Lecture Notes on Data Engineering and Communications Technologies 210

Faisal Saeed
Fathey Mohammed
Yousef Fazea *Editors*

Advances in Intelligent Computing Techniques and Applications

Intelligent Systems, Intelligent Health Informatics, Intelligent Big Data Analytics and Smart Computing, Volume 1

Springer

Lecture Notes on Data Engineering and Communications Technologies **210**

Series Editor

Fatos Xhafa, *Technical University of Catalonia, Barcelona, Spain*

The aim of the book series is to present cutting edge engineering approaches to data technologies and communications. It will publish latest advances on the engineering task of building and deploying distributed, scalable and reliable data infrastructures and communication systems.

The series will have a prominent applied focus on data technologies and communications with aim to promote the bridging from fundamental research on data science and networking to data engineering and communications that lead to industry products, business knowledge and standardisation.

Indexed by SCOPUS, INSPEC, EI Compendex.

All books published in the series are submitted for consideration in Web of Science.

Faisal Saeed · Fathey Mohammed · Yousef Fazea
Editors

Advances in Intelligent Computing Techniques and Applications

Intelligent Systems, Intelligent Health Informatics, Intelligent Big Data Analytics and Smart Computing, Volume 1

Springer

Editors
Faisal Saeed
College of Computing and Digital Technology
Birmingham City University
Birmingham, UK

Fathey Mohammed
Department of Business Analytics, Sunway Business School
Sunway University
Selangor, Malaysia

Yousef Fazea
Department of Computer Sciences and Electrical Engineering
Marshall University
Huntington, WV, USA

ISSN 2367-4512 ISSN 2367-4520 (electronic)
Lecture Notes on Data Engineering and Communications Technologies
ISBN 978-3-031-59710-7 ISBN 978-3-031-59711-4 (eBook)
https://doi.org/10.1007/978-3-031-59711-4

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

We are pleased to welcome all of you to the 7th International Conference of Reliable Information and Communication Technology IRICT 2023 that is held online on 27–28 December 2023. IRICT 2023 is organized by the Yemeni Scientists Research Group (YSRG) and Big Data Center in Universiti Teknologi Malaysia (Malaysia) in collaboration with Association for Information Systems—Malaysia Chapter (MyAIS) and College of Engineering, IT and Environment at Charles Darwin University (Australia). IRICT2023 is a forum for the presentation of technological advances in the field of Information and Communication Technology. The main theme of the conference is "Advances in Intelligent Computing Techniques and Applications".

Volume 1 includes 28 papers that discuss several research topics such as Health Informatics, Artificial Intelligence, Soft Computing, Data Science, Big Data Analytics, Internet of Things (IoT), Intelligent Communication Systems, Cyber Security, and Information System. These papers were presented in three parallel sessions during the two days.

We would like to express our appreciation to all authors, the keynote speakers for sharing their expertise with us. And we would like to thank the organizing committee for their great efforts in managing the conference. In addition, we would like to thank the technical committee for reviewing all the submitted papers.

Finally, we thank all the participants of IRICT 2023 and hope to see you all again in the next conference.

Organization

IRICT-2023 Organizing Committee

International Advisory Board

Abdul Samad Haji Ismail	Universiti Teknologi Malaysia, Malaysia
Ahmed Yassin Al-Dubai	Edinburgh Napier University, UK
Ali Bastawissy	Cairo University, Egypt
Ali Selamat	Universiti Teknologi Malaysia, Malaysia
Ayoub Al-Hamadi	Otto-von-Guericke University Magdeburg, Germany
Eldon Y. Li	National Chengchi University (NCCU), Taiwan
Kamal Zuhairi Zamil	Universiti Malaysia Pahang, Malaysia
Kamarulnizam Abu Bakar	Universiti Teknologi Malaysia, Malaysia
Mohamed M. S. Nasser	Qatar University, Qatar
Srikanta Patnaik	SOA University, Bhubaneswar, India

Conference General Co-chairs

Faisal Saeed	Birmingham City University, UK
Noorminshah A. Iahad	President of Association for Information Systems—Malaysia Chapter (MyAIS)

Program Committee Chair

Fathey Mohammed	Sunway University, Malaysia

General Secretary

Nadhmi Gazem	Taibah University, Kingdom of Saudi Arabia

Technical Committee Chairs

Faisal Saeed	Birmingham City University, UK
Tawfik Al-Hadhrami	Nottingham Trent University, UK
Mamoun Alazab	Charles Darwin University, Australia

Publications Committee

Fathey Mohammed	Sunway University, Malaysia
Yousef Fazea	Marshall University, USA
Ahlam Al-Dhamari	Universiti Teknologi Malaysia, Malaysia

Publicity Committee

Wahid Al-Twaiti	Universiti Tun Hussein Onn Malaysia
Maged Nasser	Universiti Teknologi PETRONAS
Mohammed Omar Awadh Al-Shatari	Universiti Teknologi PETRONAS

IT and Multimedia Committee

Sameer Hasan Albakri (Chair)	Sana'a University, Yemen
Amer Alsaket	Sitecore, Malaysia
Mohammed Sultan Mohammed	Universiti Teknologi Malaysia, Malaysia

Treasure and Registration Committee

Abdullah Aysh Dahawi (Chair)	Universiti Teknologi Malaysia
Hamzah Gamal Abdo Allozy	Universiti Teknologi Malaysia
Hafedh Ahmed Abdullah Almoalemi	Universiti Teknologi Malaysia

International Technical Committee

Tracks Chairs

Fuad Ghaleb	Universiti Teknologi Malaysia
Maha Idriss	University of Manouba
Mohammed Al-Sharafi	Universiti Teknologi Malaysia
Mohammed Al-Sarem	Taibah University
Qasim Alajmi	A' Sharqiyah University
Rasheed, Mohammad	Birmingham City University, UK
Samer Bamansoor	Birmingham City University
Shadi Basurra	Birmingham City University
Sinan Salih	Al-Bayan University
Tawfik Al-Hadhrami	Nottingham Trent University

