SAĞLIK ve HEMŞİRELİK YÖNETİMİ DERGİSİ
JOURNAL of HEALTH and NURSING MANAGEMENT

Özgün Araştırma
Original Article

Comparative Analysis of Joint Commission International and Healthcare Information and Management Systems - Electronic Medical Record Adoption Model Measurement Models using Text Mining

Uluslararası Ortak Komisyon (JCI) ve Sağlık Bilgi Yönetim Sistemleri Topluluğu (HIMSS) - Elektronik Sağlık Kaydı Benimseme Modelinin (EMRAM) Metin Madenciliği Yöntemi ile Karşılaştırmalı Analizi

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SHYD 2022;9(3):371-382
doi:10.54304/SHYD.2022.37801

Cite as: Cece S, Köse İ. Comparative Analysis of Joint Commission International and Healthcare Information and Management Systems - Electronic Medical Record Adoption Model Measurement Models using Text Mining. Journal of Health and Nursing Management. 2022;9(3):371-382.

Abstract

Introduction: Health service quality refers to all efforts to prevent a negative outcome in the health status of individuals. For this reason, measuring and evaluating the quality of health services is important to increase the quality of services provided.
Aim: In this study, Joint Commission International's (JCI) accepted indicator-based health service quality measurement model and the Healthcare Information and Management Systems Society's (HIMSS)-Electronic Medical Record Adoption Model (EMRAM) are discussed.
Method: This research used the bag-of-words model (BoW), a text mining method.
Result: As a result of the analysis, the similarity of keywords (as unigrams) used in all of the guides was found to be approximately 33%, the bigram similarity was 6% and the trigram similarity was 3%.
Conclusion: The fact that the similarity between the two models is not higher can be explained by the fact that, unlike JCI, the HIMSS EMRAM model handles the quality of health services with a digitalization axis. Text mining opens up new research areas as a method for comparing quality standards with new and interesting results.

Keywords: Quality of healthcare, quality indicators healthcare, medical informatics, data analysis, text mining.

Recieved / Geliş:
11.05.2022
Accepted / Kabul:
26.10.2022
Published Online / Online Yayın:
30.12.2022

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Öz

Giriş: Sağlık hizmet kalitesi, bireylerin sağlık durumlarında olumsuz bir sonucun oluşmasını önlemeye yönelik tüm çabaları belirtmektedir. Bu nedenle sağlık hizmetlerinin kalitesinin ölçülmesi ve değerlendirilmesi verilen hizmetin kalitesinin artırılması açısından önemlidir.
Amaç: Bu çalışmada, gösterge tabanlı sağlık hizmeti kalitesi ölçüm modeli Uluslararası Ortak Komisyon (Joint Commission International-JCI) ve Sağlık Bilgi Yönetim Sistemleri Topluluğu (Healthcare Information and Management Systems Society-HIMSS)-Elektronik Sağlık Kaydı Benimseme Modeli (Electronic Medical Record Adoption Model-EMRAM) ele alınmaktadır.
Yöntem: Bu araştırmada, bir metin madenciliği yöntemi olan sözcük torbası modeli (bag-of-words/BoW) kullanılmıştır.
Bulgular: Analiz sonucunda tüm rehberlerde kullanılan anahtar sözcüklerin tek harfli sözcük (unigram) benzerliği yaklaşık %33, iki harfli sözcük (bigram) benzerliği %6 ve üç harfli sözcük (trigram) benzerliği %3 olarak bulunmuştur.
Sonuç: İki model arasındaki benzerliğin fazla olmaması, JCI'dan farklı olarak HIMSS- EMRAM modelinin sağlık hizmet kalitesini dijitalleşme ekseniyle ele almasıyla açıklanabilir. Çalışmada metin madenciliği yönteminin kullanılması, kalite standartlarının yeni ve ilginç sonuçlarla karşılaştırma olanağı sağlamaktadır.

Anahtar Sözcükler: Sağlıkta kalite, sağlıkta kalite göstergeleri, tıp bilişimi, veri analizi, metin madenciliği.

