DEVELOPMENT OF MACHINE LEARNING SENTIMENT ANALYZER AND QUALITY CLASSIFIER (MLSAQC) AND ITS APPLICATION IN ANALYSING HOSPITAL PATIENT SATISFACTION FROM FACEBOOK REVIEWS IN MALAYSIA

DR. AFIQ IZZUDIN BIN A RAHIM

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In the name of Allah, the most compassionate and merciful.

So verily, with every difficulty, there is a relief. [94:5]

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DECLARATION

I, Afiq Izzudin Bin A Rahim, declare that the work presented in this thesis is originally mine. The information that has been derived from other sources is clearly indicated in the thesis.

Afiq Izzudin Bin A Rahim

Student ID: P-UD 0107/18

Signed on 7 March 2022

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During my Doctor of Public Health (DrPH) course, the following articles were successfully published in two journals which corresponded to my study's objectives.

<u>First Manuscript:</u>

Assessing Patient-Perceived Hospital Service Quality and Sentiment in Malaysian Public Hospitals Using Machine Learning and Facebook Reviews

Afiq Izzudin A. Rahim [1], Mohd Ismail Ibrahim [1,*], Kamarul Imran Musa [1], Sook-Ling Chua [2] and Najib Majdi Yaacob [3]

[1] Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia; drafiqrahim@student.usm.my (A.I.A.R.); drkamarul@usm.my (K.I.M.)

[2] Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, Cyberjaya 63100, Selangor, Malaysia; slchua@mmu.edu.my

[3] Units of Biostatistics and Research Methodology, School of Medical Sciences, Health Campus, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia; najibmy@usm.my

***** Correspondence: ismaildr@usm.my; Tel.: +60-97676621; Fax: +60-97653370

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Second Manuscript:

Facebook Reviews as a Supplemental Tool for Hospital Patient Satisfaction and Its Relationship with Hospital Accreditation in Malaysia

Afiq Izzudin A Rahim [1], Mohd Ismail Ibrahim[1*], Kamarul Imran Musa [1], Sook-Ling Chua[2]

[1] Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia

[2] Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia.

* Correspondence: Dr Mohd Ismail Ibrahim email: ismaildr@usm.my, tel: 6097676621, fax: 6097653370

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Third Manuscript

Patient Satisfaction and Hospital Quality of Care Evaluation in Malaysia Using SERVQUAL and Facebook

Afiq Izzudin A. Rahim [1], Mohd Ismail Ibrahim[1*], Kamarul Imran Musa [1], Sook-Ling Chua[2,] Najib Majdi Yaacob[3]

1 Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia.

2 Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia.

3 Unit of Biostatistics and Research Methodology, School of Medical Sciences, Universiti Sains Malaysia, Health Campus, Kubang Kerian 16150, Kelantan, Malaysia

*Correspondence: Dr Mohd Ismail Ibrahim, email: ismaildr@usm.my, tel: 6097676621, fax: 6097653370

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LIST OF ABBREVIATIONS

ADR	Adverse Drug Reactions
ANOVA	Analysis Of Variance
CAHPS	Consumer Assessment of Healthcare Providers and Systems
CI	Confidence Interval
FB	Facebook
FFT	Friends And Family Test
GPPS	General Practice Patient Survey
HCAHPS	Hospital Consumer Assessment of Healthcare Providers and Systems
IQR	Interquartile Range
JCI	Joint Commission International
LDA	Latent Dirichlet Allocation
LR	Logistic Regression
ML	Machine Learning
MLSAQC	Machine Learning Quality Classifier and Sentiment Analyzer
MOH	Ministry Of Health
MSQH	Malaysian Society for Quality in Health
NB	Naïve Bayes

NGO	Non-Governmental Organization
NHS	National Health Service
NLP	Natural Language Processing
OR	Odd Ratio
PCA	Patient-Centred Approach
POR	Patient Online Reviews
ROC	Receiver Operating Characteristic
SERVQUAL	Service Quality
SVM	Support Vector Machine
TF-IDF	Term Frequency-Inverse Document
WHO	World Health Organization

LIST OF APPENDICES

ABSTRAK

Latar Belakang: Maklumbalas pesakit atas talian (POR) di platform media sosial telah dicadangkan sebagai strategi baru untuk menilai kepuasan pesakit dan memantau kualiti penjagaan kesihatan. Data media sosial, sebaliknya, tidak tersusun dan jumlahnya amat besar. Tambahan pula, tiada kajian secara empirikal telah dijalankan di Malaysia mengenai penggunaan data media sosial dan persepsi kualiti penjagaan di hospital berdasarkan maklumbalas pesakit atas talian, serta hubungan antara pembolehubah ini dan status akreditasi sesebuah hospital awam. Objektif kajian ini adalah untuk (1) membangunkan sistem pembelajaran mesin dalam pengkelasan secara automatis ulasan Facebook (FB) hospital awam di Malaysia mengguna pakai dimensi kualiti perkhidmatan (SERVQUAL) dan analisis sentimen, (2) menentukan kesahihan ulasan FB sebagai nilai tambah kepada tinjauan kepuasan pesakit secara standard, (3) menyiasat perkaitan antara dimensi SERVQUAL, dan sentimen dan kepuasan pesakit, dan (4) menentukan perkaitan antara status akreditasi sesebuah hospital awam dan kepuasan pesakit dan sentimen.

Kaedah: Antara tempoh masa 2017 dan 2019, kami berjaya mengumpul ulasan daripada 48 halaman FB rasmi hospital awam. Dengan membuat anotasi secara manual ke atas kelompok ulasan yang dipilih secara rawak, kami berjaya membina Pengelas Kualiti secara Machine learning (MLQC) berdasarkan model SERVQUAL dan Penganalisis Sentimen secara Machine Learning (MLSA). Pengelas telah dilatih

menggunakan analisa regresi logistik (LR), Bayes Naif (NB), mesin vektor sokongan (SVM), dan beberapa pendekatan yang lain. Prestasi setiap pengelas dinilai menggunakan pengesahan silang 5 kali ganda. Kami mengguna pakai analisis regresi logistik untuk menentukan hubungkait antara pembolehubah.

Keputusan: Purata skor F1 untuk klasifikasi topik adalah antara 0.687 dan 0.757 untuk semua model. SVM secara konsisten mengatasi pendekatan lain dalam pengesahan silang 5 kali ganda bagi setiap dimensi SERVQUAL dan dalam analisis sentimen. Kami menganalisis 1852 ulasan secara keseluruhan dan mendapati bahawa 72.1% adalah ulasan positif dan 27.9% merupakan ulasan negatif yang telah diiktiraf dengan tepat oleh MLSA. Hasil laporan mendapati 73.5% responden berpuas hati dengan perkhidmatan hospital awam, manakala 26.5% tidak berpuas hati. Sebanyak 240 ulasan diklasifikasikan sebagai ketara, 1257 sebagai boleh dipercayai, 125 sebagai responsif, 356 sebagai jaminan dan 1174 sebagai empati dengan menggunakan kaedah MLQC. Selepas pelarasan pembolehubah kovariat yang terdapat dalam data hospital, semua penunjuk SERVQUAL kecuali pembolehubah ketara dikaitkan dengan sentimen positif. Tambahan pula, selepas pembetulan dilakukan terhadap pembolehubah hospital, hasil menunjukkan bahawa semua dimensi SERVQUAL kecuali pembolehubah ketara dan pembolehubah jaminan dikaitkan secara signifikan dengan ketidakpuasan pesakit. Walau bagaimanapun,

tiada assosiasi yang signifikan secara statistik antara status akreditasi hospital dan sentiment pelanggan secara atas talian dan kepuasan pesakit telah dikenalpasti.

Kesimpulan: Menggunakan data yang diperoleh daripada ulasan FB dan algoritma machine learning, satu strategi pragmatik dan lebih praktikal untuk membangkitkan persepsi pesakit terhadap kualiti perkhidmatan dan menambah baik tinjauan kepuasan pesakit secara standard telah dicipta. Tambahan, ulasan pesakit dalam talian menyediakan ukuran kualiti yang belum diterokai sehingga kini, yang mungkin memberi manfaat kepada semua pemegang taroh penjagaan kesihatan. Penemuan kami melengkapkan hasil kajian terdahulu dalam penggunaan ulasan FB sebagai tambahan kepada pendekatan lain untuk menilai kualiti penjagaan hospital di Malaysia. Di samping itu, penemuan ini memberikan data kritikal yang akan membantu pentadbir hospital dalam memanfaatkan POR melalui pemantauan masa nyata dan penilaian kualiti perkhidmatan.

Kata Kunci: Maklumbalas pesakit atas talian; kepuasan pesakit; SERVQUAL; sentimen; akreditasi

ABSTRACT

Background: Patient online reviews (POR) on social media platforms have been proposed as novel strategies for assessing patient satisfaction and monitoring healthcare quality. Social media data, on the other hand, is unstructured and huge in volume. Furthermore, no empirical study has been undertaken in Malaysia on the use of social media data and the perceived quality of care in hospitals based on POR, as well as the relationship between these variables and hospital accreditation. The objectives of this study were to (1) develop a machine learning system for automatically classifying Facebook (FB) reviews of public hospitals in Malaysia using service quality (SERVQUAL) dimensions and sentiment analysis, (2) determine the validity of FB Reviews as a supplement to a standard patient satisfaction survey, (3) investigate associations between SERVQUAL dimensions and sentiment and patient satisfaction and (4) determine the associations between hospital accreditation status and patient satisfaction and sentiment.

Method: Between 2017 and 2019, we collected comments from 48 official public hospital FB pages. By manually annotating many batches of randomly chosen reviews, we constructed a machine learning quality classifier (MLQC) based on the SERVQUAL model and a machine learning sentiment analyzer (MLSA). The classifiers were trained using logistic regression (LR), naïve Bayes (NB), support vector machine (SVM), and other approaches. Each classifier's performance was evaluated using 5-fold cross validation. We used logistic regression analysis to determine the associations.

Results: The average F1-score for topic classification was between 0.687 and 0.757 for all models. In addition, SVM consistently outperformed other approaches in a 5-fold cross validation of each SERVQUAL dimension and in sentiment analysis. We analysed 1852 reviews in total and discovered that 72.1% of positive reviews and 27.9% of negative reviews were accurately recognised by MLSA. Also, 73.5% of respondents reported being satisfied with public hospital services, while 26.5% reported being dissatisfied. 240 reviews were classified as tangible, 1257 as reliability, 125 as responsive, 356 as assurance, and 1174 as empathetic using the MLQC. After adjusting for hospital covariates, all SERVQUAL indicators except tangible were associated with positive sentiment. Furthermore, after correcting for hospital variables, it was shown that all SERVQUAL dimensions except tangible and assurance were significantly linked with patient dissatisfaction. However, no statistically significant association between hospital accreditation and internet sentiment and patient satisfaction has been identified.