Wadii Boulila	RIADI
Yousef Fazea	Marshall University

Reviewers

Abba Hassan
Abdulaleem Al-Othmani
Abdulalem Aldolah
Abdulalem Ali
Abdulalem Saleh
Abdulaziz Alashbi
Abdulaziz Alnehari
Abdullah Alamoodi
Abdullah Almogahed
Abdullah Baarimah
Abdullah Muaad
Abdulrahman A Alsewari
Abdulrazak Yahya Saleh Alhababi
Abdulrazzaq Qasem Ali Al-Yhari
Abdulwadood Mohamed Othman Alawadhi
Adel Ammar
Ahmed Hasan
Akhyari Nasir
Ala'A Al-Momani
Almuntadher Alwhelat
Amala Rose
Ammar Mohmmed
Amr Abdelazim
Ashraf Osman
Ayyub Alzahem
Azmin Ghazali
Aznida Abu Bakar
Babangida Isyaku
Doaa M. Bamasoud
Hiba Zuhair
Eid Yafi
Essa Shahra
Faitouri Aboaoja
Fatima Zahra Fagroud
Gamal Alkawsi
Godwin John Chellathurai
Hamid Chahryar
Hanen Balti
Ibrahim Mahgoub
Ibrahim Muhammed
Israa Al-Barazanchi
Jai Arul Jose G.
Jawad Alkhateeb
Khalil Almekhlafi
Lamia Berriche
Louay Al-Nuaimy
Maged Nasser
Maher Boughdiri
Mahmood Bazel
Maleh Yassine
Manel Chehibi
Manel Khazri Khlifi
Marie Marie
Mohamad Hardyman Barawi
Mohamed Errais
Mohammad Al Bukhari Marzuki
Mohammed Alasli
Mohammed Alsamman
Mowafaq Alzboon
Muazzam A Khan
Muhammad Azmin Mohamed Ghazali
Muhammad Zubair
Mukarram Almuhaya
Mumtazimah Mohamad
Mustafa Abdulsatar Noori
Mustafa Ahmed
Nada El-Gheriani
Nadhmi Gazem
Naila Naz
Nejood Hashim Al-Walidi
Noof Mahmood
Noora Jamal Ali
Omar Dakkak
Raja Inoubli
Rasha Najib Ahmed Aljabali
Rashiq Marie
Refka Hanachi

Rutvij Jhaveri
Safa Ben Atitallah
Safi Ullah
Sami Almazroai
Shaid Latif
Shruthi M K
Siham Lamzabi
Siwar Rekik
Soufiane Jounaidi
Suhailan Safei
Suresh Gowdanakatte Basavarajappa
Taha A. Taha
Taher Ben Yahya
Tariq Saeed
Waheed Ghanem
Waleed Abdulmaged Hammood
Waleed Ali
Wang Dayong
Yassine Khazeri
Younès El Bouzekri El Idriss
Yousef El-Ebiary
Zhenghua Lan

Contents

Health information quality assessment using artificial intelligence: Quality dimensions from healthcare professionals' perspective

Yousef Baqraf[1] and Pantea Keikhosrokiani[2](✉)

[1] Universiti Sains Malaysia, 11800 Penang, Malaysia
baqraf.cs@student.usm.my
[2] University of Oulu, Oulun Yliopisto, 90014 Oulu, Finland
pantea.keikhosrokiani@oulu.fi

Abstract. Recent research has shown a growing interest in the automatic assessment of health information quality on the internet. However, there is a lack of universally applicable guidelines for machine learning and deep learning practitioners to use when evaluating health information. This study seeks to address the gap by empirically identifying a set of tangible guidelines for assessing health information. Drawing from existing literature, we identified 18 criteria and collaborated with specialist doctors to convert these criteria into questionnaires. These questionnaires were then distributed through various social media platforms, including Facebook, WhatsApp, and Email, resulting in 253 responses from six Arab countries with high search volumes for health information. Our analysis revealed that the 18 criteria could be categorized into three subcategories: source quality criteria, treatment quality criteria, and content trustworthiness criteria. Each subcategory plays a crucial role in establishing the trustworthiness of the source of health information, ensuring the quality of treatment, and maintaining the general trustworthiness of the content. Furthermore, we ranked these criteria based on their perceived importance to health information quality as determined by doctors and caregivers. Our findings suggest that these dimensions are highly correlated with health information quality and can serve as valuable tools for both healthcare professionals and machine learning practitioners.

Keywords: Online health information · Quality evaluation · artificial intelligence · Machine learning · Deep learning

1 Introduction and Background

The advent of new technologies and the evolution of the internet have significantly altered how individuals seek guidance, particularly regarding health-related matters. However, the quality of online health advice raises substantial concerns due to potential misinformation, which can adversely impact public health [1, 2]. Additionally, reliance on incorrect advice obtained online, without consultation with healthcare professionals, could strain doctor-patient relationships [3]. Moreover, some individuals perceive online health information as a substitute for in-person medical care, potentially leading to dverse health outcomes [4].

F. Saeed et al. (Eds.): IRICT 2023, LNDECT 210, pp. 1–14, 2024.
https://doi.org/10.1007/978-3-031-59711-4_1

Research into determining information quality criteria and indicators encompass three primary categories, as proposed by Batini and Scannapieco [5]. One approach, grounded in an empirical methodology, focuses on end users to define Information Quality (IQ) through questionnaires, interviews, or practical methods [6]. Recent studies have applied this method to assess health information quality [7, 8]. Al-Jefri et al. [7] reviewed the literature for criteria, conducting a questionnaire-based study involving 329 participants, predominantly without medical backgrounds. Tao et al. [8] utilized qualitative and quantitative methods, identifying five primary quality criteria related to health information. However, limitations exist in relying solely on general health information users without medical backgrounds due to subjective perceptions influenced by personal and demographic factors [9, 10]. Furthermore, cognitive limitations and low health literacy hinder their ability to judge health information quality [11, 12]. A theoretical approach, originating from Wand and Wang [6] and termed an ontological approach, emphasizes theoretical understanding and empirical ranking of quality criteria's importance [5]. Another avenue involves assessing information quality through tools such as Health on the Net Code (HON), Journal of the American Medical Association (JAMA), and DISCERN [13–15]. However, these tools focus on specific aspects of information quality, lacking coverage of evidence-based information and lacking widespread usage for assessment. We add one section to our questionnaire to determine how many health specialists and caregivers are using these tools during their online health information search. Of the 253 participants taking the questionnaire, only 38 (14.4%) of them are always using these tools while searching for health information online, as shown in Fig. 1.

Fig. 1. Health information quality tools usage percentage by health specialists and caregivers

Efforts to address these gaps include combining existing tools and criteria to develop a more comprehensive assessment tool. Despite extensive research, the evaluation of health information quality remains intricate, varying between health professionals and consumers [16, 18]. Recent studies have expanded research into mobile applications, wearable devices, and automatic solutions utilizing deep learning and machine learning techniques [19–27]. The success of automatic methods extends to diverse medical domains, such as early diagnosis of heart illnesses through analyzing heart sounds [28].

