moreover, 86% of participants agreed that the implementation of the model has enhanced the quality of SNS-sourced requirements. Post-questionnaire results also showed that SNS can be used for verification of requirements relevance, on top of routine communication tasks.

5.4 Recommendation on the Impact of the Framework in Identifying and Verifying Relevance of SNS-Sourced Requirements, for a Case Study (RQ4)

An experimental case study was conducted on the "Digital healthcare implementation of CMC hospital in Ethiopia" to demonstrate and evaluate the framework's effectiveness in addressing relevance verification of users' needs sourced from SNS. The study provides recommendations to establish a comprehensive clarification of these needs from various perspectives.

Users' need obtained from participants is aligned with the specified hospital's goals and business rules, as evidenced by the 88% relevance of the proposed approach (Section 4.4.3). Issues raised include patient privacy, errors committed by doctors, lack of smooth communication between patients and healthcare providers, and the need for securing electronic payment methods. Challenges include incorrect surgery, improper drug or dose during injection, and exposing patients' private medical history. Such challenges are also consistent

with recent research performed by Shapiro et al. [51]. To address the challenges, suggestions include improving communication, enhancing decision-making, increasing patient engagement, instant checklists, wearable technology, alerting surgeons with PDAs, creating records that can be shared across surgeons, and assisting surgical operations with telemedicine, cloud service, and secure payment methods. Besides, for developing countries with resource constraints, such as Ethiopia, cloud technology is advised for private hospitals due to its accessibility and potential to reduce medical errors.

However, the risk of storing sensitive medical data on a cloud is a principal concern. Hence, the hospital's ICT section and CEO should deploy advanced encryption techniques before outsourcing and storing medical information on a third-party server and data centers.

Moreover, the hospital's digital health care system must have online interaction with pharmaceutical shops and access to the server where the original expiration date resides, "Ethiopian Drug and Food Control Authority", to allow patients to check genuine expiration dates before purchasing. Synchronizing modern medication with traditional medication is also desired, as many people visit cultural medical providers [52]. Furthermore, incorporating local language features in hospital information system software can facilitate communication with the hospital in local languages, parallel with English.

In terms of effective utilization of medical digital devices, issues highlight that insufficient technical training in healthcare digital devices in developing countries leads to inefficient use and sometimes replacement without effectively using the previous apparatus.

Users need also emphasize that there is a fragmented healthcare service effort in light of developing countries, necessitating the development of a digital healthcare framework for interoperability and standardization of healthcare systems. Related user comments are also reflected in a study by Vladimir and Tatina [53].

With regard to the impact of AI, Users' needs emphasize that the need for AI-assisted digital healthcare facilities, like remote consultation and telemedicine, is decisive in supplementing and improving physical healthcare services, especially in underprivileged regions.

Moreover, AI-based diagnostic devices can significantly improve access to professional surgeons and medical facilities in developing countries. By correlating patient data with an

enormous dataset of medical intelligence, AI algorithms can recognize patterns and offer perception that assist surgeons in their decision-making process [54].

Issues raised also highlight that, despite limited resources, AI algorithms continually improve their accuracy over time, enabling surgeons in developing countries to access the most recent medical knowledge and offer more tailored treatment strategies, due to their continuous learning and analytical capabilities concerning patient data, medical records, and research databases. Such related issues have been also investigated by Anita Zarghami [55].

Alternatively, though, AI's perspective in healthcare is significant, its widespread implementation in developing countries faces obstacles due to limited infrastructure, such as internet access and consistent power supply. Cooperation between governments, healthcare organizations, and technology firms is essential for overcoming these hurdles.

Therefore, designers and developers can use verified requirements which are acquired based on the proposed framework, to develop software products and recommend hardware needs related to digital healthcare systems, specifically in developing nations.

5.5 Limitations

This section highlights the study's limitations and suggests potential areas for future enhancements. The study's limitations include its focus on one popular social media platform, Twitter. Future direction emphasizes the potential for the research to utilize multiple platforms for more enhanced results. The study also focused on a single case study and suggested future research on the framework's impact on various case studies across different domains, thereby analyzing the findings in each case study. Moreover, studying additional cases helps to identify patterns and enhances the possibility of detecting more relevant users' needs.