Conclusion: Using data acquired from FB reviews and machine learning algorithms, a pragmatic and practical strategy for eliciting patient perceptions of service quality and supplementing standard patient satisfaction surveys has been created. Additionally, online patient reviews provide a hitherto untapped measure of quality, which may benefit all healthcare stakeholders. Our findings complement earlier studies and the use of FB reviews, in addition to other approaches for assessing the quality of hospital care in Malaysia. Additionally, the findings give critical data that will assist hospital administrators in capitalising on POR through real-time monitoring and evaluation of service quality.

Keywords: patient online review; patient satisfaction; SERVQUAL; sentiment; accreditation

CHAPTER 1: INTRODUCTION

1.1 Quality of Care and Patient-Centred Approach

Numerous central governments put a priority on the quality of health care services. Over the last decade, quality management studies have emphasised the need for a patient-centered approach as a critical component of providing high-quality treatment (Greaves *et al*., 2012; Hincapie *et al*., 2016; Rozenblum *et al*., 2015). Patients may be the most reliable journalists when it comes to some aspects of the health care process; their perspectives should be taken into account when advocating for reforms to improve patient safety (Millman *et al*., 2011). The Scottish Health Agency is an example of a healthcare organisation that has moved its focus to a patient-centred approach. Their health and social care policies have shifted in recent years from a hierarchical paradigm centred on hospitals to an integrated, co-management, and community-based model (Chute and French, 2019). The balance of patient demands, and quality improvement programmes is critical, as it influences patient safety, life and death, and long-term health (Gardner *et al.*, 2018). According to reports, patient mortality is growing in the United States because of substandard hospital care (Allen, 2013; James, 2013). Apart from the critical nature of a patient-centred approach, understanding and improving patients' perceptions of care quality can help reduce the likelihood of medical, drug, and laboratory mistakes (Hincapie *et al.*, 2016).

As healthcare prepares for the effects of Industrial Revolution 4.0 by becoming more patient-centred and value-driven, quality management programmes must incorporate activities that identify and appreciate patients' interests, wishes, and beliefs (Institute of Medicine, 2001). Because such reports can only be created by patients, healthcare stakeholders must build methods to track patient-reported impacts and promote their usage at both the individual, community, and hospital level (Lagu *et al*., 2013).

1.2 Traditional Patient Satisfaction Survey

Patient satisfaction is a critical indicator that is considered to indicate the quality of care provided in a hospital environment (Manaf and Nooi, 2009; Sack *et al.*, 2011). By identifying and comprehending the quality elements that influence patient perceptions, healthcare practitioners may better position themselves to meet or exceed demand for high-quality treatment (Sohail, 2003). Structured patient satisfaction surveys, such as the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) and Service Quality (SERVQUAL) questionnaires, are frequently used to assess patient satisfaction with service quality characteristics (Hawkins *et al.*, 2016; Ranard *et al.*, 2016; Shafiq *et al.*, 2017; Zun *et al.*, 2018). The SERVQUAL and HCAHPS assessments are the result of years of evaluative analysis, are conducted and analysed in a systematic manner, and are capable of capturing a high number of patient answers per facility (Alanazi *et al.*, 2017; Dean, 1999; Giordano *et al.*, 2009; Lam, 1997; Shafiq *et al.*, 2017; Westbrook *et al.*, 2014). Nonetheless, they are expensive to implement, time consuming, have poor response rates, large delays between hospitalisation and public dissemination of findings, frequently fail to identify the cause of reported issues, and are subject to selection and response bias (Greaves *et al.*, 2013b; Hawkins *et al.*, 2016; Hong *et al.*, 2019; Ranard *et al.*, 2016). The mismatch between the standard patient survey and other sources of data revealed the necessity for additional data sources to gauge public sentiment about healthcare services (Hu *et al.*, 2019). As a result, the internet and social media have been recommended as new instruments for assessing patient satisfaction and monitoring healthcare services (Geletta, 2018; Greaves *et al.*, 2013b; Lagu and Greaves, 2015).

1.3 Internet, Social Media and Quality Management

Individuals are increasingly turning to the Internet to discuss their clinical experiences and to compare physicians and therapies (Emmert *et al.*, 2018; Yaraghi *et al.*, 2018). The ubiquitous presence of the Internet has altered online customer behaviours, particularly the impact of "electronic word of mouth" (Hennig-Thurau *et al.*, 2004). Individuals go online to rate the products and services they purchase, and they consult the ratings prior to making any online transaction (Grewal *et al.*, 2003). The digital consumer movement has affected patient autonomy and self-determination in medical care, emphasising the critical role of online patient experience and satisfaction in deciding the quality of health care (Fung *et al.*, 2008; Giordano *et al.*, 2009; Jung *et al.*, 2015).

Patients and families have an unprecedented chance to publicly discuss their clinical experiences and communicate with healthcare practitioners via social media sites such as Facebook (FB), Yelp, Google Reviews, and Twitter. The relationship between healthcare practitioners and patients will result in dramatic changes, combining patient-centered healthcare, the internet, and social media, creating a perfect storm atmosphere (Rozenblum and Bates, 2013; Rozenblum *et al.*, 2015). Individuals' remarks on social media sites will supply a wealth of real-time data about public or private healthcare concerns (Cao and Smith, 2018; McCaughey *et al.*, 2014; Straton *et al.*, 2016). As a result, the use of social media data in health research is quickly growing across a variety of sectors of medicine and health science.

The widespread use of social media and the influence of online word of mouth have aided healthcare clients in making decisions about where to get treatment, what to anticipate from the service, and even their impression of healthcare practitioners (Glover *et al.*, 2015; Ha and Lee, 2018; Johari *et al.*, 2017; Martin, 2017). Social media posts are organic, freely accessible, and continually updated, and frequently illustrate an ongoing issue or positive occurrence that has impacted the patient's or family member's life following hospital treatment. However, the majority of evaluations on social media are unorganised, mainly dishonest, and potentially dangerous for manipulation (Moorhead *et al.*, 2013; Verhoef *et al.*, 2014). While there are legitimate concerns about privacy and the social, ethical, and legal implications of social media use, patients frequently use these platforms to obtain or share information about healthcare providers (Giustini *et al*., 2018; Straton *et al*., 2016).

1.4 Facebook Reviews as A Tool for Measuring Patient Satisfaction

FB Reviews section is a function that enables users to leave narrative reviews on businesses and organisations' FB pages. Since its inception in 2013, the FB Reviews section has been included into several hospital FB sites and has been gradually used by patients and their family. Previously, FB employed a five-star rating system but switched to a binary yes or no suggestion system in 2018, greatly simplifying the review process for FB users.

As with other social media sites, FB ratings shed light on how the public views healthcare services (e.g., former, and present patients, their relatives, or friends, past or current employees and so on). Numerous research have been undertaken in the past to examine FB evaluations for hospital services and nursing homes and discovered a low to moderate association between FB ratings and metrics from systematic patient satisfaction surveys (Bjertnaes *et al.*, 2019; Campbell and Li, 2018; Gaudet Hefele *et al.*, 2018; Lee *et al.*, 2018a).

FB is widely used in Malaysia, and its market share continues to grow year after year. As of 2018, Malaysia has 24.6 million social networking users, 97.3 % of whom had a FB account, becoming FB the country's most popular social networking site (MCMC, 2018). With an increasing number of patients seeking and publicly sharing FB ratings and reviews for hospitals, data collected through the feedback channel may be objectively related to traditional patient satisfaction surveys such as SERVQUAL and other hospital quality measures such as accreditation status, clinical outcome indicators, and patient safety goals (Lee *et al.*, 2018a).

1.5 Machine Learning, Topic Classification and Sentiment Analysis

Sentiment analysis on social media is beneficial for determining how people feel about products, events, individuals, and services. The National Health Service (NHS) in England emphasised the potential use of sentiment analysis data as a unique source of information for patients in making hospital selection decisions (NHS, 2012). Sentiment may be quantified in a variety of ways, allowing for the categorization of the underlying emotional data as positive or negative. Few studies on social media sentiment analysis in health research have been undertaken (Gohil *et al.*, 2018; Greaves *et al.*, 2013a; Huppertz and Otto, 2018; Wallace *et al.*, 2014). Textual data or sentiment analysis assists health policymakers in collecting and analysing patient experiences and satisfaction with healthcare services (Jung *et al.*, 2015).

However, social media data is frequently large, posing issues such as data cleansing, data processing, and the construction of an existing theoretical model of social media content quality (Lee *et al.*, 2018b). While this may be accomplished manually through human input, the validity and reliability are mainly suspect. This data processing difficulty can be solved using computer software or machine learning (ML) algorithms that have been taught to execute this task.

A verified and accurate ML technique for measuring sentiment and classifying SERVQUAL topics from large amounts of social media data presents an incredible potential for both patients and healthcare practitioners to better identify and address different health-related concerns (Gohil *et al.*, 2018; Lee *et al.*, 2018b). As a result, healthcare services may be changed and considerably enhanced by listening to digital voices (Rozenblum *et al.*, 2015).

1.6 Hospital Accreditation Standard

There are many hospital accreditation standards, including the United States-developed Joint Commission International (JCI) standard, Accreditation Canada, and the Australian Council on Health Care Standards. Additionally, the International Organization for Standardization, Six Sigma, Quality Awards, and the European Foundation for Quality Management have produced standards. Meanwhile, Malaysia has its own accreditation programme for hospitals, which is handled by the Malaysian Society for Health Quality (MSQH). Several nations or organisations have developed certification systems that are flexible to local needs and conditions based on the experience of mature accreditation models (Mosadeghrad, 2016). For instance, scholars have advocated the establishment of a worldwide Islamic accreditation standard in response to the global rise of Islamic medical tourism (Kamassi *et al.*, 2021).

Accreditation standards assessment is crucial for assuring the high quality, safety, and effectiveness of healthcare services provided in hospitals. Accreditation systems are only effective if their methods, standards, and surveyors are suitable, high-quality, and consistent. According to Iranian hospital managers, reducing the number of standards and criteria while boosting openness may increase the efficiency of the certification process (Mosadeghrad *et al.*, 2017). Brazilian research validated this conclusion, identifying leadership action as a critical component of the certification process (Corrêa *et al.*, 2018).