The study proposes an optimized Adaptive NeuroFuzzy Inferences System (ANFIS) via artificial bee colony (ABC) to categorize heartbeat sounds for the early identification of cardiovascular diseases, representing a novel approach in this domain. In order to achieve the objective of this study, we have adopted the definition of data quality put forth by Wand and Wang [6], which defines data quality as the fitness for use by data users or consumers, or in other words, the suitability of information for a specific use case. Additionally, in this study, we use the terms criteria and dimensions interchangeably. The focus of our investigation is on emergency medical cases such as heart disease, hypertension, and stroke. These emergency cases are being examined through the lens of health information quality criteria and indicators. Our research aims to develop a conceptual framework for understanding health information quality criteria as perceived by caregivers and health specialists from Arab countries. This will be achieved through three approaches: practical, theoretical, and common sense, as well as drawing on the experience of specialist doctors. The primary aim is divided into two sub-questions: firstly, identifying the criteria that caregivers and health specialists consider most relevant to information quality; and secondly, exploring potential differences in perspectives between caregivers and health specialists regarding information quality.

The remainder of this paper is structured as follows: The next section outlines the methodology employed in determining the health information quality criteria. The following section presents an extensive analysis of all measurements conducted during the execution of the methodology. The next section delves into a discussion of our findings in relation to existing studies on health information quality, highlighting what sets our research apart. Finally, the last section provides a summary and conclusion that draws upon our main findings.

2 Method

2.1 Participants

The research utilized convenience sampling [29–31] to recruit participants from six Arab countries (Egypt, Saudi Arabia, Sudan, Iraq, Jordan, and Yemen) with the highest search for health information according to Google trends. The target participants were doctors and caregivers from any medical specialization. The apriori sample size estimation method was employed to specify the sample size using Gpower software [32], resulting in an estimated sample size of 210, a statistical power of 0.95, an α error probability of 0.5, an effect size of 0.25, and a number of groups of 2. The effect size was determined based on prior studies in information quality [7, 33–35].

2.2 Study Procedure

To generate quality criteria for use by health professionals, deep learning, and machine practitioners, the study followed three methods suggested by Batini and Scannapieco [5], as shown in Fig. 2. This involved identifying all the quality criteria used by health professionals and deep learning machine practitioners, converting these criteria into questions, and refining the questionnaire based on health specialists' practical experience and common sense. Additional details about the questionnaire's validity and reliability can be found in the related section dedicated to these aspects. Furthermore, for the DISCERN tool, the study includes all the quality criteria recently used by Kinkead et al. [23] and suggested by Khazaal et al. [36]. Table 1 lists the 18 specified quality criteria, while Table 2 provides detailed information for each dimension.

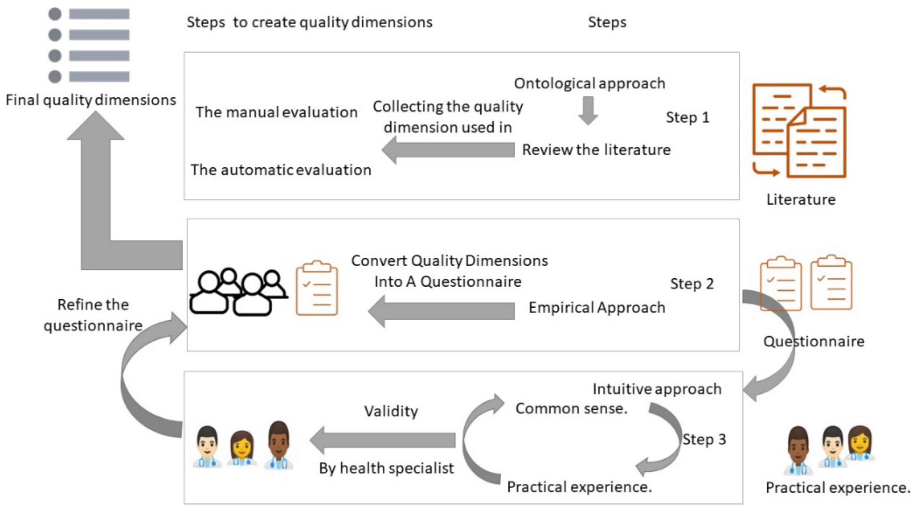

Fig. 2. The 3 Steps of Developing the Quality Dimensions

2.3 Quality Criteria

The study proposes a categorization of health information quality criteria based on their function, drawing from existing literature, as shown in Table 1. The criteria are divided into two categories: source quality criteria, which establish the trustworthiness of the information source, and content quality criteria, which ensure the credibility of the information. The latter category is further divided into treatment quality criteria, ensuring the quality of treatment, and content trustworthiness criteria, ensuring the overall trustworthiness of the content.

2.4 Materials and Data Collection

The data collection for this study took place over a period of four months, from March 4, 2022, to July 30, 2022. A web-based questionnaire was utilized, created using Google Forms, and presented in the form of a Likert scale, with a range from one to five, where a rating of five indicated 'Very related' and a rating of one indicated 'Not very related'. The questionnaire was disseminated through various social media platforms, including Facebook groups, WhatsApp, and Email, to reach a wider audience. To prevent duplicate responses, Google Forms restricted participants to only one response. The questionnaire

Table 1. The 18 Criteria for Assessing the Quality of Health Information

Source Quality	Criteria	Content Quality Criteria			
Quality Criteria	Ref.	Treatment Quality Criteria		Content Trustworthiness Criteria	
1. Authorship	[13, 14]	Quality Criteria	Ref.	Quality Criteria	Ref.
2. Privacy	[13, 14]	8. Treatment works	[15]	14. Attribution	[13–15]
3. Disclosure	[13, 14]	9. Treatment benefits	[15]	15. Complementarity	[13]
4. Currency	[14, 15]	10. Treatment risks	[15]	16. Justifiability	[13]
5. Transparency	[13]	11. The effect of Treatment on quality of life	[15]	17. Evidence-based medicine	[37, 38]
6. Advertising policy	[13]	12. The side effect of no treatment	[15]	18. Emergency	[39]
7. Website Type	[37]	13. Areas of Uncertainty	[15]		

was divided into several sections: the initial section collected participants' personal details, including their profession type, educational level, academic field, and country of residence. The following sections focused on source quality criteria, content quality criteria, and search behavior, encompassing questions related to the type of website, author information, currency of content, complementarity, treatment risks, justifiable- ity, and search terms used for seeking health information online. Additionally, participants were asked about their utilization of quality evaluation tools such as JAMA benchmarks, DISCERN tool, and the HON Code during their online health information searches. The detailed breakdown of the 18 quality criteria related to source and content is presented in Table 2.