Introduction

Joint Commission International (JCI), which is the first accreditation body in the health sector, was established in 1951 as the "Joint Commission on Accreditation of Hospitals" (JCAH) with the participation of the American College of Surgeons, American College of Physicians, American Hospital Association, American Medical Association, and Canadian Medical Association (JCI, 2019). When accreditation programs were developed for healthcare organizations other than hospitals in 1987, the commission was renamed to "Joint Commission on Accreditation of Healthcare Organizations" (JCAHO). The Joint Commission International (JCI) is a unit of JCAHO that conducts international accreditation programs to enhance the quality and safety of healthcare services. The scope of JCI programs includes standards for hospitals, outpatient care, continuity of care, clinical laboratories, medical transport services, primary care, and clinical care services. These programs are used by private and public organizations to evaluate and improve the safety and quality of care provided to patients (JCI, 2019).

The Healthcare Information and Management Systems Society's (HIMSS) Electronic Medical Record Adoption Model (EMRAM) is a global, cause-based, non-profit organization founded in the US in 1961. The aim of HIMSS-EMRAM is to improve health issues and healthcare outcomes by using information and technology. HIMSS provides a global service that measures technology-based development in the health sector through its evaluation models, such as EMRAM, The Outpatient Electronic Medical Record Adoption Model (O-EMRAM), The Continuity of Care Maturity Model (CCMM), The Adoption Model for Analytics Maturity (AMAM), The Digital Imaging Adoption Model (DIAM), The Infrastructure Adoption Model (INFRAM), and Value Score (HIMSS, 2019).

Within the scope of the research, the documents related to the JCI Accreditation Standards for Hospitals 6th Edition and the HIMSS-EMRAM Preparatory Guide 2020 indicator-based evaluation criteria were reviewed to measure the quality of healthcare services by using text mining methodology.

Literature Review

The literature includes studies suggesting that the use of quality indicators to measure the performance of hospitals has a positive effect. The use of indicator-based standards has been shown to have a positive impact on quality improvement in allowing practitioners to understand current conditions and giving them the opportunity to compare data over the years, and the standards used improve quality (Friebel & Steventon, 2019). Quality indicators are also used for countries to benchmark measure performance. Countries can evaluate themselves as comparisons thanks to the quality indicators they have. Also, it provides the opportunity to make comparisons between countries quality indicators. The quality indicators used in primary care in the United Kingdom (UK) and the United States of America (USA) were considered as comparisons, and it was concluded that the application of criteria used in different countries was beneficial in developing quality of care measures, but such indicators could not be directly transferred between countries (Marshall, Shekelle, McGlynn, Campbell, Brook & Roland, 2003). In comparison with 21 quality indicators in the USA, Canada, New Zealand, Australia and the UK, it has been seen that quality indicators create positive results for improving health care standards (Hussey et al., 2004).

The use of quality indicators to measure the performance of health services is very effective. For example, used indicators such as death rate, birth rate, life expectancy in the measurement of health care quality provides the opportunity for countries to evaluate according to years. (Docteur & Berenson, 2011). In comparisons, it is argued that the use of quantitative and qualitative data together will give more accurate results in order to increase the quality of health services (Pope, van Royen & Baker, 2002).

It has been revealed that the implementation of the quality management system in health institutions will help increase the service quality and increase the service quality of the personnel (Tamer & Çetinkaya, 2018). Various methods are used while developing quality management systems and accordingly indicators to measure quality. Delphi method is one of the methods used for this purpose. When the studies that preferred the Delphi method to develop quality indicators were examined, it was concluded that this method alone would not be sufficient for indicator selection and should be supported by other methods (Boulkedid, Abdoul, Loustau, Sibony & Alberti, 2011).

International or national accreditation programs are very effective on the quality of health services. Also, accreditation programs have a positive effect on evaluating the quality performances of countries. Accreditation programs are used as a tool for countries to increase the quality of health services, improve clinical conditions and quality of care (Alkhenizan & Shaw, 2011). Considering the various accreditation programs used by Canada, Australia, New Zealand, UK, USA and France, it is seen that the accreditation programs have advantages and disadvantages, and the accreditation programs applied in the USA and Canada are more advantageous (Tabrizi, Gharibi & Wilson, 2011).

Countries can develop accreditation programs themselves as well as existing accreditation programs. The accreditation program that Iran called the Avrupa Kalite Yönetim Vakfı (The European Foundation for Quality Management- EFQM) model and developed by itself was created based on the programs used in other countries. The developed program was applied to hospitals in Iran and it was observed that there was a significant improvement in quality indicators (Semnani & Asadi, 2016).