Apart from the standard review, research has demonstrated that hospital accreditation benefits organisational processes and structures by strengthening the safety and quality culture, promoting patient care, and fostering professionalism and staff skills (Almasabi *et al.*, 2014; Araujo *et al.*, 2020; Mosadeghrad *et al.*, 2019; Yunita and Amal Chalik, 2019). However, other studies indicate that when hospitals establish an accrediting scheme, there is no difference in quality improvement, clinical care, or patient satisfaction (Almasabi and Thomas, 2017; Brubakk *et al.*, 2015). Most importantly, for patients, accreditation leads to improve health treatment. By establishing a relationship between accreditation and patient satisfaction or experience, patients' trust in and propensity to choose a recognised hospital would grow (Yaraghi *et al.*, 2018).

1.7 Problem Statement and Study Rationale

Given the exponential growth of social media and its penetration into nearly every industry in Malaysia and Southeast Asia, it is critical to use technology to enhance healthcare services. Meanwhile, FB is a social media behemoth. However, only a small number of studies have been undertaken on ML and quality measurements using FB data (Abirami and Askarunisa, 2017; Huppertz and Otto, 2018; Zaman *et al.*, 2021). Given FB popularity in Malaysia and its growing use in healthcare, this research seeks to fill a void by examining whether patient comments in FB Reviews can be used in conjunction with patient satisfaction surveys and as a creative tool for assessing patient-perceived hospital quality of service. Additionally, the majority of research on patient online reviews (POR) has concentrated on people in Western countries. Few studies have explored patient annotations in the Chinese (Hao and Zhang, 2016; Hao *et al.*, 2017; Hu *et al.*, 2019), Indian (Abirami and Askarunisa, 2017), and Korean populations (Jung *et al.*, 2015). Due to a dearth of research on Asian populations, we argue that our proposed study adds value to POR from another Asian demographic from a Malaysian perspective.

Meanwhile, in terms of ML methodologies, our suggested research employs supervised learning to integrate two approaches—topic classification and sentiment analysis. According to the study, traditional patient satisfaction surveys have a number of limitations, and social media has been offered as a feasible option for monitoring patient contentment and mood in real time. Additionally, a systematic review of the use of natural language processing (NLP) and ML to process and analyse patient experience data concluded that manual classification of free text comments remains the analysis 'gold standard' and is currently the only way to ensure that all pertinent patient comments are coded and analysed (Khanbhai *et al.*, 2021). Additionally, the research reveals that patient inputs obtained through free-text augmenting structured questionnaires are stable in nature, making them an appealing source of data for supervised learning. Numerous research studies have classified subjects and attitudes using supervised ML (Abirami and Askarunisa, 2017; Alemi *et al.*, 2012; Cole-Lewis *et al.*, 2015; Daniulaityte *et al.*, 2016; Greaves *et al.*, 2013b; Jung *et al.*, 2015; Zaman *et al.*, 2021). Furthermore, we advised that SERVQUAL dimensions be used to train our ML topic classifier. Few studies, using SERVQUAL survey (Lee *et al.*, 2021), CAHPS Dental Plan survey (Lin *et al.*, 2020), and HCAHPS survey (Ranard *et al.*, 2016), have allocated domains to categorise themes in POR. The potential results may be compared to traditional patient satisfaction surveys or quality-of-care indicators.

Another area of focus for our own ML development is that the majority of software products and open-source tools used in topic or sentiment classification were originally developed to identify opinions about products in non-healthcare settings or other commercial industries, or to be compatible with specific healthcare systems, particularly in Western countries (Gohil *et al.*, 2018). As a result, it may have an effect on the classification's accuracy and reliability in a variety of healthcare contexts. Furthermore, commercial software is sometimes prohibitively costly and unsuitable for long-term use. Thus, our study established a unique strategy for constructing a new classifier and sentiment analyzer for detecting SERVQUAL dimensions in hospital FB Reviews.

Also, our study should go beyond basic descriptive analysis and evaluate hypotheses derived from theory in order to have additional clinical and policy implications. As such, we aim to use rigorous statistical techniques such as regression analysis to discover the factors that contribute to positive sentiment. Previous research has employed analysis of variance (ANOVA) (Lin et al., 2020), regression analysis (Hawkins *et al.*, 2016; Huppertz and Otto, 2018; James *et al.*, 2017; Ko *et al.*, 2019; Wallace *et al.*, 2014), Pearson correlation (Abirami and Askarunisa, 2017; Ranard *et al.*, 2016), or Spearman's rank correlation (Abirami and Askarunisa, 2017; Boylan *et al.*, 2020a).

Moreover, we aim to compare POR to known health care quality measurements, such as SERVQUAL, HCAHPS, hospital accreditation, and national quality indicators. There was a modest link between online patient feedback and the General Practice Patient Survey (GPPS) and the Friends and Family Test (FFT) in a previous study (Boylan *et al.*, 2020a). Likewise, studies have discovered that several topics correspond to the CAHPS Dental Plan Survey (Lin et al., 2020) or the HCAHPS survey (Zaman *et al.*, 2021), that patients' informal comments on FB help predict the HCAHPS survey (Huppertz and Otto, 2018), and that certain topics on Yelp are associated with positive or negative reviews but are not included in the HCAHPS survey (Ranard *et al.*, 2016). However, Twitter sentiment was not related to the HCAHPS (Hawkins *et al.*, 2016) or the NHS inpatient survey (Greaves *et al.*, 2014), and there were only weak to moderate relationships between subjects defined by NHS Choices comments to the national inpatient survey (Greaves *et al.*, 2013b). Additionally, by increasing the emotion score, one may elevate their hospital's ranking (Abirami and Askarunisa, 2017). The results may be used to enhance hospital services and to provide more information to officials through POR in order to assist them in making better informed decisions.

1.8 Research Questions

1. Can Machine Learning Quality Classifier and Sentiment Analyzer (MLSAQC) accurately classify and analyse SERVQUAL dimensions and sentiment in hospital FB Reviews?
2. Can the FB Reviews be an additional tool to supplement a conventional patient satisfaction survey?
3. Is there any association between sentiment and patient satisfaction with SERVQUAL dimensions in hospital FB Reviews?
4. Does hospital accreditation relate with patient satisfaction and sentiments in hospital FB Reviews?

1.9 Objective

1.9.1 General

To accurately classify sentiment and SERVQUAL dimensions using Machine Learning Sentiment Analyzer and Quality Classifier (MLSAQC) and to determine the usability of hospital FB Reviews as a supplement to a conventional patient satisfaction survey.

1.9.2 Specific

Phase 1:

1. To develop a Machine Learning Sentiment Analyzer and Quality Classifier (MLSAQC) that can accurately classify SERVQUAL dimensions and sentiments in the hospital's FB Reviews.
2. To validate FB Reviews of the hospital's official FB page as a supplement to a conventional patient satisfaction survey.

Phase 2:

3. To determine the relationships between SERVQUAL dimensions and sentiment and patient satisfaction in hospital FB Reviews.
4. To determine the relationship between hospital accreditation status and patient satisfaction and sentiment in hospital FB Reviews.

1.9.3 Hypothesis

1. Machine Learning Sentiment Analyzer and Quality Classifier (MLSAQC) can accurately classify the SERVQUAL dimensions and analyse the sentiments in hospital FB Reviews.
2. FB Reviews can be an additional tool to supplement a conventional patient satisfaction survey.
3. There are associations between sentiment and patient satisfaction with SERVQUAL dimensions in hospital FB Reviews.
4. There are relationships between patient satisfaction and sentiment with hospital accreditation in hospitals FB Reviews.

CHAPTER 2: LITERATURE REVIEW

2.1 Patient Satisfaction Survey and Social Media Data

Academics have been assessing hospital patient satisfaction for years using a range of approaches and conceptual frameworks. Earlier study found that patients with reasonable expectations reported the highest levels of satisfaction, whereas those with exaggerated expectations reported the lowest levels of satisfaction (Swan *et al.*, 1985). Patients reported satisfaction with health services when their expectations matched the reality of such services (Batbaatar *et al.*, 2016). Since those early attempts, the number of factors related with patient satisfaction has increased dramatically and varies greatly among research (Almasabi *et al.*, 2014; Batbaatar *et al.*, 2016; Yunita and Amal Chalik, 2019). However, one systematic review showed that two significant indicators of patient satisfaction are variables affecting the healthcare provider and patient characteristics (Batbaatar *et al.*, 2016). That evaluation found that characteristics connected to the hospital provider were the strongest predictor of patient satisfaction across trials.

There were nine identified determinants of healthcare services: technical care, interpersonal care, physical environment, accessibility, availability, financial resources, organisational characteristics, continuity of treatment, and care result. Interpersonal skills and technical care qualities exhibited the most positive associations with service-related factors. Meanwhile, patient characteristics such as age, gender, education, socioeconomic position, marital status, race, religion, regional factors, visit frequency, duration of stay, health status, personality, and expectations were all explored to establish their correlations with patient satisfaction (Batbaatar *et al.*, 2016). However, these relationships were weak and inconsistent throughout the sample. As a consequence, the research concluded that it may be worthwhile to attempt to create patient satisfaction using determinants of hospital provider characteristics.

SERVQUAL and HCAHPS are two examples of systematic surveys that assess healthcare service quality. Results of patient satisfaction surveys may be very valuable to healthcare professionals and patients alike. They aid healthcare workers in finding areas in which their services may be improved. Increased patient satisfaction with healthcare services boosts public hospital responsiveness (Draper *et al.*, 2001). According to research, satisfied patients are more likely to follow their physicians' recommendations for treatment and follow-up visits, resulting in better health outcomes and willingness to suggest the hospital (Batbaatar *et al.*, 2016).

Meanwhile, social media has gradually altered health care over the last decade by providing an increasing amount of data to patients and institutions. Social media platforms may give new avenues for supplementing traditional measures of patient satisfaction, including as surveys, and analysing the public's impression of treatment quality, such as hospital reviews and ratings (Verhoef *et al.*, 2014). The social media material is easily available and would assist in resolving quality-of-service problems as well as alerting hospitals to potential patient safety concerns sooner (Bjertnaes *et al.*, 2019; Fung *et al.*, 2008; Lagu *et al.*, 2013).