Table 2. The Quality Criteria with the Associated Survey Question

No	The quality criteria	The survey question
1	Authorship	Online health documents must include the author's information, affiliations, and relevant credentials
2	Privacy	Online Health information providers must respect the privacy and confidentiality of personal data

(*continued*)

Table 2. (*continued*)

No	The quality criteria	The survey question
3	Disclosure	Online health information providers must identify funding sources
4	Currency	Online health information providers must indicate the dates of the content posted and updated
5	Transparency	Online health information providers must show a straightforward way of contacting, such as Email
6	Advertising policy	Online health information providers must clearly distinguish advertising from editorial content
7	Website Type	Online health information providers affiliated with the government, educational agencies, and international organizations are of higher quality than others (.edu,.org,.gov)
8	Treatment works	Online health document must describe how each treatment works
9	Treatment benefits	Online health documents must describe the benefits of each treatment
10	Treatment risks	Online health documents must describe the risks of each treatment
11	The effect of treatment on quality of life	Online health documents must describe how the treatment choices affect the overall quality of life
12	The side effect of no treatment	Online health documents must explain what will happen if no treatment is used
13	Areas of Uncertainty	Online health information providers must identify any areas of uncertainty (ex., uncertainty as to who will benefit or suffer from the treatment option)
14	Attribution	Online health information providers must cite the source(s) of published information
15	Complementarity	Online health document Information must support, not replace, the doctor-patient relationship

(*continued*)

Table 2. (*continued*)

No	The quality criteria	The survey question
16	Justifiability	Online health information providers must provide evidence for any claims relating to the benefits and performance of the medicine
17	Evidence-based medicine	Online health information providers must provide evidence-based medicine
18	Emergency	Online health information providers must provide the best practices to handle emergency

2.5 Validity and Reliability

To ensure the validity of the questionnaire, a panel of ten professionals from relevant specializations was selected to assess the content validity of the developed questionnaire, as recommended by Lynn [40] and cited by Yusoff [41]. The panel consisted of three experts in critical care nursing, two in critical care medicine, two in medical and surgical treatment, two in cardiothoracic medicine, and one in cardiothoracic surgery. After their evaluation, all recommended adjustments were implemented. While content validity assessment remains subjective, this study utilized the content validity index for both item-level and scale-level assessments, as advocated by Yusoff [41].

Content validity is defined as the extent to which the components of an assessment tool accurately represent the intended construct for a specific assessment objective [42]. It comprises relevance and representativeness. The content validity index was employed to demonstrate content validity evidence. The scale content validity index averages for each section of the questionnaire were as fol lows: S-CVI Average = 0.91 for source of information criteria, S-CVI Average = 0.88 for content criteria, S-CVI Average = 0.75 for high blood pressure search terms, S-CVI Average = 0.80 for strokes search terms, and S-CVI Average = 0.83 for heart disease search terms. All were deemed acceptable according to Lynn [40] and Yusoff [41], except for high blood pressure search terms, which fell below the threshold of 0.78.

The reliability of the questionnaire was assessed using α Cronbach's coefficient for Source Quality Criteria R = 0.69, Content Quality Criteria R = 0.84, Search Terms For High Blood Pressure R = 0.82, Search Terms For Strokes R = 0.84, and Search Terms For Heart Disease R = 0.87, all of which were considered acceptable.

2.6 Statistical Analysis

The questionnaire data were analyzed using the Pingouin open-source statistical package in Python [43] and Scipy.stats model [44], another statistical package in Python. An ANOVA test was utilized with the type of profession (caregivers or doctors), education level, academic field, and country of residence as the independent variables and the quality criteria as the dependent variable. The study aimed to examine the impact of different factors and their levels on the perception of health information quality criteria. Statistical significance was determined by considering a p-value less than 0.05 as statistically significant.

3 Results

The data from 253 participants were analyzed, with 130 (51.3%) being caregivers and 123 (48.6%) being doctors. The participants were from six different countries, with 77 (30.4%) from Egypt, 53 (20.9%) from Yemen, 41 (16.2%) from Iraq, 38 (15%) from Sudan, 33 (13%) from Saudi Arabia, and 11 (4%) from Jordan. The participants represented 25 different academic fields, with the majority specializing in nursing (26.8%), medical and surgical medicine (17.3%), and general medicine (22.1%). In terms of education level, 49.4% had Graduate certification, 23.3% had a Master's degree, and 17.7% had a PhD certification.

Before analysis, three participants' responses were removed due to uniform or irrelevant answers. The independent variables were converted into binary classes for analysis: participation group (caregivers and doctors), educational level (higher education and graduate), and country of residence (Africa and Asia).

3.1 Analysis

The study aims to explore the perceptions of caregivers and doctors regarding various quality criteria. Specifically, we sought to determine which criteria these groups consider most relevant to information quality. Our findings reveal that all 18 criteria are perceived to be equally related to information quality, with slight variations in perception (Table 3, Fig. 3, Fig. 4, and Fig. 5). However, when considering overall perception, the currency dimension received the lowest arith- metic mean, while privacy received the highest (Table 3).

Additionally, we utilized ANOVA tests with participation group (caregivers, doctors), educational level (higher education, graduate), and continent of residence (Africa, Asia) as independent variables, and various quality criteria as depen- dent variables. The results indicate a non-significant difference in perception between the groups for all quality criteria, except for currency and emergency dimensions ($p < 0.05$). Specifically, the mean for currency was lower in Asia ($M = 4.4$, $SD = 0.94$) compared to Africa ($M = 4.6$, $SD = 0.76$), with a p-value of 0.009 and $F(1) = 6.8$. Similarly, the mean for emergency was lower in Asia ($M = 4.2$, $SD = 0.9$) than in Africa ($M = 4.4$, $SD = 0.84$), with a p-value of 0.01 and $F(1) = 6.5$.

3.2 Quality Criteria Rating

Table 3 presents mean ratings across all criteria by 250 participants, highlighting the highest mean in green and significant statistical differences in red among groups. Additionally, the table showcases mean ratings based on participation groups, educational levels, and continents of residence.