In studies comparing quality measurement models and accreditation programs, existing quality indicators often have similar content. Servqual and Servpent measurement models are generally preferred in health institutions to measure health service quality. In both models, patients evaluate the benefit they get from health care. On the other hand, an evaluation is provided according to patient satisfaction. However, it is argued that the Servperf model is more suitable for measuring service quality in studies (Shafei, Walburg, Taher, 2019). It is seen that the components of the JCI accreditation program are like the quality measurement models inspected in the Expert project (Donahue & Vanonstenberg, 2000).

When the Health Quality Indicator (Sağlıkta Kalite Standartları-SKS) and Health Accreditation Standards (Sağlıkta Akreditasyon Standartları-SAS) used as the national quality assessment models in Turkey and JCI standards are compared, it is seen that the standards are similar but different in structure. It has been seen that the SAS-Hospital set standards have been prepared quite extensively for hospitals and are like JCI standards at many points, and some parts are even more detailed (Şahin, 2020). As a result of the comparison made for JCI and HIMSS-EMRAM standards, it was concluded that there are standards that are related to each other. It has been seen that EMRAM has fulfilled many standards expected to be made by JCI. It is argued that the standards found in JCI but not in EMRAM will contribute to the development of the model (Virginio & Dos Reis, 2019).

It is understood that the text mining method is not used as a comparison method in studies deal with the comparison of quality measurement models and their effects in health institutions. In addition, as a result of the literature review we conducted in this study, no study was found that compared JCI and HIMSS-EMRAM evaluation criteria using text mining method. This study aims to reveal the similarity between the text mining method and the JCI and HIMSS EMRAM models.

Method

Aim and Design: Within the scope of the research, the documents related to the JCI and the HIMSS-EMRAM indicator-based evaluation criteria were reviewed to measure the quality of health services using text mining methodology.

Instrument and Data Collection: The data were collected using the JCI Accreditation Standards for Hospitals 6th Edition and the HIMSS-EMRAM Preparatory Guide 2020.

Data Analyses: Text mining is defined as the process of analysing texts for a specific purpose and extracting useful information. Many components, such as web pages, books, documents, and customer comments, can be analysed in text mining (Canbolat & Pinarbasi, 2020).

Text Mining Techniques: There are different machine learning algorithms and models that are currently used in text classification. One of the oldest machine learning approaches used for text classification is the Naïve Bayes classifier. It is known as one of the simplest and fastest text classification algorithms based on statistical modelling. Other models that have been adapted and used for document classification include neural networks and clustering. Among these, learning vector quantization (LVQ) is a type of simple neural network for text classification. The other model adapting neural networks for text classification uses hierarchical sensors. A third type is k-nearest neighbors algoritması (k-nn) that utilizes vector representations of documents and classifies documents using some similarity criteria. Finally, the Rocchio classifier is an example-based learning algorithm that uses similarity measures, and centre and vector space models (Eminağaoğlu & Gökşen, 2020).

Some of the kernel-based functions used in machine learning are also used for text classification, such as those used in support vector machines. Additionally, Bag-of-words (BoW) is widely used in information retrieval and text mining. In BoW, each word corresponds to a dimension in the resulting data space, and each document then becomes a vector of non-negative values in each dimension. Here, we use the frequency of each term as the weight. This means that terms that appear more frequently are more important and descriptive for the document. It is argued that the BoW analysis gives better results if the documents contain a multitude of words (Huang, 2008). Since the JCI and HIMSS-EMRAM documents consist of tens of pages, the BoW model was preferred as a research method to measure the similarity between the guides in this study.

Research Phases: In the first phase of the study, JCI and HIMSS-EMRAM documents were subjected to a series of processes described below to make them ready for text mining analysis (Figure 1). The KNIME version 4.4.2 was used for analysis and the processes were carried out using text processing nodes (PDF Parser, POS Tagger, Punctuation Erasure, Number Filter, Tag Filter, N Chars Filter, and Stop Word Filter).
Data Pre-processing: This phase primarily consists of conversion, scanning and marking, removing unwanted words, and rooting. All these processes are detailed below.
Conversion (PDF Parser): HIMSS-EMRAM and JCI documents were converted into PDF format. Documents in English were translated into Turkish by experts working in healthcare informatics and quality fields.
Screening and Marking (Number Filter, Tag Filter, N Chars Filter, POS Tagger and Punctuation Erasure): In this step, multiple spaces, unused numbers, unnecessary subjects (he, us, you, etc.) and excess elements (so, however, but, etc.) contained in the text were removed.
Removal of Unwanted Words (Stop Word Filter): Words including prepositions, conjunctions, and pronouns, which are frequently used in the text but have no meaning in the text classification (such as for, with, like, until, according, etc.), were removed from the text.