Given the increasing importance of chances to improve patient satisfaction, researchers are starting to acknowledge social media as an open and credible source of reviews and are investigating the relationship between traditional hospital performance indicators and social media data (Campbell and Li, 2018; Hong *et al.*, 2019). Studies have compared social media reviews to traditional patient experience surveys (Greaves *et al.*, 2012; Verhoef *et al.*, 2014), clinical outcomes such as readmission or mortality rates (Damodar *et al.*, 2019; Hawkins *et al.*, 2016; Lee *et al.*, 2018a), and gold standard patient satisfaction or quality indicator surveys (HCAHPS, SERVQUAL, or national quality health indicator) (Bardach *et al.*, 2013; Bjertnaes *et al.*, 2019; Campbell and Li, 2018; Hawkins *et al.*, 2016; Huppertz and Otto, 2018).

Additionally, other studies have been conducted on several social media platforms, including Twitter (Gohil *et al.*, 2018; Greaves *et al.*, 2014; Hawkins *et al.*, 2016), Yelp (Geletta, 2018; Johari *et al.*, 2017; Perez and Freedman, 2018; Ranard *et al.*, 2016), and FB (Bjertnaes *et al.*, 2019; Campbell and Li, 2018; Cao and Smith, 2017; Lee *et al.*, 2018b). The social media site chosen is determined by the platform's popularity with the general public and the researchers' preferences. FB is the most popular social media network in Malaysia, accounting for 97.3% of all social media users. Additionally, it is more popular with local healthcare groups than other platforms (MCMC, 2018). As a result, the popularity of FB among local communities and healthcare institutions provides an excellent chance to collect sufficient information and data for our research.

The majority of research used criterion validity testing to determine the validity of social media reviews, particularly FB as a new patient satisfaction survey. Any additional instrument that analyses the same parameter is referred to as a criteria. Correlation analysis was used to examine the degree to which the various tools measure the same variable (Heale and Twycross, 2015). Convergent findings indicated a high degree of connection between FB ratings and conventional patient satisfaction surveys. For example, previous research has discovered a low to moderate correlation between FB Ratings and the HCAHPS patient experience survey (Campbell and Li, 2018; Huppertz and Otto, 2018; Lee *et al.*, 2018b) as well as FB Ratings and other national patient experience measures (Bjertnaes *et al.*, 2019; Timian *et al.*, 2013). Meanwhile, research conducted on other social media platforms discovered a moderate to strong link between social media evaluations and conventional patient satisfaction surveys (Geletta, 2018; Ranard *et al*., 2016). Several studies, however, have shown no association between social media review and traditional patient satisfaction surveys or traditional quality indicators (Greaves *et al.*, 2014; Hawkins *et al.*, 2016; Johari *et al.*, 2017). Nonetheless, it was uncertain if social media review was incompatible with more established metrics of patient satisfaction.

Furthermore, the literatures indicate that FB ratings are mostly associated with a limited number of standardised patient experience indicators, some of which include simply overall satisfaction, hospital recommendations, or a cumulative score (Huppertz and Otto, 2018; Perez and Freedman, 2018). Meanwhile, other studies have an insufficient breadth or a very limited coverage of hospitals, such as covering hospitals located in urban area only (Campbell and Li, 2018; Huppertz and Otto, 2018). As a result, the generalizability of past research on hospital association is very uncertain. Additional research is required to elucidate several healthcare disciplines and those operating in rural locations.

Also, recent study has compared social media and online reviews to established patient satisfaction indicators and clinical outcomes. However, the most recent literatures are constrained by a lack of regular social media and online review coverage; an inadequate amount of sophisticated statistical analysis; and a lack of relation to quality metrics (Hong *et al.*, 2019). Thus, further empirical research of relevant ideas, methodical development, and effective data processing are necessary to close the knowledge gap (Hong *et al.*, 2019).

Another point to consider was the possibility of selection bias, which has been noted in earlier research (Greaves *et al.*, 2013b; Hawkins *et al.*, 2016; Ranard *et al.*, 2016. Only a tiny percentage of patients will provide feedback on their patient experience. For instance, online reviewers are more likely to be younger, female, reside in urban areas, and spend more time on social media. Moreover, risk of gamification has been noted as a potential danger to the validity of social media reviews or ratings (Bjertnaes *et al.*, 2019).

2.2 SERVQUAL: A Quality Assessment Tool

The SERVQUAL model is a commonly used technique for assessing service quality across a range of service settings, industries, and countries (Ladhari, 2009). The approach enables the assessment of both customer service needs and perceptions of customer service (Parasuraman *et al.*, 1985; Parasuraman *et al.*, 1988). The SERVQUAL measure was developed to assess five characteristics of perceived quality: tangibles, reliability, responsiveness, assurance, and empathy. All physical parts of the service quality experience are included in the tangible dimension (e.g., equipment, facilities, personnel). Reliability and assurance are phrases that allude to customers' opinions of a service provider's capacity to supply the service. The former entails evaluating the service provider's dependability and correctness, while the latter entails evaluating the service provider's characteristics such as knowledge and courtesy, which may inspire trust and confidence to their customer. The responsiveness component is concerned with the service provider's perceived helpfulness and promptness. Finally, the empathy component refers to how customer perceive personalised or caring services (Parasuraman *et al.*, 1988).

SERVQUAL dimensions have been used to assess service quality in hospitals and other healthcare settings, mostly using survey methodologies. Numerous research carried out in Malaysia created and validated the SERVQUAL model for assessing the quality of healthcare services (John *et al.*, 2011; Muhammad Butt, 2010; Tan *et al.*, 2019; Zun *et al.*, 2018). SERVQUAL and other quality indicators are the result of years of evaluation, are done and analysed systematically, and have the capacity to collect a large number of patient responses per institution (Alanazi *et al.*, 2017; Shafiq *et al.*, 2017). Nonetheless, the surveys have a number of disadvantages, including being expensive to administer, time consuming, requiring significant time between hospitalisation and public release of results, frequently failing to identify the underlying cause of reported problems, and being subject to selection and response bias (Hawkins *et al.*, 2016; Hong *et al.*, 2019; Ranard *et al.*, 2016). The disparity between traditional patient surveys and real-time public opinion on healthcare services demonstrates the need to use other data sources for analysing real-time public opinion about healthcare services (Hu *et al.*, 2019). As a result, the internet and social media platforms have been advocated as a new way to evaluate and monitor the quality of healthcare services (Geletta, 2018; Greaves *et al.*, 2013a; Greaves *et al.*, 2013b; Lagu and Greaves, 2015).

However, social media data is often vast and provides a variety of issues, including data cleaning, data processing, and establishing a theoretical model of the quality of social media material. While this may be achieved manually by human input, the procedure is laborious, and the validity and trustworthiness of the approach are often questioned. A comprehensive evaluation of POR developed and advocated the use of new analytical techniques such as ML to expedite the processing of massive volumes of online review data (Hong *et al.*, 2019). Monitoring SERVQUAL dimensions using hospital social media platforms may aid all stakeholders in identifying and resolving quality concerns, hence reducing the need for costly and time-consuming surveys. Despite their rarity, the FB content analysis study reveals a correlation between social media quality categories and conventional quality evaluations (Campbell and Li, 2018; Richter and Kazley, 2020; Synan *et al.*, 2021).

2.3 Machine Learning for Sentiment Analysis and Quality Classification.

Apart from finance and marketing, ML is often used in clinical medicine and healthcare quality improvement. Patient care (Ben-Israel *et al.*, 2019), stroke prediction (Wang *et al.*, 2020), cardiology (Friedrich *et al.*, 2021), and personal health investigations have all benefited from the ML technology (Yin *et al.*, 2019). Additionally, ML is utilised to quantify information from patients' experiences, which is often accomplished via sentiment analysis and text categorization (Gohil *et al.*, 2018; Khanbhai *et al.*, 2021). Sentiment analysis on social media is helpful for determining how people feel about products, events, people, and services. It analyses word patterns in patient feedback to identify whether a comment is a complaint or a complement. This automated technique benefits healthcare organisations by producing results more quickly than a human strategy would (Zunic *et al.*, 2020). Meanwhile, topic or text analysis is a method for analysing large volumes of unstructured data in order to decipher the key topics of the text (Doing-Harris *et al.*, 2017). Placona and Rathert (2021) discovered that social media data had the same enormous potential for investigating health-related topics or themes as a vetted and established traditional survey.

For text and sentiment analysis, unsupervised and supervised learning were the two most commonly used methodologies (Khanbhai *et al*., 2021). Between the two learning approaches, the most often used strategy is supervised learning, which entails manually categorising a portion of data based on themes and sentiment (Cole-Lewis *et al.*, 2015). Comprehensive reading of all comments included within the dataset remains the "gold standard" method for free text comment analysis, since it is the only way to ensure that all relevant comments are coded and analysed (Khanbhai *et al.*, 2021). The most often used classifiers in supervised learning are SVM and NB, both of which regularly display great classification performance. A supervised technique is often used to analyse online reviews in structured patient surveys (Alemi *et al.*, 2012; Greaves *et al.*, 2014; Hawkins *et al.*, 2016).

On the other hand, topic modelling is an unsupervised ML approach that utilises Latent Dirichlet Allocation (LDA) to find subjects within a given comment automatically (Kherwa and Bansal, 2018). LDA is a model for text production that is predicated on the idea that the words in a document constitute a collection of hidden themes (each word relates to a specific subject). Apart from finding the most often discussed subjects in individual comments, a topic model may be used to mine the free text for new insights. As a result, this approach is often used for the analysis of unstructured social media comments (Hao *et al.*, 2017; Lee *et al.*, 2018a; Liu *et al.*, 2017).

Meanwhile, ML performance may be measured using a variety of metrics, including accuracy, sensitivity, recall, specificity, precision, hamming loss, and the F-measure. The F1 score assigned to a model shows its quality (Bari *et al.*, 2020). In a ML performance evaluation of cancer treatment experience, the SVM algorithm achieved the highest overall sensitivity (78%), accuracy (83.5%), and sentiment analysis f-score of 80% (Wagland *et al*., 2016). As shown by research conducted on the RateMD website, sentiment analysis employing the NB classifier has a positive score of 0.94 and a negative score of 0.68, with an average score of 0.825 for text categorization (Alemi *et al.*, 2012). Similarly, when the NB classifier was applied to assess patient satisfaction at the Utah Health Care System, a sentiment score of 0.84 and a text score of 0.74 were identified (Doing-Harris *et al.*, 2017). According to another study, patient tweets from NHS England had a sentiment score of 0.89, a theme score of 0.85 for dignity and respect, and a text classification score of 0.84 for cleanliness when using the NB algorithm (Greaves *et al.*, 2014). However, a ML sentiment analysis of FB comments using the SVM technique yielded an F1 score of 0.87 (Huppertz and Otto, 2018), which is comparable to the average of 0.89 and 0.84 in topic categorization studies of NHS tweets (Bahja and Lycett, 2016; Hawkins *et al.*, 2016). The results show that SVM and NB may be employed interchangeably in a supervised situation as preferred classifiers, since they outperformed other classifiers in sentiment analysis and text classification.