Table 3. Summarizes Quality Criteria Ratings by Participants' Profession, Continent, and Education Level Using Mean and Standard Deviation

No	Quality Criteria	Mean-All	Caregivers-Mean	Doctors-Mean	Africa-Mean	Asia-Mean	H Education-Mean	Graduate-Mean
1	Authorship	4.0 ± 1.0	4.0 ± 0.9	3.9 ± 1.1	4.0 ± 1.0	4.0 ± 1.0	3.9 ± 1.0	4.1 ± 1.0
2	Privacy	**4.5 ± 0.7**	**4.5 ± 0.7**	**4.5 ± 0.7**	**4.6 ± 0.7**	**4.5 ± 0.7**	**4.5 ± 0.7**	**4.6 ± 0.7**
3	Disclosure	4.2 ± 1.8	3.5 ± 1.1	3.5 ± 1.1	3.4 ± 1.0	3.7 ± 1.0	3.3 ± 1.2	3.7 ± 1.2
4	Currency	3.5 ± 0.8	**4.5 ± 0.8**	**4.5 ± 0.9**	*4.6 ± 0.8*	*4.4 ± 0.9*	**4.5 ± 0.9**	4.5 ± 0.8
5	Transparency	4.3 ± 0.8	4.2 ± 0.9	4.2 ± 0.9	4.2 ± 0.9	4.2 ± 0.8	4.2 ± 0.8	4.2 ± .09
6	Advertising Policy	4.4 ± 0.8	4.4 ± 0.7	4.2 ± 1.0	4.4 ± 0.9	4.3 ± 0.8	4.2 ± 0.9	4.2 ± 0.8
7	Website Type	4.0 ± 1.0	4.0 ± 1.0	4.1 ± 1.0	4.1 ± 1.0	4.0 ± 1.0	4.1 ± 1.1	4.1 ± 1.0
8	Treatment Works	4.1 ± 0.9	4.1 ± 0.9	4.1 ± 0.9	4.2 ± 09	4.0 ± 1.0	4.1 ± 0.8	4.1 ± 1.0
9	Treatment Benefits	4.4 ± 0.7	4.4 ± 0.8	4.4 ± 0.7	4.5 ± 0.8	4.3 ± 0.7	4.4 ± 0.6	4.4 ± 0.8
10	Treatment Risks	4.4 ± 0.9	**4.5 ± 0.9**	4.3 ± 0.8	4.5 ± 0.9	4.3 ± 0.8	4.4 ± 0.7	4.4 ± 1.0
11	The effect of treatment on quality of life	4.2 ± 0.9	4.2 ± 0.9	4.2 ± 0.8	4.3 ± 0.9	4.2 ± 0.8	4.2 ± 0.8	4.2 ± 0.9
12	The side effect of no treatment	4.1 ± 0.9	4.1 ± 0.9	4.1 ± 0.9	4.1 ± 1.0	4.1 ± 0.8	4.1 ± 0.9	4.1 ± 1.0
13	Areas of uncertainty	4.0 ± 1.0	4.0 ± 1.0	4.1 ± 1.0	4.0 ± 1.0	4.0 ± 0.9	4.0 ± 1.0	4.0 ± 1.0
14	Attribution	4.4 ± 0.8	**4.5 ± 0.8**	4.4 ± 0.8	4.5 ± 0.8	4.4 ± 0.8	**4.5 ± 0.7**	4.4 ± 0.8
15	Complementarity	4.3 ± 0.9	4.3 ± 0.9	4.3 ± 0.8	4.3 ± 0.9	4.4 ± 0.8	4.4 ± 0.8	4.3 ± 0.9
16	Justifiability	4.1 ± 0.9	4.2 ± 0.9	4.1 ± 0.8	4.1 ± 0.9	4.2 ± 0.8	4.2 ± 0.8	4.1 ± 0.9
17	Evidence-based medicine	4.2 ± 0.9	4.3 ± 0.9	4.1 ± 0.9	4.3 ± 0.9	4.2 ± 0.9	4.2 ± 0.9	4.3 ± 0.9
18	Emergency	4.3 ± 0.9	4.4 ± 0.9	4.3 ± 0.8	*4.5 ± 0.8*	*4.2 ± 0.9*	4.4 ± 0.9	4.4 ± 0.9

The source quality criteria comprising seven dimensions with an overall median of 4, Fig. 3 displays individual criterion medians and Interquartile ranges, ranking criteria by participant ratings. The distribution among the 250 participants (caregivers and doctors) is depicted. As a result, Currency and Privacy emerge as the highest-rated criteria within source quality criteria, boasting a median of 5.

The treatment quality criteria rating, with six dimensions and an overall median of 4.0, is presented in Fig. 4, which demonstrates individual criterion medians and interquartile ranges, ranked by participant ratings. Additionally, the figure illustrates the distribution of criteria based on ratings by health specialists and caregivers. Consequently, the criteria of Treatment Risks and Treatment Benefits stand out as the most highly rated elements among the criteria for assessing treatment quality, with a median score of 5.

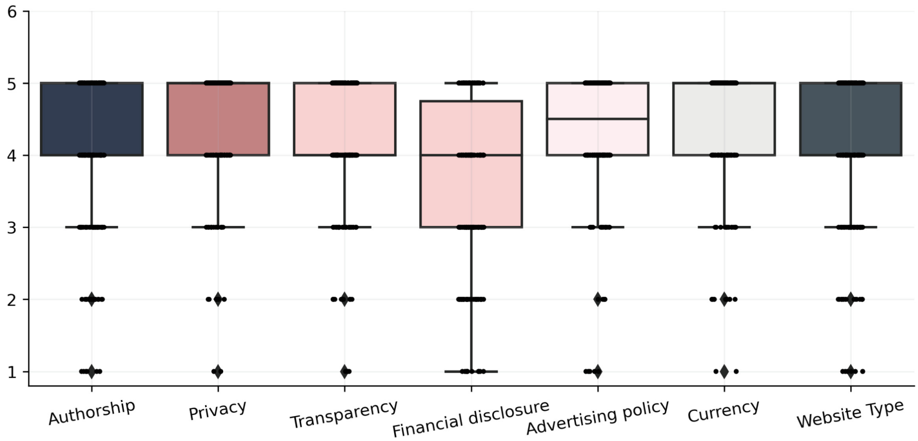

Fig. 3. Shows the Data Distribution of Source Quality Dimensions Including Interquartile Range and Median

The content trustworthiness criteria comprise five criteria with an overall median of 5. Figure 5 showcases criterion medians and interquartile ranges, ranking them based on participant ratings, along with the overall distribution of content trustworthiness criteria. Therefore, Complementarity, Emergency, and Attribution stand out as the most highly rated factors in the criteria for content trustworthiness, with a median score of 5.