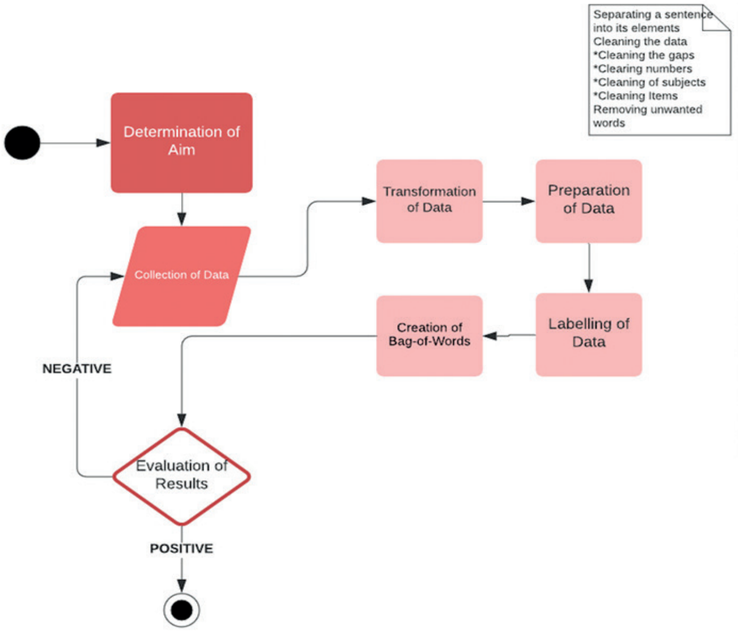

Figure 1. Classification phases

In the second phase, a bag-of-words was created for the words in the text using the BoW text mining method. In this step, separate analyses were conducted for JCI and HIMSS-EMRAM documents (Figure 2).