2.4 Quality Topics and Sentiments in Patient Online Review.

Prior research indicates that POR often address issues such as waiting times, the efficiency of the healthcare system, and interpersonal quality (Doing-Harris *et al.*, 2017; Hawkins *et al.*, 2016; Ranard *et al.*, 2016; Zaman *et al.*, 2021). Other difficulties, however, such as communication, treatment effectiveness, patient safety, the environment, and hospital fees, were cited as key concerns (Alkazemi *et al.*, 2020; Hawkins *et al.*, 2016; Hu *et al.*, 2019; Zaman *et al.*, 2021).

Meanwhile, comprehensive assessments of POR revealed that the overwhelming majority of answers were positive (Boylan *et al.*, 2020b; Hong *et al.*, 2019). Comprehensive research conducted utilising supervised learning found that patients who earned a positive rating on Health Grades had a lower wait time (Lin *et al.*, 2020). Positive sentiment often mentions empathy, friendliness, and explanation while negative sentiment expresses worries about appointment access, appointment waiting time, and time spent with a physician (Doing-Harris *et al.*, 2017). Additionally, a FB study of hospitals in the United States revealed that the criteria most significantly connected with patients' overall evaluations include waiting times, treatment effectiveness, communication, diagnostic quality, environmental cleanliness, and economic concerns (Zaman *et al.*, 2021). Another study of patient feedback obtained through Press Ganey surveys discovered that the phrases "nurse" and "doc" are the most frequently used in positive patient responses. However, physical aspects such as "room," reliability-related subjects such as "discharge," and responsiveness-related factors such as "tests and treatments" garnered the most negative remarks (Nawab *et al.*, 2020). According to a survey done on Chinese social media platforms, the majority of Chinese people have a negative view about healthcare, with the highest proportion of negative sentiment directed at doctor–patient relationships, service efficiency, and nurse service (Hu *et al.*, 2019). However, both Chinese and American patients emphasised medical care, bedside manner, and appreciation or recommendation in their good ratings, with Chinese patients emphasising medical therapy more than American patients. Additionally, Chinese patients' perceptions of bedside manner were more positive toward doctors while American patients' perceptions were more favourable toward personnel (Hao *et al.*, 2017). It's not surprising that certain topics elicited more negative responses than others. For example, discussions about time, money, or pain are unlikely to be constructive (Hawkins *et al.*, 2016).

According to previous studies conducted utilising the LDA approach, the most commonly addressed topics in patient online feedback were healthcare systems, human interactions, and technological factors (James *et al.*, 2017; Lee *et al.*, 2021; Ranard *et al.*, 2016). Positive sentiment is significantly connected to interpersonal and technical quality, whereas negative feelings are often associated with personnel, timeliness, and diagnostic difficulties (James *et al.*, 2017). Positive sentiment, on the other hand, was connected with interpersonal quality and surgical care, but negative sentiment was associated with insurance, billing, and the cost of the hospital visit, according to a study of Yelp reviews (Ranard *et al.*, 2016). Another research examined NHS tweets using the SERVQUAL model and LDA and revealed that the dimensions of responsiveness and assurance are often addressed in negative sentiment, but empathy receives fully positive sentiment ratings (Lee *et al.*, 2021).

While several earlier studies have shown the proportion of topics or themes with positive or negative sentiment, investigations of POR should go beyond simple descriptive analysis and test theory-based hypotheses in order to provide further clinical and policy consequences (Hong *et al.*, 2019). We have seen an increase in recent years in studies comparing POR and sentiments to traditional patient surveys (Boylan *et al.*, 2020a; Greaves *et al.*, 2014; Huppertz and Otto, 2018; Lin *et al.*, 2020; Zaman *et al.*, 2021), clinical outcomes (Hawkins *et al.*, 2016), and hospital ranking (Abirami and Askarunisa, 2017). However, the current body of information remains limited as a result of the scarcity of advanced statistical research and its relation to other quality measures. A systematic review advised doing further empirical research on POR using relevant hypotheses, rigorous design, and data analytics (Hong *et al.*, 2019).

2.5 Association of Hospital Accreditation and Patient Satisfaction.

Accreditation is a powerful tool that hospitals may use to produce a consistent quality improvement strategy and to train new leaders in quality improvement activities. Accreditation status, in an ideal world, assures compliance with standards while encouraging continual quality improvement. A hospital must submit periodic accreditation evaluations to an independent quality organisation in order to be recognised as an accredited hospital (MSQH, 2017).

Previous research compared patient satisfaction assessments to the treatment received at accredited and non-accredited hospitals to evaluate if patient satisfaction is related to the accreditation status of the hospital. There were conflicting conclusions about the link. According to studies conducted in the United States of America, accreditation is unrelated to the quality of care provided to patients and may not be the primary factor influencing patients' desire to refer hospital services (Fong *et al*., 2008; Sack *et al*., 2011). Additionally, another study conducted in the United States of America using large amounts of hospital data discovered that the Joint Commission certification did not result in substantially different patient experience ratings in certified hospitals compared to other independent organisations (Lam *et al.*, 2018). Other investigations conducted outside the United States, in Lebanon (Haj-Ali *et al.*, 2014) and Malaysia, corroborated this (Hayati *et al.*, 2010).

Though, several studies have shown a favourable correlation between accreditation and patient satisfaction. Research conducted in Egypt discovered that associating accreditation with patient satisfaction has favourable short-term impacts (Al Tehewy *et al.*, 2009). Meanwhile, research conducted in Saudi Arabia corroborated their findings (Al-Qahtani *et al.*, 2012). This short-term impact, however, happened during the first year after the healthcare provider got the accreditation certificate.

Lastly, these studies raise a number of methodological concerns. To begin with, the assessment was conducted within a hospital unit only, such as the medical and surgical department (Hayati *et al.*, 2010), the laboratory (Al Tehewy *et al.*, 2009), or the ambulatory centre (Al-Qahtani *et al.*, 2012), rather than the entire health facility in the state or country, which appears to be more accurate but also more complicated. Furthermore, the sample sizes employed in the research were somewhat small (Al-Qahtani *et al.*, 2012).

2.6 Conceptual framework

Our analysis consolidated significant findings or conceptual frameworks from published research on patient satisfaction-related factors. There are four key aspects that may impact patient satisfaction and sentiment in hospital FB Reviews: SERVQUAL dimensions (Tan *et al.*, 2019), hospital characteristics (Batbaatar *et al.*, 2016; Bjertnaes *et al.*, 2019), patient characteristics (Batbaatar *et al.*, 2016) and hospital's FB page features (Bjertnaes *et al.*, 2019; Campbell and Li, 2018). The conceptual framework for this study is shown in Figure 1.

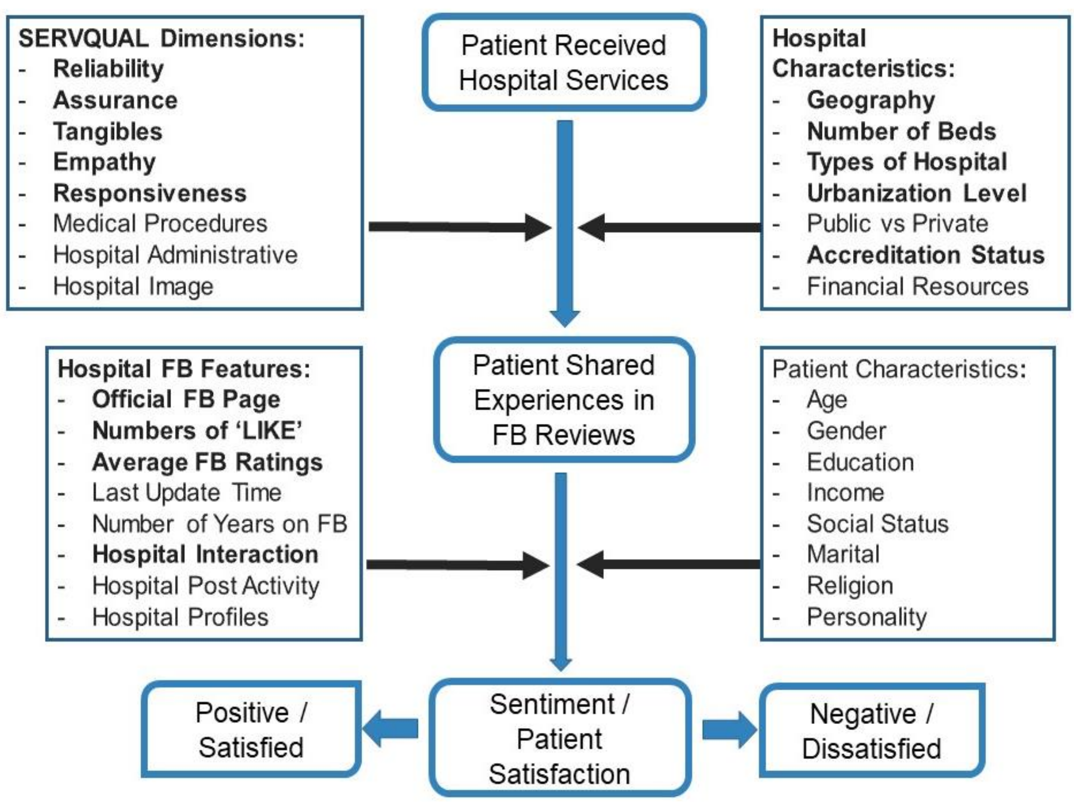

Figure 1: Conceptual framework

CHAPTER 3: METHODOLOGY

3.1 Phase 1: Objective 1

3.1.1 Study designs

We used cross sectional as our study design.