Furthermore, few users have expressed their need by writing in ambiguous language, a local native language written with English letters. The "Abyssinica" transliteration plug-in [56] is used to analyze such comments, but some challenges persist due to the low-resourced Amharic language. Future directions should focus on improving the plug-in to entertain users who mix native and English languages.

6. CONCLUSION AND FUTURE WORKS

This research examines a novel multi-criteria dynamic relevance verification of requirements sourced from SNS platforms. Despite SNS platforms being rich sources of user-generated content, reflecting current trends and sentiments through miscellaneous fields, relevance verification of users' needs has not been adequately examined, leading to challenges in filtering and prioritizing relevant information. Issues such as data overload, interpretation difficulties, jargon, informal language, and diverse expressions in user comments highlight the complexity of conducting relevance verification of user requirements. An intelligent multi-criteria relevance verification approach has been investigated, balancing the need for user-centered software with the reuse of existing service features and organizational goals. The specified approach also ensures that requirements accurately reflect stakeholder needs and expectations, establishing relevance of requirements before proceeding to design and implementation phases.

The research, based on survey results, informal meetings, and key features like research objectives, scope, input, output, research questions, and literature review assessment, has developed a conceptual framework to verify the relevance of requirements sourced from SNS platforms, thereby significantly enhancing the RE process. The framework uses consolidated concepts from organizational goals, business rules, the application's TOR as initial requirements, and related service datasets to create equilibrium between users' needs and organizations' interests, minimizing user requirement problems detected during the process of fetching user needs from SNS. That is, the combined feature is used as a regulation mechanism in verifying relevance of users' needs. To address the specified challenges in identifying relevant users' needs, a detailed literature review was conducted, and a need assessment was gathered from the experts' team. Then, a qualitative approach was used to construct the framework.

The study conducted an experimental case study to quantitatively evaluate and demonstrate the practical applicability of the framework. To this effect, the framework has been examined with digital healthcare systems in Ethiopia's "CMC General Hospital" by analyzing 800 users' needs from a GUI and extracting 540 and 900 key phrases from initial requirements (business goal and TOR) and related service datasets, respectively. The

algorithm representing the framework was applied to three test cases: users' needs and related service datasets, users' needs and initial requirements, and users' needs with an integrated effect of initial requirements and related service datasets. The results showed that combining multiple attributes from business objectives and related service datasets improved the relevance verification of SNS-sourced requirements, achieving a relevance rate of 88%. The framework learns and uses consolidated criteria features as regulation mechanisms, comprehensively addressing challenges in isolating relevant users' needs and minimizing traditional method limitations.

In addition, the study utilized optimized word-embedding models to compare the specified test cases and analyze results with previous related works. Assessment of the cases study and a post-questionnaire that was distributed to experts' teams, demonstrates the potential of the proposed approach in verifying relevance of SNS-sourced requirements, generating innovative ideas, prioritizing, and suggesting related requirements. This approach also enhances organizations' decision-making and customer satisfaction by ensuring user requirements are relevant, reusable, and aligned with organizational goals. Discussions and recommendations were given by revisiting research questions.

The research has some tasks that need future work, such as considering multiple case studies for evaluation and linking the dynamic multi-criteria relevance verification framework with other software development phases, such as predicting the success of the design and testing phases. The demo prototype mainly allows input in English, but future studies consider full local language support, to enable participants to express their interests in native languages alongside English.

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Appendix A

Table 8: Questionnaires provided to experts group for conceptual framework design