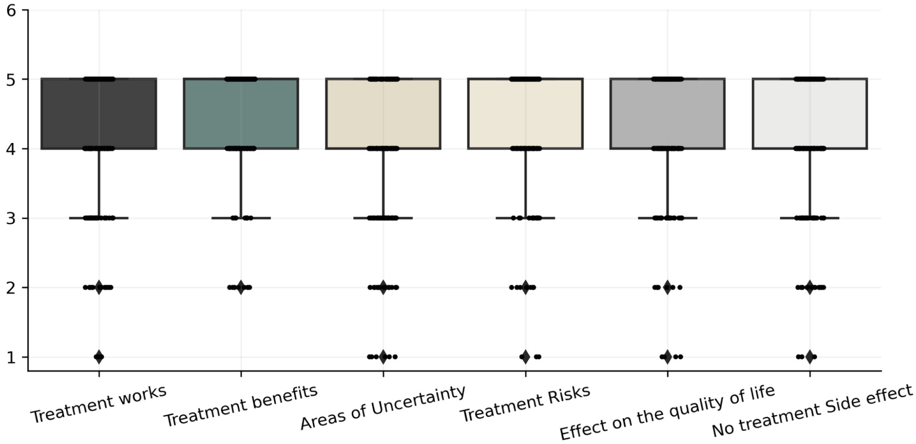

Fig. 4. Shows the Data Distribution of Treatment Quality Dimensions, Including Interquartile Range and Median

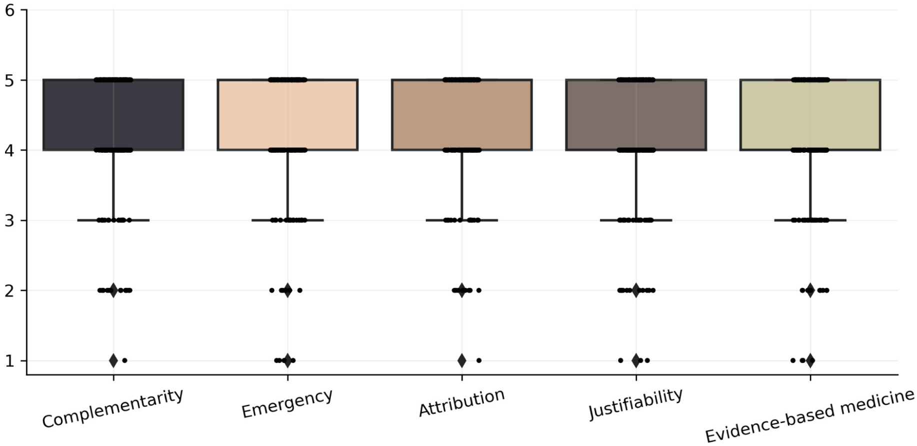

Fig. 5. Shows the Data Distribution of Content Trustworthiness Dimensions Including Interquartile Range and Median

4 Discussion

4.1 Summary of the Contribution

The primary aim of this research is to delineate comprehensive guidelines tailored for health professionals and practitioners in machine and deep learning to assess the quality of health information. Addressing two pivotal queries regarding health information quality, the study delves into discerning the most relevant quality criteria perceived by doctors and caregivers, unveiling 18 distinct criteria categorized as Source Quality Criteria and Content Quality Criteria (Treatment Quality and Content Trustworthiness Criteria). These criteria exhibit a strong correlation with information quality, revealing slight variations in perspectives. Notably, a statistically significant disparity in perceptions between caregivers and doctors regarding the currency and emergency dimensions surfaced (p-value < 0.05), linked to their continent of residence, specifically in Africa and Asia.

Unprecedentedly, this study uniquely examines the pragmatic aspects of health information quality criteria for machine learning and deep learning models, incorporating practitioners' empirical expertise and intuitive understanding. Categorization of quality criteria into functional groups, namely source and content criteria (treatment and trustworthiness), is a novel approach expounded in this study. Aligning with prior research [7, 8], this study also combines disparate tools to detect health misinformation, covering diverse aspects of data quality [44, 45].

The non-significant outcomes from the ANOVA test, evaluating perceptions among distinct participant groups based on educational levels and continents of residence, hint at a crucial implication: the determination of data quality ought to rely on a health professional's insights, considering factors like health background and cognitive abilities [11, 12]. This finding contradicts previous notions [45] advocating for determining data quality based on users' perspectives. Overall, our results indicate a tendency among individuals with medical backgrounds to share similar perceptions concerning the importance of health information quality criteria.

4.2 Source Quality Criteria

The source quality criteria in Fig. 3 reveal that currency and privacy are ranked highest, indicating the importance of updated health information and clear privacy policies for healthcare consumers. Additionally, the advertising policy dimension is of high importance, suggesting that individuals with medical backgrounds prioritize the ethical perspective of health information providers, aligning with previous findings of Al-Jefri et al. [7]. However, contrary to Al-Jefri et al.'s study, the disclosure dimension, considered an ethical criterion, ranks lowest with the highest variance in perception. Interestingly, authorship receives a lower ranking, contrasting with Al-Jefri et al.'s findings for general health information consumers, considering that individuals in the medical environment place greater importance on authors and their information.

4.3 Treatment Quality Criteria

The treatment quality criteria in Fig. 4 show that all treatment criteria are ranked highest by caregivers and doctors, emphasizing the importance of detailed treatment information, including risks, benefits, and effects on quality of life. These findings support Khazaal et al.'s study [35] using a brief version of DISCERN included in this study to evaluate mental health web page content. Additionally, Kinkead et al.[22] implemented an automatic version of DISCERN from Khazaal et al. [35] using deep learning models. The highest ranking of treatment risk and benefit suggests that participants from emergency fields prioritize these criteria due to their impact on emergency cases. This emphasizes the critical nature of treatment risk and benefit in emergency situations [22, 35].

4.4 Content Trustworthiness Criteria

Figure 5 presents the content trustworthiness criteria, which expand upon the treatment and source criteria to assess five crucial aspects of health information quality. The complementarity dimension, prioritizing the patient-physician relationship and the discussion of treatment options, receives a high ranking among caregivers and doctors. Additionally, the emergency dimension, ensuring the accuracy and concurrence of health information with reliable evidence, is highly valued by medical professionals. The attribution dimension, emphasizing clear sourcing and copyright information, also ranks high. Surprisingly, the justifiability and evidence-based medicine criteria receive lower rankings among caregivers and doctors, in contrast to previous findings Al-Jefri et al. [7], although they still hold considerable importance.

4.5 Implications

This study has several implications for evaluating health information quality. It provides concrete guidance for health information professionals to conduct subjective and objective evaluations, facilitating comparisons between human and machine learning performance. The results can be used to create benchmark datasets for evaluating health information quality and suggest a new grouping of quality criteria based on function and purpose. This grouping will help understand the impact of omitting any quality dimension on overall information quality.

4.6 Limitations

Our study has several important limitations. Firstly, the use of convenience sampling may result in an unrepresentative sample. However, it is worth noting that the study collected data from six different countries, encompassing a diverse range of professions, education levels, and countries of residence. Secondly, the study focused exclusively on doctors and caregivers from Arab countries, limiting the generalizability of the findings. Thirdly, the use of apriori sample size estimation for calculating the sample needed to estimate effect size is based on previous studies, which typically reported big and medium effect sizes. Nonetheless, it is important to acknowledge that this technique is consistent with the approach used by Al-Jefri et al. [7].