3.1.2 Study population

Our reference population consisted of all hospital reviews in Malaysia, whereas our target population consisted of all MOH hospital reviews on Malaysia social media platforms. Our source population, or sample pool, consisted of all reviews on hospital FB sites in Malaysia, and our sampling frame consisted of a list of all official hospital FB pages in Malaysia.

3.1.3 Subject criteria

- **Inclusion Criteria**: We included all reviews or complaints posted in the FB Reviews section of official hospital FB Page in 2017 and 2018.

- **Exclusion Criteria**: All irrelevant reviews, such as those promoting businesses or marketing, as well as those from hospital departments' FB pages or those from health institutions or agencies such as the Ministry of Health (MOH), the Institute of Medical Research (IMR), non-governmental organisations (NGOs), and long-term care facilities, were excluded.

Additionally, we eliminated any evaluations or complaints written in a language other than Malay or English.

3.1.4 Sample Size Estimation

The minimum sample size required for the development of MLSAQC was 506 reviews using the Kappa agreement test with a minimum acceptable kappa (K0) of 0.40 (Bujang and Baharum, 2017), an expected kappa (K1) of 0.6, proportion of domains in a patient satisfaction survey automatically classified by a ML analysis (p) of 0.22 (Ranard *et al.*, 2016), a significance level (a) of 0.05, 80% power of the study, and a 10% dropout rate. The sample size was determined using an online sample size calculator developed by Arifin (2019).

3.1.5 Sampling Method

There was no sampling method applied in this study because we used all samples collected for our big data analysis.

3.1.6 Research Tool

To construct a ML algorithm, we used Python software (CreateSpace, Scotts Valley, CA) and FB reviews acquired from local official hospital FB pages.

3.1.7 Machine Learning Formula.

The ML formula is composed of experience data multiplied by the task, and the formula's output is the performance. We included positive and negative sentiments, as well as SERVQUAL topics, as input data in our study. Then, we provided a set of tasks to the computer, including classifying SERVQUAL themes and sentiments. Later, we evaluated the machine's accuracy in properly classifying high-quality themes and sentiments in social media. Figure 2 depicts a summary of ML.

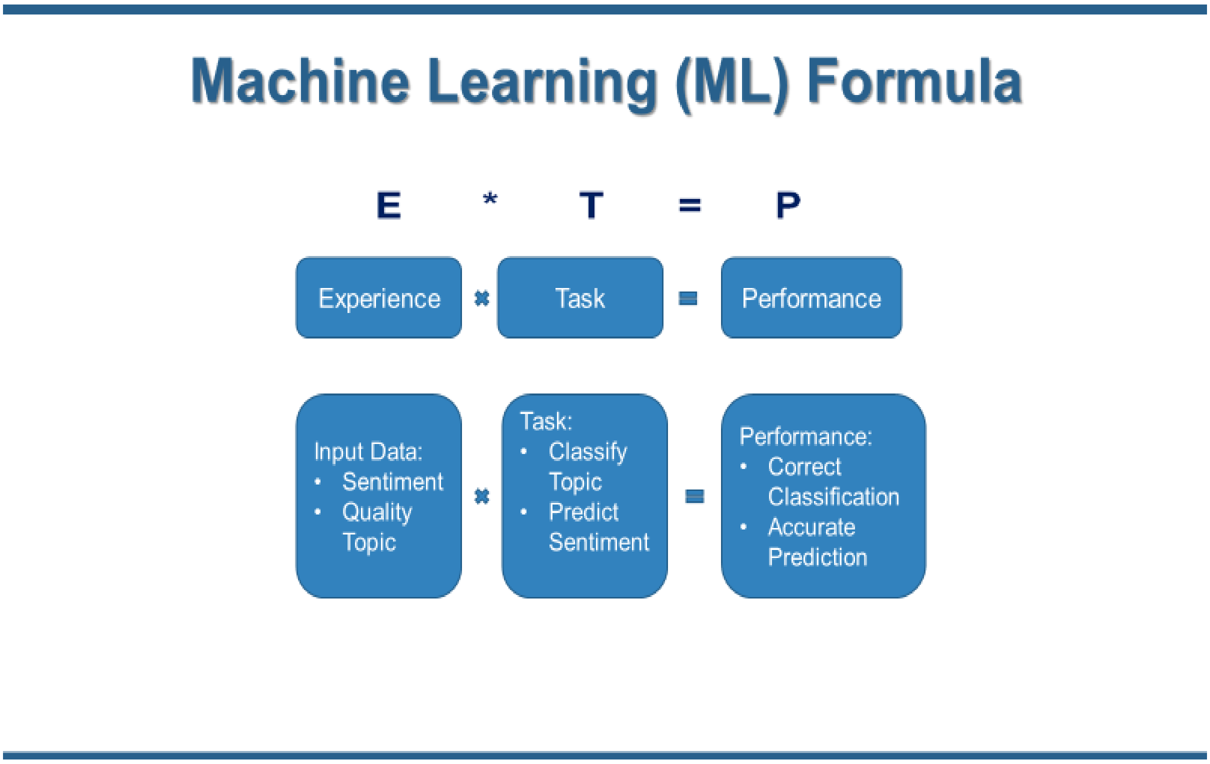

Figure 2: The Machine Learning Formula

3.1.8 Machine Learning Development.

Step 1: Searching the Official Hospital FB Page

To begin, we gathered hospital reviews from the hospital's official FB page. We personally searched for official hospital websites using the Google Search engine. We looked for a link to the hospital's official FB page on the hospital's website. If there was no connection to the hospital's official FB page on the hospital's website, we continued our search on the FB platform. When we discovered an official hospital FB page, we validated the information using information obtained from the Ministry of Health, hospital administrators, or by referring to our operational definition of an official hospital FB page. We defined an "official hospital FB page" as one with a "verified tick" (Moore *et al.*, 2017); or one with the official name ("RASMI" in Malay or "Official" in English) included in the FB page name; or one with the official name ("RASMI" in Malay or "Official" in English) mentioned in the FB page's description; or one with a direct link to the hospital's website. All data obtained from the official FB page is stored in a proforma checklist (Appendix A). Figure 3 illustrates some of the data obtained from the FB page.

Figure 3: Data collected from the hospital official FB Page.

Step 2: Data Mining from the FB Data

We gathered primary data from Malaysian hospital's FB pages. The data was gathered using the WebHarvy software (SysNucleus, Kochi, India) to compile all the reviews on the hospital's official FB page from 2017 to 2019. This study examined only totally public FB reviews (no privacy settings were adjusted by the researcher to extract the data). Additionally, the administrator of the page is unable to erase any reviews made on their hospital's FB Reviews section. It is a policy that FB has developed to ensure the review section's openness and validity. Example of data that we collected from the FB Reviews section was shown in the Figure 4.

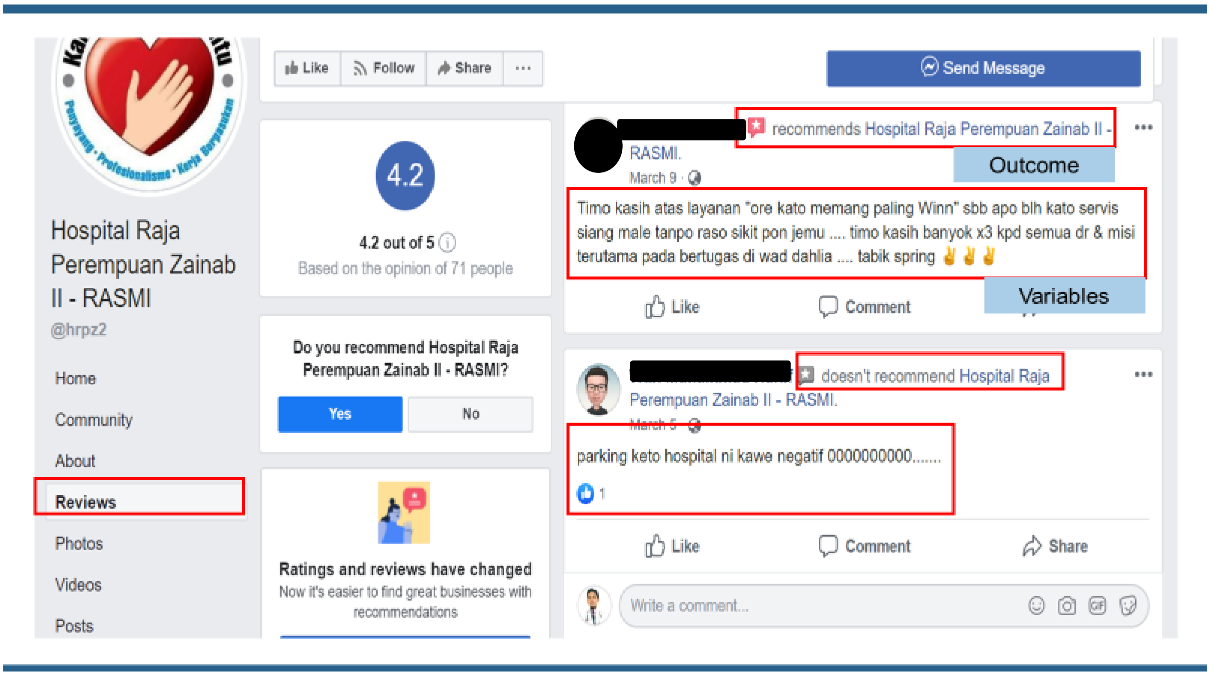

Figure 4: Data collected from the Hospital FB Reviews section

Step 3: Building the Machine Learning Quality Classifier (MLQC)

Manual coding was used to build a labelled data set that would serve as a "gold standard" for quality classifiers trained using machine learning (MLQC). The word "classifier" refers to the class labels applied during the manual annotation phase that attempt to be appropriately labelled by the machine classification models. To begin, two hospital quality managers or SERVQUAL model specialists were engaged to do an initial "open" coding on repeated batches of 100–300 FB reviews based on the MOH SERVQUAL patient satisfaction survey in order to create source coding rules (Appendix B). Additionally, we supplemented the descriptions in the respective dimensions with survey items from other SEVRQUAL research. The reviews were chosen at random to elicit attitudes and subjects about patient experiences in accordance with the SERVQUAL model: (1) Reliability (2) Assurance (3) Responsiveness (4) Empathy and (5) Tangibility.