S. No	Questionnaire	Remark
1	Integrating concepts from organizational business rules in the framework enables system analysts to generate pertinent user needs sourced from SNS, for the intended application 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
2	Integrating concepts from organizational objectives in the framework enables to generate pertinent requirements sourced from SNS for the intended application 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
3	Integrating concepts from existing service dataset in the framework enables to generate pertinent requirements source from SNS for the intended application 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
4	Applying the proposed model makes it hard to reach a consensus on requirements verification 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
5	Integrating concepts from organizational business rules and objectives in the framework creates difficulty in the process of verifying relevance of requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
6	Utilizing concepts from related services in the model facilitates identification of relevant requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
7	By implementing the proposed framework, recommendation of updates for requirements feature can be facilitated via existing service datasets and business rules. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
8	Utilizing synergy of business rule of enterprise and related service dataset from another application boosts verification of requirements than individual approach. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
9	The proposed study has an impact in classifying requirements 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
10	The proposed study might have an impact in prioritizing requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
11	The proposed study has an impact to reuse requirement from related previous systems. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
12	Consistency of requirements cannot be achieved by implementing the proposed model. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
13	Conflicting requirements cannot be detected by implementing the proposed model 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
14	Comparison of the proposed model must be made with traditional approach 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
15	The proposed model can be applicable in various domains. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
16	The proposed model cannot be applicable for large scale software development settings. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
17	Clustered approach in the model is used to identify allied terms and assign common delegate phrase. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
18	Implementation of the model is helpful to Facilitates Visualization of categorized requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
19	The model assists verification of creative ideas detected form SNS users comment 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
20	The study contributes important concepts for future research in relation to SNS based RE. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	

Appendix B

Algorithm 1: Algorithm for conducting relevance verification of SNS-sourced user comments

Procedure Examine Relevance of User Requirements

```

Read input data from Source 1 # business rule and objective dataset on a file (as Initial Requirements)
Read input data from Source 2 # existing service dataset on a file
Read input data from Source 3 # user requirements fetched from GUI
    For i in range (total documents) # preprocessing
        Corpus[i].split (), Corpus[i].lower (), Corpus[i].lemmatize ()
    End for
Combined Corpus=Corpus (Initial Requirements). Append (Corpus (Existing Service)) # concatenation
    Model 1=Word2Vec ( )
    Model1. Train (Combined Corpus)
    Word2Vec Words= Word2Vec Model 1[Word]
    Model 2=Tf-Idf ( )
    For each word in User Requirements
        Calculate Tf-Idf
        Tf-Idf Feature [word] =Model2. Get Feature name [word]
    End for
    For each Row in Word2Vec Words
        For each word in Word2Vec Words
            If word in Tf-Idf Feature
                Weighted Word2Vec=Word2Vec X (Tf-Idf Feature [word])
            End If
        End For
        Row++
    End For
    Select case (test case number)
    Case 1: test case 1
        Relevance Score=Weighed Word2Vec.Relevance (Corpus User feedback, Business goal Corpus)
        If Relevance Score<65#base line value
            Print (“User Feedback Didn’t Pass Relevance Check, so Discard”)
        End If
        Print (Relevance Score)
    Case 2: test case 2
        Relevance Score=Weighed Word2Vec. Relevance(Corpus User need, Existing Service Corpus)
        If Relevance Score<65#base line value
            Print (“User Feedback Didn’t Pass Relevance Check, So Discard”)
        End If
        Print (Relevance Score)
    Case 3: test case 3
        Relevance Score=Weighed Word2Vec. Relevance (Corpus User need, Combined Corpus)
        If Relevance Score>=65 #base line value
            Print (Relevance Score)
        Else
            Print (Discard need)
        End if
    End Case
End Procedure

```

Appendix C

Algorithm 2: Algorithm for clustering relevant user comments

Procedure Perform User Comment Clustering

Import all essential libraries

Fetch user requirements from GUI, integrated with SNS

Save digital health user comments on a file

```
# Load user comments from a text file
with open('digital_health_comments.txt', 'r', encoding='utf-8') as file:
    user_comments = file.read()

if not user_comments:
    raise ValueError("The file is empty or not properly formatted.")

# Convert to a Data Frame for easier processing
df = pd.DataFrame(user_comments, columns=['user comment'])

#Text Preprocessing Function
def preprocess_text(text):

# Apply preprocessing to all user comments
df['processed_user comment'] = df['user comment'].apply(preprocess_text)

# Vectorize the processed text
vectorizer = TfidfVectorizer()
X = vectorizer.fit_transform(df['processed_user comment'])

# Apply K-means Clustering
num_clusters = 5 # Choose the number of clusters you want
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
kmeans.fit(X)

# Add Cluster Labels to the Data Frame
df['cluster'] = kmeans.labels_

# Print Out the Results
for i in range(num_clusters):
    print(f"\nCluster {i}:")
    print(df[df['cluster'] == i]['user comment'].to_list())
End Procedure
```