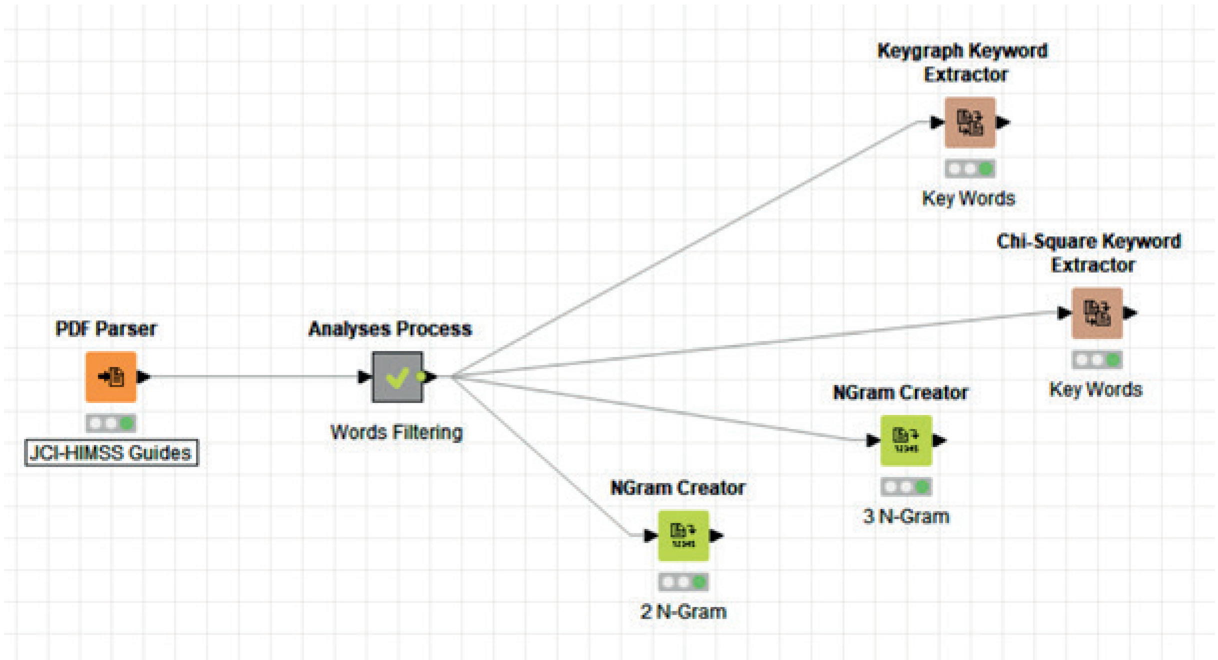

Figure 2. KNIME text mining model

The third phase established Unigram, 2N-gram (bigram), and 3N-gram (trigram) models which are the most used evaluation criteria in HIMSS-EMRAM and JCI documents, only preceded by tokenisation. Thus, the differences between the keywords and phrases used in the two evaluation criteria in the relevant documents were determined.

N-Gram: N-gram is important for the frequency distribution of words. N-grams are n word segments of a string of words. N-gram-based classification method is a process based on the frequency of use of word-based n-grams in the document (Stilwell, von Winterfeldt, & John, 1987). Additionally, it helps produce more meaningful data from a single word. Word N-grams can be explained as follows:

- In the Unigram model, the probability of a word depends on the 0 word order before it.
- In the Bigram model the probability of a word depends on the 1 word before it.
- In the Trigram model, the probability of a word depends on the on the last 2 orders of word before it.
- N-gram models are used to predict letter order in speech recognition problems.

Ethical Considerations: Before the study was conducted, permissions were obtained from the institutions. Additionally, ethical approval was obtained from the Ethical Committee (Date: April 26, 2022; Approval number: 56).

Study Limitations, Challenges, and Strength: The strength of the study is the fact that the literature does not include any study that has deal with two models and used the text mining method before. The words used in the documents discussed as part of the study are similar in meaning. However, different words conveying the same meaning are used. This is considered a limiting factor for the study since it reduces the similarity rate.

Results

Within the scope of the study, all stage and requirements between 0-7 in the HIMSS-EMRAM Preparatory Guide 2020 and 1.300 evaluation criteria in the JCI Accreditation Standards for Hospitals, 6th Edition were reviewed.

Table 1. Unigram JCI and HIMSS-EMRAM documents

Keywords used in the JCI documents	Score	Keywords used in the HIMSS documents	Score
hospital	3490.0	review	346.0
care	2311.0	data	288.0
patient	2257.0	EMR	268.0
staff	1538.0	documentation	233.0
medical	1525.0	patient	230.0
service	1363.0	clinical	225.0
process	1334.0	blood	220.0
data	1228.0	process	194.0
leadership	1188.0	system	193.0
program	1168.0	paper	170.0
information	1132.0	hospital	165.0
measurable	1126.0	medication	145.0
elements	1121.0	expect	132.0
provided	1096.0	medical	130.0
education	990.0	information	128.0
procedures	949.0	nursing	123.0
management	936.0	organization	119.0
include	908.0	analytics	118.0
clinical	882.0	technology	116.0
example	881.0	care	115.0
safety	866.0	products	112.0
risk	837.0	structured	111.0
required	819.0	administration	109.0
control	796.0	discrete	106.0
identified	785.0	bedside	104.0
regulations	779.0	scanned	97.0
quality	779.0	required	95.0
health	764.0	product	93.0
research	755.0	demonstrate	92.0
medication	588.0	alerts	92.0

In this analysis, the most frequently used 30 words and their frequencies were extracted from all the guides (Table 1). The analysis demonstrated that the similarity of the keywords (as unigrams) used in all guides was approximately 33.3%. A word cloud was created for the similarly used keywords (in blue colour) and dissimilar keywords (in grey colour) in the two guides (Figure 3).

Figure 3. Most common keywords - Cloud of words

The Bigram word phrases used in HIMSS-EMRAM and JCI documents as reviewed as part of the study were extracted (Table 2). Accordingly, the phrases contained in the bigram indicators in the two guides show similarity at a rate of 6%. The phrases “medical record” and “patient safety” are the most frequently used bigrams in both guides.