After that, a randomly selected subsample of 300 FB reviews was used to assess intercoder reliability. The reliability subsample was coded individually by the raters using Microsoft Excel. Cohen's Kappa values were used to determine inter-rater agreement for each SERVQUAL dimension. Cohen's agreement for tangible (Cohen's = 0.885, $p \leq 0.001$), empathy (Cohen's = 0.875, $p \leq 0.001$), reliability (Cohen's = 0.736, $p \leq 0.001$), and responsiveness (Cohen's = 0.72, $p \leq 0.001$) traits from FB ratings was high, while agreement for assurance (Cohen's = 0.626, $p \leq 0.001$) was modest. Cohen's coefficient averaged 0.769 across all dimensions. If they were unable to reach an agreement, they contacted a third rater for settlement. Our MLQC method was trained on a sample of 900 manually labelled FB reviews.

For topic classification, a variety of multi-label approaches were trained, including Binary Relevance, Label Powerset, Classifier Chain, RAkEL: RAndom k-labELsets, MLkNN: Multi-Label k-Nearest Neighbours, and BRkNN: Binary Relevance k-NN. These approaches to multi-label problems are used to reduce them to one or more single-label problems. This modification enables the application of single-label classifiers. We trained three basic classifiers for each technique: Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR). To verify that the training and test sets contain all of the quality labels, we used iterative stratification sampling. The multi-label classifiers were tested using the scikit-multilearn module in Python.

Step 4: Building the Machine Learning Sentiment Analyzer (MLSA)

As with topic classification, we used manual coding to build a labelled data set for our machine learning sentiment analyzer (MLSA). Again, our hospital quality managers were entrusted with doing open coding on 100–300 randomly chosen FB reviews in order to establish a coding guideline (Appendix C). Following that, an intercoder reliability assessment was conducted using a randomly selected subsample of 300 FB reviews. The agreement between positive and negative sentiment coding (Cohen's = 0.721, $p \leq 0.001$) was good. The neutral or unnamed category of review, on the other hand, exhibited a lower degree of agreement (Cohen's = 0.43, $p = 0.027$), which might be explained by the category's more amorphous and heterogeneous character. Thus, both quality managers reviewed and re-evaluated the group of sentiments that were neutral or unidentified. If the review remains neutral or unidentified, it was deleted, as we preferred binary sentiment classification for reviews. Following that, we labelled and pre-processed 1393 randomly selected data instances in preparation for ML training. The training data for sentiment analysis is chosen using a stratified sample strategy in which 80% of reviews in each class are chosen for training. Our ML model was trained using the Python libraries nltk, spacy, and scikit-learn, utilising three different basic classifiers: NB, SVM, and LR.

Step 5: Text Pre-processing

Malaysia is a multicultural nation with a rich linguistic and dialectal diversity. Malay is our national language, while English is our second language. As a consequence, we collected reviews in those languages solely. The Malay language data was standardised and then translated into English. We hired a few junior doctors as our language translators to harmonise the language and manage the dialects.

Following that, the ML approach analyses the features of individual phrases used in FB reviews and utilises this information to construct a high-quality domain classifier. To begin, the labelled dataset was pre-processed to remove URLs, digits, punctuation marks, and stop words, as well as to reduce words to their simplest forms using a lemmatization approach (e.g., treating as treat). Following that, we used the term frequency-inverse document frequency (TF-IDF) approach to estimate the weight assigned to words, which shows their importance to the documents and corpus. For each term $t(i)$ in a FB review j, the TF-IDF score was computed as $w(i,j) = tf\ (i,j)\ x\ idf\ (i)$. The term frequency $tf(i, j)$ document frequency, which equal to $log(N/df(i))$ where N denotes the total number of FB reviews in the dataset and $df(i)$ was the number of FB reviews that include term $t(i)$. Each FB review was expressed as a feature vector, with each item representing the feature’s tf-idf. The data was then stored in an encrypted database for further analysis. The development of MLSAQC is summarised in Figure 5.

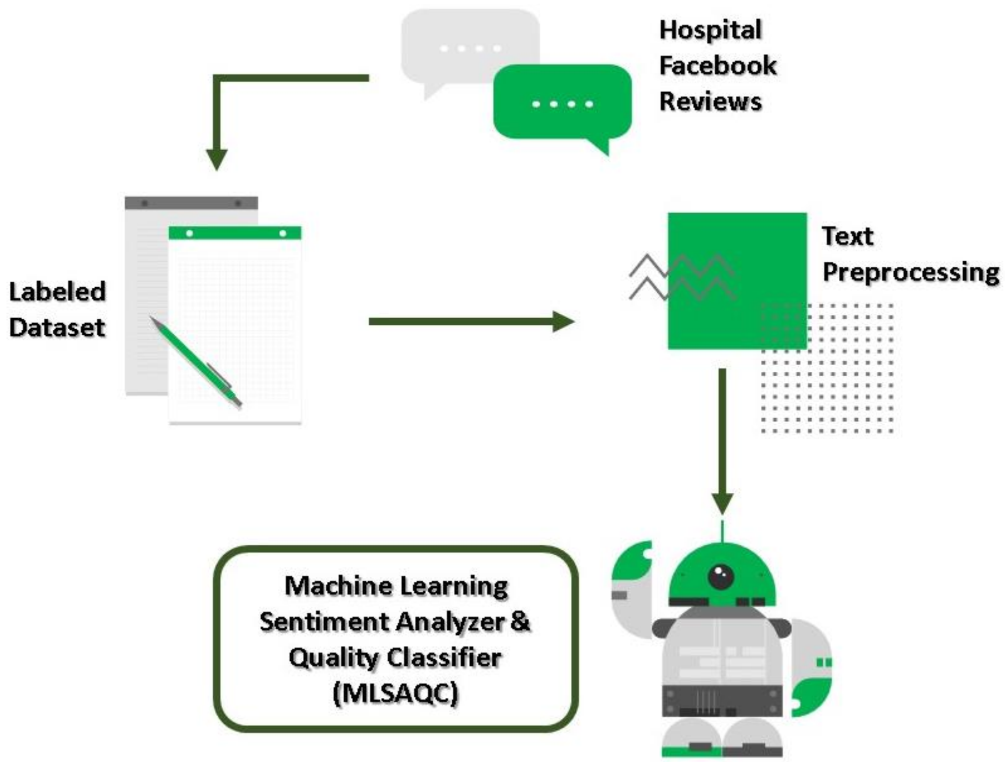

Figure 5: Development of MLSAQC

<u>Step 6: Evaluation of Machine Learning Performance</u>

5-fold cross validation is a commonly used technique for evaluating classification algorithms because it minimises the bias in estimating classifier performance (Khanbhai *et al.*, 2021). This approach trains and tests on the labelled dataset. Cross-validation is performed on randomly selected equal-sized subsets of the manually labelled data set. Five times, the cross-validation technique is performed (the folds). The test data is always maintained as a single subsample, while the remaining four are used as training data. After obtaining the results of five distinct folds, an average is calculated for accuracy, precision, recall, and F-score. Precision is defined as the ratio of correctly classified positive occurrences to the total number of positive instances classified by the model. Recall, which is sometimes referred to as sensitivity, is the ratio of detected positive cases to real positive examples in manually coded data. The F-score is the harmonic mean of the accuracy and recall scores. The greater the F1 score, the better, with zero denoting the worst-case scenario and one denoting the best-case scenario (Khanbhai *et al.*, 2021).

3.2 Phase 1: Objective 2

3.2.1 Study designs

Our second aim was accomplished through the implementation of a validation study.

3.2.2 Study area

The study examined hospital FB pages in Malaysia.

3.2.3 Study population

Our reference population consisted of all hospital reviews in Malaysia, whereas our target population consisted of all MOH hospital reviews on Malaysia social media platforms. Our source population, or sample pool, consisted of all reviews on hospital FB sites in Malaysia, and our sampling frame consisted of a list of all official hospital FB pages in Malaysia.

3.2.4 Subject criteria

- **Inclusion Criteria**: Hospital recommendation posted in the FB Reviews section of official hospital FB Page in 2018 and 2019.
- **Exclusion Criteria**: Hospital recommendations made on non-official or hospital department FB accounts; or hospital recommendations made on the FB pages of health institutions, non-governmental organisations, and long-term care hospitals.

3.2.5 Validation Test

In this study, we employed Spearman's rank correlation to determine the validity.

3.2.6 Sample Size Estimation

We utilised the Correlation Hypothesis Testing formula with an expected correlation (r) of 0.4, a two-tailed significance threshold of 0.05, 80% power of the research, and an estimated dropout rate of 10%. Arifin (2019) designed an online sample size calculator to determine the sample size, and using the calculator, we needed 104 reviews for our validation research.

3.2.7 Sampling Method

There was no sampling method applied for this objective because we selected all data available for our study.

3.2.8 Research Tool

Our second aim was accomplished through the employment of two primary research instruments. To begin, we determined overall patient satisfaction using the SERVQUAL Questionnaire, which was issued by the Ministry of Health to all hospitals in Malaysia. The Ministry of Health conducts an annual study of patient satisfaction in all public hospitals in order to create a standard for high-quality hospital care. The survey is based on the SERVQUAL questionnaire; results are collected by each hospital's quality unit and sent to the Ministry of Health in Putrajaya for analysis. Patients are given the survey during admission, and it is collected before release. Satisfaction is determined by contrasting the service's quality with the patient's expectations. SERVQUAL is associated with customer expectations before and during service delivery, as well as their subsequent judgments of service quality. A positive SERVQUAL difference implies that the patient was satisfied with the service and that his or her expectations were met. On the other hand, negative SERVQUAL values indicate dissatisfaction, such as when a service is not completed entirely. While these statistics are not publicly available, they are available for research at the Medical Division of the Ministry of Health in Putrajaya. The MOH, however, enabled us to study just overall patient satisfaction statistics from 2018 and 2019 for each hospital rather than the complete SERVQUAL domain, due to technical concerns.

Second, we compiled hospital FB recommendations via the hospital's official FB Reviews section. Social media users take advantage of the FB Reviews tool to leave narrative reviews on the FB sites of groups and businesses. Since its inception in 2013, the FB Reviews area has been included in the FB pages of a growing number of hospitals and is increasingly being utilised by patients and their families. FB had a five-star rating system until early 2018, when it transitioned to a binary rating system — "Recommends" or "Does Not Recommend" — which considerably simplified the evaluation process for FB users, as seen in Figure 4. As with other social media platforms, FB reviews offer insight on how important stakeholders (e.g., previous, and current patients, their family or friends, former or current staff, and so on) see healthcare services. Numerous studies have been undertaken to assess FB reviews or ratings of hospital services, as well as patient satisfaction or quality measures (Bjertnaes *et al.*, 2019; Campbell and Li, 2018; Zaman *et al.*, 2021).