Appendix D

Algorithm 3: Algorithm for continuous update model for SNS-sourced user comments

Procedure Conduct Continuous Update

Import all essential libraries

Preprocessing

def preprocess_user comment (user comment):

Initial function to train the weighted_Word2Vec model

def train_weighted_word2vec_model(user comment _list):

Preprocessing user comment

processed_user comment = [preprocess_user comment (user comment) for user comment in user comment _list]

Creating and training the weighted Word2Vec model

model = Word2Vec(sentences=processed_user comment, vector_size=100, window=5, min_count=1, workers=4)

return model

Function to update the model with new user comment

def update_model(model, new_user comment):

processed_new_user comment = preprocess_user comment (new_user comment)

model.build_vocab([processed_new_user comment], update=True) # **Update list**

model.train([processed_new_user comment], epochs=model.epochs) # Train model

Function to save and load the model

def save_model(model, filepath):

model.save(filepath)

def load_model(filepath):

return Word2Vec.load(filepath)

New user comment

new_user comment = "fetch new user comment"

Update the model with new user comment

update_model(model, new_user comment)

Save the updated model

save_model(model, 'healthcare_user comment _model.model')

Load the model later

new_model = load_model('healthcare_user comment _model.model')

End Procedure

Appendix E



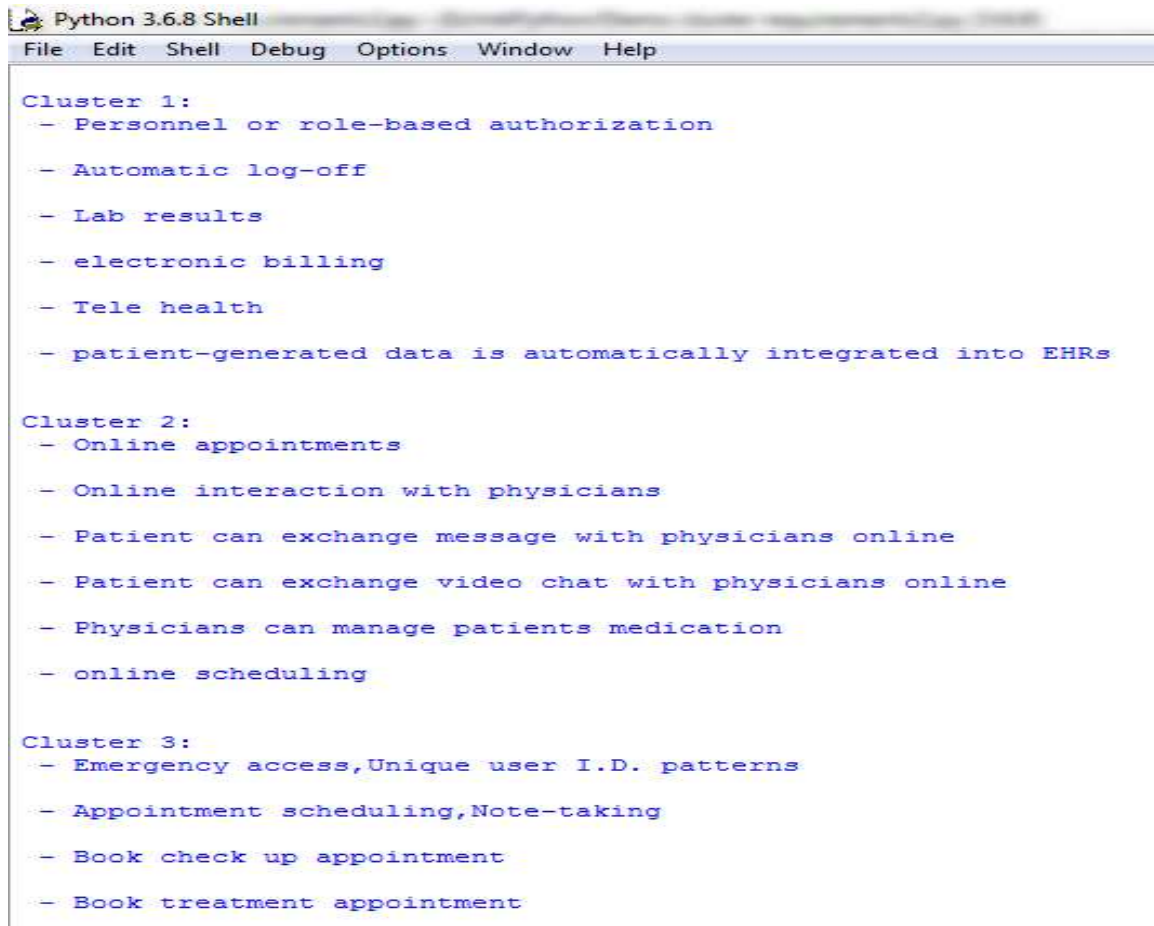
Figure 3: GUI for gathering User comments and Verifying its Relevance