References

1. Chou, W.Y.S., Oh, A., Klein, W.M.: JAMA **320**(23), 2417 (2018)
2. Swire-Thompson, B., Lazer, D., et al.: Annu. Rev. Public Health **41**(1), 433 (2020)
3. Tan, S.S.L., Goonawardene, N.: J. Med. Internet Res. **19**(1), e9 (2017)
4. Popovac, M., Roomaney, R.: Br. J. Health Psychol. **27**(3), 756 (2022)
5. Maguire, H.: Int. J. Inf. Qual. **1**(4), 444 (2007)
6. Wand, Y., Wang, R.Y.: Commun. ACM **39**(11), 86 (1996)
7. Al-Jefri, M., Evans, R., Uchyigit, G., Ghezzi, P.: Front. Med. **5**, 260 (2018)
8. Tao, D., LeRouge, C., Smith, K.J., De Leo, G., et al.: JMIR Hum. Factors **4**(4), e6455 (2017)

9. Diviani, N., Van den Putte, B., Meppelink, C.S., van Weert, J.C.: Patient Educ. Couns. **99**(6), 1017 (2016)
10. Song, S., Zhao, Y., Song, X., Zhu, Q.: In: 2019 IEEE International Conference on Healthcare Informatics (ICHI), pp. 1–3. IEEE (2019)
11. Pan, X., Lin, Y., He, C.: Qual. Reliab. Eng. Int. **33**(7), 1299 (2017)
12. Sørensen, K., et al.: Euro. J. Public Health **25**(6), 1053 (2015)
13. Boyer, C., Selby, M., Scherrer, J.R., Appel, R.: Comput. Biol. Med. **28**(5), 603 (1998)
14. Silberg, W.M., Lundberg, G.D., Musacchio, R.A.: JAMA **277**(15), 1244 (1997)
15. Charnock, D., Shepperd, S., Needham, G., Gann, R.: J. Epidemiol. Community Health **53**(2), 105 (1999)
16. Sun, Y., Zhang, Y., Gwizdka, J., Trace, C.B.: J. Med. Internet Res. **21**(5), e12522 (2019)
17. Zhang, Y., Sun, Y., Xie, B.: J. Am. Soc. Inf. Sci. **66**(10), 2071 (2015)
18. Mohammed, F., Al-Kumaim, N.H., Alzahrani, A.I., Fazea, Y.: The impact of social media shared health content on protective behavior against COVID-19. Int. J. Environ. Res. Public Health **20**(3), 1775 (2023)
19. Keikhosrokiani, P., Mustaffa, N., Zakaria, N., Abdullah, R.: Cognition Technol. Work **22**, 281 (2020)
20. Keikhosrokiani, P.: Perspectives in the Development of Mobile Medical Information Systems, pp. 75–99 (2020)
21. Keikhosrokiani, P., Mustaffa, N., Zakaria, N.: Telematics Inform. **35**(4), 753 (2018)
22. Di Sotto, S., Viviani, M.: Int. J. Environ. Res. Public Health **19**(4), 2173 (2022)
23. Kinkead, L., Allam, A., Krauthammer, M.: BMC Med. Inform. Decis. Mak. **20**(1), 1 (2020)
24. Upadhyay, R., Pasi, G., Viviani, M.: Multimedia Tools Appli. **82**(4), 5271 (2022)
25. Upadhyay, R., Pasi, G., Viviani, M.: In: Proceedings of the Conference on Information Technology for Social Good, pp. 19–24 (2021)
26. Bal, R., Sinha, S., Dutta, S., Joshi, R., Ghosh, S., Dutt, R.: In: Proceedings of the International AAAI Conference on Web and Social Media, vol. 14, pp. 924–928 (2020)
27. Samuel, H., Zaïane, O.: In: Advances in Artificial Intelligence: 31st Canadian Conference on Artificial Intelligence, Canadian AI 2018, Toronto, ON, Canada, 8–11May 2018, Proceedings 31, pp. 108–120. Springer (2018)
28. Keikhosrokiani, P., Naidu A/P Anathan, A.B., Iryanti Fadilah, S., Manickam, S., Li, Z.: Digital health **9**, 20552076221150741 (2023)
29. Battaglia, M.P.: Encyclopedia of survey research methods **1**, 523 (2008)
30. Etikan, I., Musa, S.A., Alkassim, R.S., et al.: Am. J. Theor. Appl. Stat. **5**(1), 1 (2016)
31. Stratton, S.J.: Prehosp. Disaster Med. **36**(4), 373 (2021)
32. Faul, F., Erdfelder, E., Lang, A.G., Buchner, A.: Behav. Res. Methods **39**(2), 175 (2007)
33. Lee, Y.W., Strong, D.M., Kahn, B.K., Wang, R.Y.: Inform. Manag. **40**(2), 133 (2002)
34. Pitt, L.F., Watson, R.T., Kavan, C.B.: MIS Q., 173–187 (1995)
35. Wang, R.Y., Strong, D.M.: J. Manag. Inf. Syst. **12**(4), 5 (1996)
36. Khazaal, Y., et al.: Patient education and counselling **77**(1), 33 (2009)
37. Yaqub, M., Ghezzi, P.: Front. Public Health **3**, 204 (2015)
38. Al-Jefri, M.M., Evans, R., Ghezzi, P., Uchyigit, G.: In: Proceedings of the 2017 International Conference on Digital Health, pp. 167–174 (2017)
39. Hinkle, J.L., Cheever, K.H., Overbaugh, K. (2021)
40. Lynn, M.R.: Nurs. Res. **35**(6), 382 (1986)
41. Yusoff, M.S.B.: Education in Medicine Journal **11**(2), 49 (2019)
42. Haynes, S.N., Richard, D., Kubany, E.S.: Psychol. Assess. **7**(3), 238 (1995)
43. Vallat, R.: J. Open Source Softw. **3**(31), 1026 (2018)
44. Virtanen, P., et al.: Nat. Methods **17**(3), 261 (2020)
45. Frické, M., Fallis, D., Jones, M., Luszko, G.M.: Am. J. Med. **118**(2), 168 (2005)
46. Strong, D.M., Lee, Y.W., Wang, R.Y.: Commun. ACM **40**(5), 103 (1997)

Leveraging ICT Technologies in the Battle Against COVID-19: A Review for Applications, Challenges, and Solutions

Abdulaziz Aborujilah[1(✉)], Samir Hammami[1], and Kabir Hasibul[2]

[1] Dhofar University, Salalah, Sultanate of Oman
aaborujilah@du.edu.com
[2] University of Kuala Lumpur, MIIT, Kuala Lumpur, Malaysia

Abstract. The COVID-19 pandemic has profoundly impacted our daily lives, with technology playing a pivotal role in the fight against the virus. Consequently, numerous groundbreaking technologies, such as telemedicine, contact tracing apps, and online learning platforms, have been swiftly developed and adopted. These technological advancements have not only assisted in mitigating the spread of the virus but have also allowed us to maintain some semblance of normalcy. However, they have encountered various challenges, including issues related to accessibility, data security, and privacy. This paper explores the threats posed by COVID-19 that current technologies have addressed. It delves into the challenges faced during innovation, development, and implementation. The article also offers suggestions and analysis on how information technology researchers can contribute to combating the COVID-19 pandemic. The objective is to advance technological progress and research, enhancing strategies for battling the ongoing COVID-19 crisis and potential future pandemics.