Table 2. 2N-gram HIMSS-EMRAM and JCI documents

2Ngram (JCI)	Corpus Frequency	Sentence frequency	2Ngram (HIMSS)	Corpus Frequency	Sentence frequency
Measurable Elements	2595438	326	review team	130830	68
health care	1464677	176	discrete data	26166	13
patient care	1274952	150	blood products	26166	12
medical record	1191473	144	clinically relevant	22428	12
laws regulations	1100405	139	structured templates	22428	12
hospital leadership	1085227	138	blood bank	22428	10
patient safety	918269	111	alerts active	26166	9
care practitioners	880324	106	expect understand	14952	8
medical staff	887913	81	analytics program	13083	7
services provided	584353	75	information exchange	13083	7
patients' families	591942	74	medication administration	14952	7
patient family	546408	68	administration process	13083	7
medical equipment	629887	68	interfaced EMR	13083	7
policies procedures	508463	67	medical imaging	16821	7
hospital develops	584353	67	medications blood	11214	6
safety program	553997	67	allied health	11214	6
implements process	531230	66	relevant paper	13083	6
prevention control	553997	65	CDS alerts	11214	6
governing entity	523641	64	human milk	9345	5
infection prevention	538819	63	analytics strategy	9345	5
data information	508463	60	intended help	9345	5
hospital identifies	440162	56	scanned bedside	9345	5
informed consent	432573	53	generate discrete	9345	5
develops implements	440162	51	drive CDS	9345	5
throughout hospital	432573	51	templates document	9345	5
quality improvement	379450	47	documented EMR	9345	5
diagnostic imaging	402217	47	medical devices	9345	5
medical records	387039	45	Summary reports	7476	4
patient's condition	356683	44	Medical Records	5607	4
care services	341505	41	patient safety	1869	4

Table 3. 3N- gram HIMSS-EMRAM and JCI documents

3Ngram (JCI)	Corpus Frequency	Sentence frequency	3Ngram (HIMSS)	Corpus Frequency	Sentence frequency
health care practitioners	804434	96	review team expect	54201	29
patient's medical record	576764	74	team expect understand	14952	8
infection prevention control	516052	60	review team understand	13083	7
quality patient safety	432573	52	Doctors structured templates	13083	7
hospital develops implements	379450	43	medications blood products	9345	5
patient safety program	318738	39	generate discrete data	9345	5
develops implements process	303560	36	structured templates document	9345	5
hospital establishes implements	288382	36	clinical decision support	7476	4
applicable laws regulations	280793	34	expressed breast milk	7476	4
documented patient's medical	265615	33	blood specimen / sample collection	7476	4
patient medical record	258026	31	clinically relevant paper	7476	4
prevention control program	242848	31	Exceptions ideal paperless	7476	4
Governance Leadership Direction	235259	30	ideal paperless flow	7476	4
Staff Qualifications Education	212492	28	Summary reports include	5607	3
diagnostic imaging services	197314	25	process medications blood	5607	3
improvement patient safety	212492	25	blood specimen collection	5607	3
radiology diagnostic imaging	197314	23	nursing allied health	5607	3
quality improvement patient	197314	23	Medical Records Department	5607	3
establishes implements process	159369	21	efforts plan implement	5607	3
Facility Management Safety	166958	21	international model intended	5607	3
Access Care Continuity	151780	20	provides structured prescriptive	5607	3
medical students trainees	159369	19	structured prescriptive roadmap	5607	3
Standards Intents Measurable	250437	18	blood bank personnel	5607	3
International Patient Safety	144191	18	relevant paper scanned	5607	3
Patient Safety Goals	144191	18	scanned hours creation	5607	3
local laws regulations	136602	18	interaction alerts active	11214	3
clinical practice guidelines	144191	18	specific percentage requirement	5607	3
medical student trainee	159369	18	templates generate discrete	5607	3
Prevention Control Infections	121424	16	drive CDS alerts	5607	3
research clinical investigations	121424	16	quality patient safety	1869	3

The similarity rate of trigram phrases used in HIMSS-EMRAM and JCI documents is 3%. The phrase "quality patient safety" is the most used trigram in both guides.