Appendix F

Table 9: Second round survey questions provided to experts group for framework verification

S.No	Questionnaire	Remark
1	Implementation of the framework has enabled system analysts to better visualize verification of requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
2	Integrating concepts from related service dataset in the framework has enabled analysts to generate pertinent requirements from SNS user needs. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
3	The proposed model has reduced effort of gathering better number of verified requirements 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
4	Integrating concepts from organizational business rules and objectives in the framework has created difficulty in the process of verifying relevance of requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
5	The proposed research has simplified the task of verifying and aligning business rules and constraints with business requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
6	Utilizing synergy of business rule of enterprise and related service dataset from another application has improved verification of requirements than individual approach. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
7	Implementation of the proposed study had shown an impact in classifying requirements 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
8	The proposed study has facilitated the task of prioritizing the verified requirements. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
9	The proposed model could be applicable in various domains. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	
10	The clustered approach in the proposed model has simplified the task of identifying the related terms and assigning common representative term. 5. Strongly Agree 4. Agree 3. Undecided 2. Disagree 1. Strongly Disagree	

Appendix G



```
Python 3.6.8 Shell
File Edit Shell Debug Options Window Help

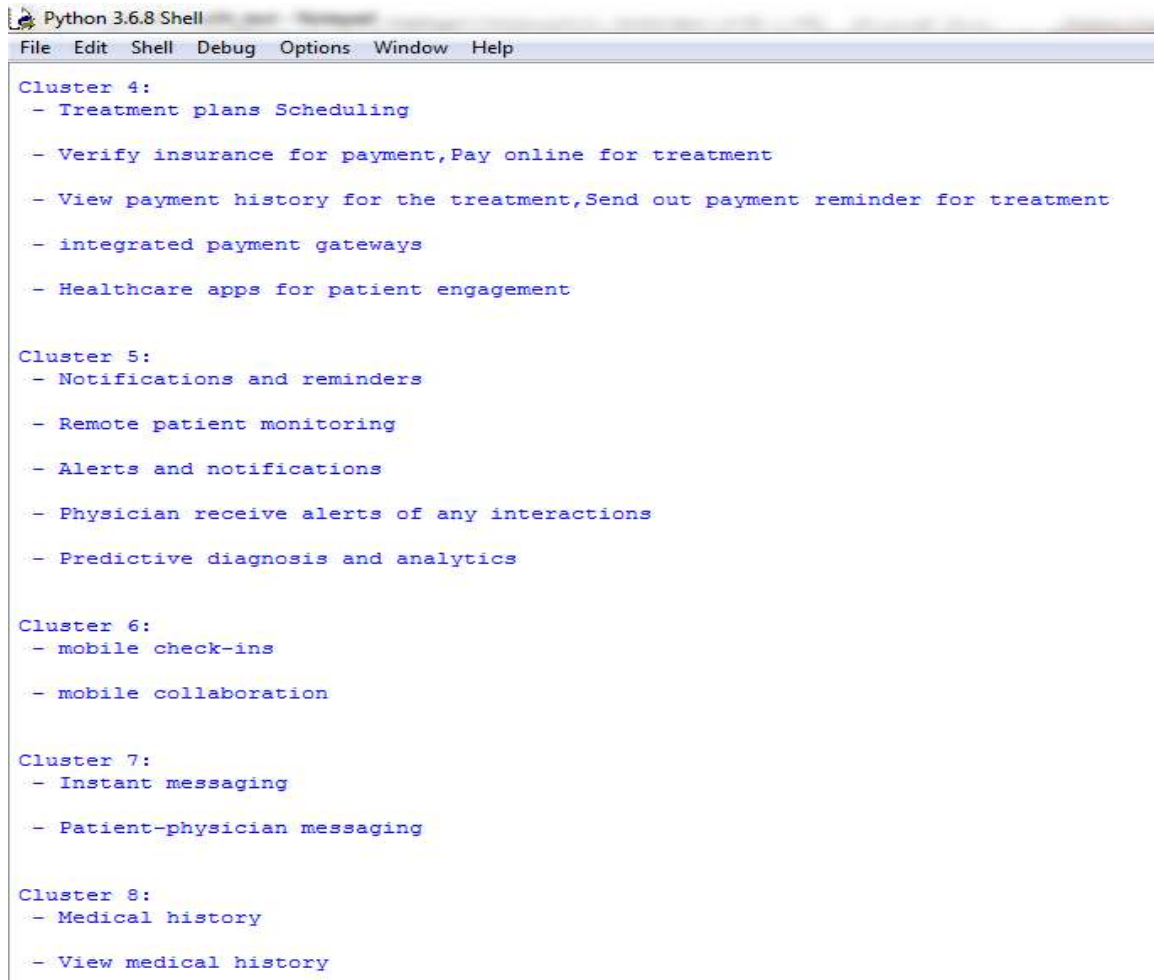
Cluster 1:
-- Personnel or role-based authorization
-- Automatic log-off
-- Lab results
-- electronic billing
-- Tele health
-- patient-generated data is automatically integrated into EHRs

Cluster 2:
-- Online appointments
-- Online interaction with physicians
-- Patient can exchange message with physicians online
-- Patient can exchange video chat with physicians online
-- Physicians can manage patients medication
-- online scheduling

Cluster 3:
-- Emergency access, Unique user I.D. patterns
-- Appointment scheduling, Note-taking
-- Book check up appointment
-- Book treatment appointment
```