Keywords: Telemedicine · Contact tracing apps · Data Security · Privacy issues · Pandemic technology challenges

1 Introduction

The COVID-19 epidemic has significantly impacted hospital systems, businesses, educational institutions, and the economy [1]. It has presented unprecedented challenges to global healthcare systems, and the use of information technology (IT) has been crucial in mitigating the spread of the virus [14]. The fight against the coronavirus is increasingly emphasizing telehealth, remote work, and online learning. The demand for cutting-edge technology programs to alleviate the impact of COVID-19 has risen due to the epidemic [8]. Digital technology has made a substantial contribution to the struggle against COVID-19, with comprehensive surveys offered on the subject [13]. The epidemic has also created a unique opportunity to study technology research and practice, including information systems, workplace procedures, and technology design and usage. In addition, there are opportunities to advance technology-based solutions [9, 10]. It serves as a reminder that digital technology has many benefits and could help manage and reduce

F. Saeed et al. (Eds.): IRICT 2023, LNDECT 210, pp. 15–26, 2024.
https://doi.org/10.1007/978-3-031-59711-4_2

the risks associated with the lockdown during and after the pandemic. This is evidenced by the rapid adoption of telemedicine, remote work, and online learning in response to the coronavirus danger [11].

Despite the growing use of information technology (IT) in the fight against COVID-19, there is a lack of research on the specific challenges faced by countries in implementing IT solutions and their effectiveness in reducing the spread of the virus [12]. Furthermore, there is a need to identify the limitations of IT strategies and propose solutions to address these limitations. The implementation of IT solutions has been fraught with challenges, including concerns over privacy, data security, and the lack of infrastructure and resources [15]. This study aims to identify the challenges faced by countries in implementing IT solutions in the fight against COVID-19 and evaluate their effectiveness in reducing the spread of the virus. Furthermore, the study seeks to propose solutions to address the limitations of IT strategies and provide recommendations for policymakers and healthcare professionals on how to effectively leverage IT in the fight against the pandemic. Our contributions are listed in the paragraph that follows: We enumerate various sectors affected by the COVID pandemic, thus struggling in a worldwide pandemic, and demonstrate how IT-based solutions may assist these industries in reducing the impact of COVID-19 with the use of IT. We compare implementation tactics used during and after a world health pandemic to provide an overview of the difficulties associated with pandemic-focused IT.

We reviewed and summarized some real-life applications such as contact tracing apps and software for healthcare related to the COVID pandemic.

2 Method and Material

A structured mapping research methodology [16] has been adapted for this study, offering an overview of the research on the use of IT for combating the COVID-19 pandemic. The structured mapping research methodology is a systematic approach used to identify, analyze, and synthesize existing literature on a specific research topic or question. The methodology involves a rigorous and transparent process of searching and screening relevant literature, extracting data, and analyzing and synthesizing the data to create a comprehensive and organized map of the literature [17]. The shortcomings of the various sectors of present systems have been acknowledged, and the reasons why we should utilize IT to combat COVID-19 have been underlined. All the applicable scientific articles on the study topic have been found, and the documents pertaining to technical IT assistance for COVID-19 outbreak prevention efforts have been mapped. To filter and choose the most pertinent technical publications for our survey, topics like IT, Cloud, social media, Health Information Systems, and Mobile learning connected to COVID-19 have been employed as our search strings. Then, scientific databases were selected for the searches. In the meanwhile, articles with low content standards, papers with restricted text access, and papers authored in languages other than English have been omitted. The keywording phase was the fourth. As we read the abstract, we have looked for words and phrases that best captured the paper's contribution. Then, for the analysis of the research, groups and categories have been formed using the keywords. The final step has been data extraction, which has compiled all the data required to evaluate the technological contributions and elements of IT in the context of COVID-19. The internet has been utilized to locate relevant data.

2.1 Inclusion and Exclusion Criteria

2.1.1 Inclusion Criteria

- Scientific articles related to the use of IT for combating theCOVID-19 pan demic between 20192023.Articles discussing technical IT assistance for COVID-19 outbreak prevention efforts.
- Articles focusing on topics such as IT, Cloud, social media, Health Information System, and Mobile learning in relation to COVID-19.
- Articles published in English.
- Articles with relevant and substantial content.

2.1.2 Exclusion Criteria

- Articles with low content standards or lacking substantial information.
- Papers with restricted text access.
- Articles authored in languages other than English.

2.2 Initial Screening of COVID 19 and IT Related Techniques

The current study has scanned public interested of Covid 19 and IT related techniques such as contact tracking application, telemedicine, AI and big data the on-Internet search, photo and news search. And synthesis of the collected information has employed Google Patterns to highlight the international focus and search patterns of the keywords and

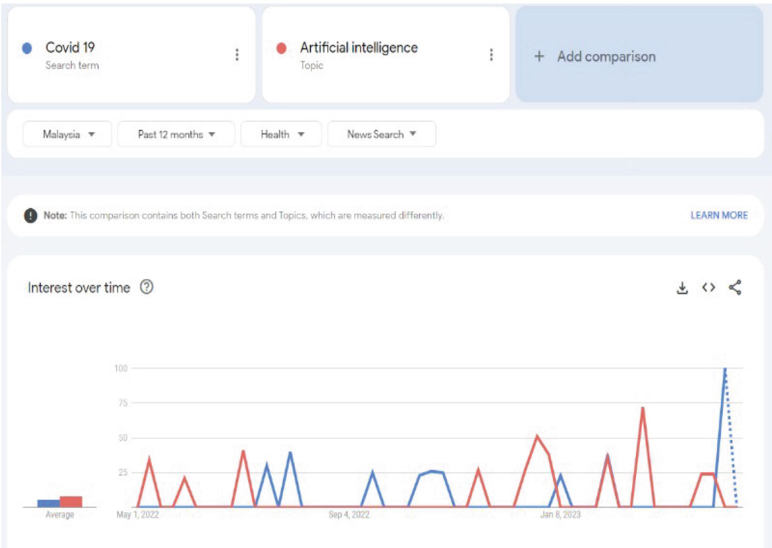

Fig. 1. Google Trends of Covid 19 and AI