Table 4. Rates of similarity between the frequently used words in HIMSS-EMRAM and JCI documents

Compared Models	Frequently Used Words Similarity Rates	2N-grams Similarity Rates	3N-gram Similarity Rates
JCI-HIMSS	33.3%	6%	3%

Upon the analysis, it is understood that the rate of similarity between the frequently used words in HIMSS-EMRAM and JCI documents is very high (Table 4). The rate of similarity between the two evaluation criteria is 33.3%. This rate suggests that the evaluation criteria of the two guides are not very similar. This can be explained by the fact that JCI and HIMSS adopt different perspectives. The bigram similarity rate is 6%, while the trigram similarity rate is 3%. In pairwise comparisons, the similarity rate for bigram and trigram in documents appears to be very low. In addition, the other noticeable aspect here is that the words frequently used in HIMSS-EMRAM and JCI documents are not similar to bigram and trigram.

Discussion

This study identified the similar words used in JCI and HIMSS EMRAM documents and examined the rates of similarity between these documents. Upon the study, it was agreed that the rate of similarity between the two documents was low. It is considered that this may result for two reasons. The first reason is the use of different words conveying the same meaning when inquiring about similar processes in documents. The second reason is that the JCI document covers the processes in hospitals more comprehensively. Comparison of other quality assessment models used on an international scale will contribute to this study.

This study examines HIMSS-EMRAM and JCI evaluation criteria and indicator-based models, which are used in healthcare quality measurement. The analysis conducted as part of the study revealed how often the words in the guidelines of measurement models were used, and which words were used predominantly in each guideline. And the remarkable result is the similarity rate of the most frequently used words in the two guides (33.3%). Based on this result, we can interpret that the two guides feature evaluation criteria from different perspectives in hospitals. This argument is supported by words that exist in one model but that do not exist in the other model. These words demonstrate that both guides focus on different processes in hospitals.

In both guides, the most frequently used unigrams are “hospital, care, patient, medical, process, data, information, clinical, required, medication”, while the most frequently used bigrams are “patient safety, medical records” and the most common trigram is “quality patient safety”. In addition, the dissimilarity of these word phrases used in bigrams and trigrams from the common words used in documents shows the contribution of text mining to the study.

The strength of the study is the fact that the literature does not include any study that has deal with two models and used the text mining method before. The words used in the documents discussed as part of the study are similar in meaning. However, different words conveying the same meaning are used. This is considered a limiting factor for the study since it reduces the similarity rate.

An innovative aspect of this study is that no analysis was carried out previously using text mining method along with any guidelines. Considering the earlier studies in the literature to compare quality measurement models, it is understood that quantitative methods are used mostly. In addition, it is recommended that future studies should be supported by using qualitative data in all these studies (Donahue & Vanonstenberg, 2000; Semnani & Asadi, 2016; Shafei, Walburg, Tahel, 2019). The study is distinct from others in this field for the method used in it. Text mining analysis was used to support this study along with the qualitative data suggested in other studies. For this reason, it is believed that a new perspective has been conducted to the studies in this field.

This study indicates which words the evaluation models use the most in indicators. If hospitals intend to be certified by these evaluation models, they can improve the relevant processes in the hospital with focus on these words. Comparing other internationally valid quality measurement models by using data mining method in future studies will support this study.

Conclusion and Recommendations

The low rate of frequently used words among JCI and HIMSS-EMRAM documents is caused by the adoption of different evaluation principles in models. The HIMSS-EMRAM criteria evaluate the processes in hospitals in terms of digitalisation. Thus, it is considered that a hospital that meets the digitalisation criteria in the JCI document will further meet the EMRAM criteria, where HIMSS-EMRAM is regarded as an important tool to meet the JCI criteria.

Etik Kurul Onayı: Medipol Üniversitesi Sosyal Bilimler Bilimsel Araştırmalar Etik Kurulu tarafından onaylanmıştır (Tarih: 26.04.2022 - Karar No: 56).
Çıkar Çatışması: Bildirilmemiştir.
Finansal Destek: Yoktur.
Katılımcı Onamı: Çalışma kişiler üzerinde yapılmayıp ilgili kurumlardan yazılı izinler alınmıştır.

Ethics Committee Approval: Medipol University Social Sciences Scientific Research Ethics Committee approval was obtained (Date: 26.04.2022 - Number: 56).
Conflict of Interest: Not declared.
Funding: None.
Informed Consent: The study was not conducted on humans, and written permissions were obtained from the relevant institutions.

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