Figure 9: Sample screen shot of most discussed user requirements from Python shell.

Appendix H



```
Python 3.6.8 Shell
File Edit Shell Debug Options Window Help

Cluster 4:
- Treatment plans Scheduling
- Verify insurance for payment, Pay online for treatment
- View payment history for the treatment, Send out payment reminder for treatment
- integrated payment gateways
- Healthcare apps for patient engagement

Cluster 5:
- Notifications and reminders
- Remote patient monitoring
- Alerts and notifications
- Physician receive alerts of any interactions
- Predictive diagnosis and analytics

Cluster 6:
- mobile check-ins
- mobile collaboration

Cluster 7:
- Instant messaging
- Patient-physician messaging

Cluster 8:
- Medical history
- View medical history
```

Figure 10: Sample screen shot of most discussed user requirements from Python shell.

Appendix I

```
Python 3.6.8 Shell
File Edit Shell Debug Options Window Help
-----
Mostly Discussed Users' Requirements:
-----
Score: 81.7, Phrase: profile register patient add patient assign patient id consultation
Score: 80.2, Phrase: bed available medical matter management assign doctor inform doctors
Score: 78.2, Phrase: manage patient electronic health records record medical history
Score: 76.5, Phrase: hospital management system staff adds new patient records
Score: 69.3, Phrase: extracting meaningful insights mandatory patient information every patient
Score: 65.5, Phrase: easy navigation comprehensive search functionalities incorporate analytics tools
Score: 63.7, Phrase: healthcare providers system generates report including patient demographics
Score: 63.6, Phrase: surgery information materials nursing pharmaceutical radiology pathology maintain
Score: 61.5, Phrase: profile information allow update personal details
Score: 49.3, Phrase: financial report laboratory inpatient outpatient operation
Score: 48.5, Phrase: book online appointments billing management integrated billing
Score: 41.7, Phrase: bill payments appointment management patients visiting
Score: 39.0, Phrase: user feedback allows recording
Score: 36.3, Phrase: consultation prescription management manage commonly
Score: 35.3, Phrase: handle data growth efficiently support interoperability
Score: 34.2, Phrase: system must provide information
Score: 32.6, Phrase: send electronic prescriptions
Score: 31.7, Phrase: prevent duplicate entries registered patients shall
Score: 31.6, Phrase: appointment patient registration
Score: 31.5, Phrase: discharge summary automatic notification
```

Figure 11: Sample screen shot of most discussed users requirements from Python shell.