3.2.9 Operational Definition for Phase 1

Term	Definition
FB Page	An open profile created by the hospital administration to publicly share content and promote themselves via the FB platform.
Official FB Page	FB page which had a "verified tick"; or an official name included in the FB page name or in the description site of the FB page; or a FB page linked directly from the hospital's website.
FB Reviews	A section and feature on a FB page that allows patients or their relatives to leave narrative feedback and share their hospitalisation experiences.
FB review	A narrative feedback or hospitalisation experience shared by a patient or his/her relatives in the hospitals' FB Reviews section
Hospital FB Recommendation	Willingness of the patient or his/her relatives to recommend the hospital's services to other social media users on the hospital's FB page.
Patient Satisfaction	A hospital FB recommendation in the FB Reviews section of a given hospital's FB page

3.2.10 Statistical Analysis

To assess the validity of FB Reviews as a complement to traditional patient satisfaction surveys, we compared the degree of hospital patient satisfaction as evaluated by the MOH survey to the proportion of patient recommendations on the hospital's FB page. We computed the average percentage of patient satisfaction surveys and the proportion of FB recommendations for each institution using the 2018 and 2019 statistics. We then used Spearman's rank correlation coefficient to determine their link. Correlations of less than 0.2 were classified as weak, those between 0.2 and 0.5 as moderate, and those larger than 0.5 as strong. IBM SPSS software version 26 (IBM Corp, Armonk, NY, USA) was used to analyse the data.

3.3 Phase 2: Objective 3 and 4

3.3.1 Study designs

To accomplish our third and fourth objectives, we conducted a cross-sectional study.

3.3.2 Study area

The study examined all hospital FB pages in Malaysia.

3.3.3 Study population

Our reference population consisted of all hospital reviews in Malaysia, whereas our target population consisted of all MOH hospital reviews on Malaysia social media platforms. Our source population, or sample pool, consisted of all reviews on hospital FB sites in Malaysia, and our sampling frame consisted of a list of all official hospital FB pages in Malaysia.

3.3.4 Subject criteria

- **Inclusion Criteria**: All reviews or complaints posted in the FB Review section of official hospital FB Page from first of July 2018 till end of December 2019.

- **Exclusion Criteria**: All irrelevant reviews, such as those promoting businesses or marketing, as well as those from hospital departments' FB pages or those from health institutions or agencies such as the Ministry of

Health (MOH), the Institute of Medical Research (IMR), non-governmental organisations (NGOs), and long-term care facilities, were excluded. Additionally, any reviews written in a language other than Malay or English were omitted.

3.3.5 Study Duration

The duration of our study was between June 2020 until June 2021

3.3.6 Sample Size Estimation

3.3.6.1 Sample Size of SERVQUAL Topics, Sentiment, and Patient Satisfaction

We estimated the sample size for SERVQUAL topics, sentiment, and patient satisfaction using the Single Proportion Formula. A literature study determined the proportion (P) of SERVQUAL themes. The 95% confidence interval (CI) of 1.96 was used to calculate the Z value. The precision was set to 0.02 (2%), dropout rate was 10% and the sample size was labelled as n. The following table details our third objective's sample size estimation.

Table 1: Sample Size Estimation for Objective 3

Variables	Z value (95% CI)	Δ	P	n	Literature Review
Reliability	1.96	0.02	0.04	410	(Jung *et al.*, 2015)
Assurance	1.96	0.02	0.25	2002	(Jung *et al.*, 2015)
Tangibility	1.96	0.02	0.15	1362	(Jung *et al.*, 2015)
Empathy	1.96	0.02	0.10	962	(Jung *et al.*, 2015)
Responsiveness	1.96	0.02	0.10	962	(Jung *et al.*, 2015)
Positive Sentiment	1.96	0.02	0.85	1362	(Bjertnaes *et al.*, 2019)
Negative Sentiment	1.96	0.02	0.09	875	(Bjertnaes *et al.*, 2019)
Patient Satisfaction	1.96	0.02	0.20	1708	(Gaudet Hefele *et al.*, 2018)

3.3.6.2 Association of SERVQUAL Topics and Patient Satisfaction.

Meanwhile, to determine the sample size for the relationship between SERVQUAL topics and patient satisfaction, we used the two independent proportions formula with power of study of 80%, significance level (α) of 0.05 two-tailed and expected dropout rate was 10%. The proportion of reviews on assurance linked with patient satisfaction (P0) was 0.20 (Ranard *et al.,* 2016), while the expected proportion of reviews on empathy associated with patient satisfaction (P1) was estimated to be 0.40. As a result, a sample size of 184 reviews was determined.

3.3.6.3 Association of SERVQUAL Topics and Positive Sentiment.

To compute the sample size for the relationship of SERVQUAL topics with positive sentiment, we continued to use the two independent proportions formula with power of study of 80%, significance level (α) of 0.05 two-tailed and expected dropout rate was 10%. The estimated proportion of reviews on reliability topics related to positive sentiment (P0) was 0.44 (Moore *et al.*, 2017), whereas the expected proportion of reviews on empathy topics associated with positive sentiment (P1) was 0.60. As a result, a sample size of 338 reviews was determined.

3.3.6.4 Relationship of Hospital Accreditation Status and Patient Satisfaction

The sample size for the association between hospital accreditation status and patient satisfaction was computed using the two independent proportions formula with power of study of 80%, significance level (α) of 0.05 two-tailed and expected dropout rate was 10%. The estimated proportion of non-accredited hospitals related to patient satisfaction (P0) was 0.31 (Hayati *et al.*, 2010), whereas the expected proportion of accredited hospitals associated with patient satisfaction (P1) was 0.50. As a result, a sample size of 232 reviews was necessary.

3.3.6.5 Relationship of Hospital Accreditation Status and Sentiments

We estimated the sample size for the relationship between hospital accreditation status and sentiments using the two independent proportions method with power of study of 80%, significance level (α) of 0.05 two-tailed and expected dropout rate was 10%. The proportion of reviews with a negative sentiment about a hospital's accreditation status (P0) was 0.33 (Gaudet Hefele *et al.*, 2018), whereas the expected proportion of reviews with a positive sentiment about a hospital's accreditation status (P1) was assessed to be 0.60. As a result, a sample size of 118 reviews was necessary.

3.3.6.6 Sample Size Required

Finally, a sample of 2002 reviews was required for our analysis based on all calculations.

All sample size calculations for third and fourth objective were performed using an online sample size calculator designed by Arifin (2019), a lecturer at Universiti Sains Malaysia's Unit of Biostatistics and Research Methodology.

3.3.7 Sampling method

There was no sampling method applied in the second phase and we utilized all samples gathered in this study.

3.3.8 Research Tool

In phase 2, we used the newly built Machine Learning Sentiment Analyzer and Quality Classifier (MLSAQC), as well as hospital FB reviews and recommendations on their official FB sites, along with a list of accredited public hospitals.

In 2018 and 2019, the MSQH published a list of approved accreditations of hospitals via their website. MSQH is a non-profit organisation that was established in collaboration with the Malaysian Ministry of Health, the Malaysian Association of Private Hospitals, and the Malaysian Medical Association. Its objective is to improve Malaysia's healthcare quality through enhancing organisational performance and patient care. MSQH is Malaysia's sole accreditor. Its accreditation criteria cover a broad range of quality characteristics, including treatment accessibility, appropriateness, efficacy, and safety, as well as patient-centered activities, efficiency, and governance (MSQH, 2017). Safety is a critical component of the standards; an organisation that meets all other criteria but does not meet the required level of safety will be denied certification. The MSQH criteria are applicable to all types of hospitals seeking accreditation, whether public or private, large or small. Prior to the accreditation survey, a hospital seeking accreditation must do a self-assessment. The evaluation is conducted by a team of surveyors, who then analyse and vote on their report with members of the Malaysian Council for Health Care Standards. Malaysia had 69 accredited public hospitals in 2018, and 69 certified public hospitals in 2019.

One of the performance criteria used to evaluate service standards in the MSQH certification process is a hospital-wide patient satisfaction survey. It is used to assess the quality of patient-centered care and patient satisfaction (MSQH, 2017). A hospital is not required to perform a particular survey to check compliance with service standards. As a result, public hospitals frequently incorporate the Ministry of Health's patient satisfaction survey into their certification process (MSQH, 2017).

3.3.9 Data Collection Method

The first phase's retrieved FB metadata was then continuously used in the second phase. Then, the SERVQUAL topics were classified using the MLSAQC, and the sentiments in the FB Reviews of the hospital's official FB page were analysed. All data was encrypted and saved in Microsoft Excel and SPSS documents that were only accessible to our team.

3.3.10 Operational Definition for Phase 2

Term	Definition
Reliability	The ability of the hospital to perform the promised service dependably and accurately.
Assurance	The hospital employees' knowledge and courtesy, and their ability to convey trust and confidence.
Tangibility	The hospital’s physical facilities, equipment, and appearance of the hospital personnel.
Empathy	The caring, individualised attention the hospital staff provides to their patients and relatives
Responsiveness	The willingness of hospital staff to help patients and their relatives and provide prompt services.
Hospital with Accreditation	A hospital whose quality dimensions achieved quality standards and was awarded by the Malaysian Society for Quality in Health (MSQH).

Patient Satisfaction	A hospital FB recommendation in the FB Reviews section of a given hospital's FB page
Positive Sentiment	People feel good about the hospital service provided.
Negative Sentiment	People feel bad about the hospital service provided.

3.3.11 Statistical Analysis

Due to the data's non-normal distribution, categorical data were presented as frequencies and percentages for statistical analysis, while numerical data were presented as medians (interquartile range [IQR]). Following that, we employed binary logistic regression to ascertain the link between SERVQUAL topics and sentiment and patient satisfaction in FB reviews. The relationships were adjusted for hospital characteristics (region, bed count, urban or rural location, and type of hospital) and FB page characteristics such as previous star ratings, acceptable hospital information on the FB page, and administrator reaction in the FB Reviews area. We examined the data in terms of those that were statistically significant at p value less than 0.05. All statistical test assumptions have been validated and met. The Hosmer and Lemeshow test, as well as the area under the receiver operating characteristic curve, were utilised to corroborate the model fitness of our research. The data were analysed using IBM's SPSS software version 26 (IBM Corp, Armonk, NY, USA).

3.4 Study flowchart

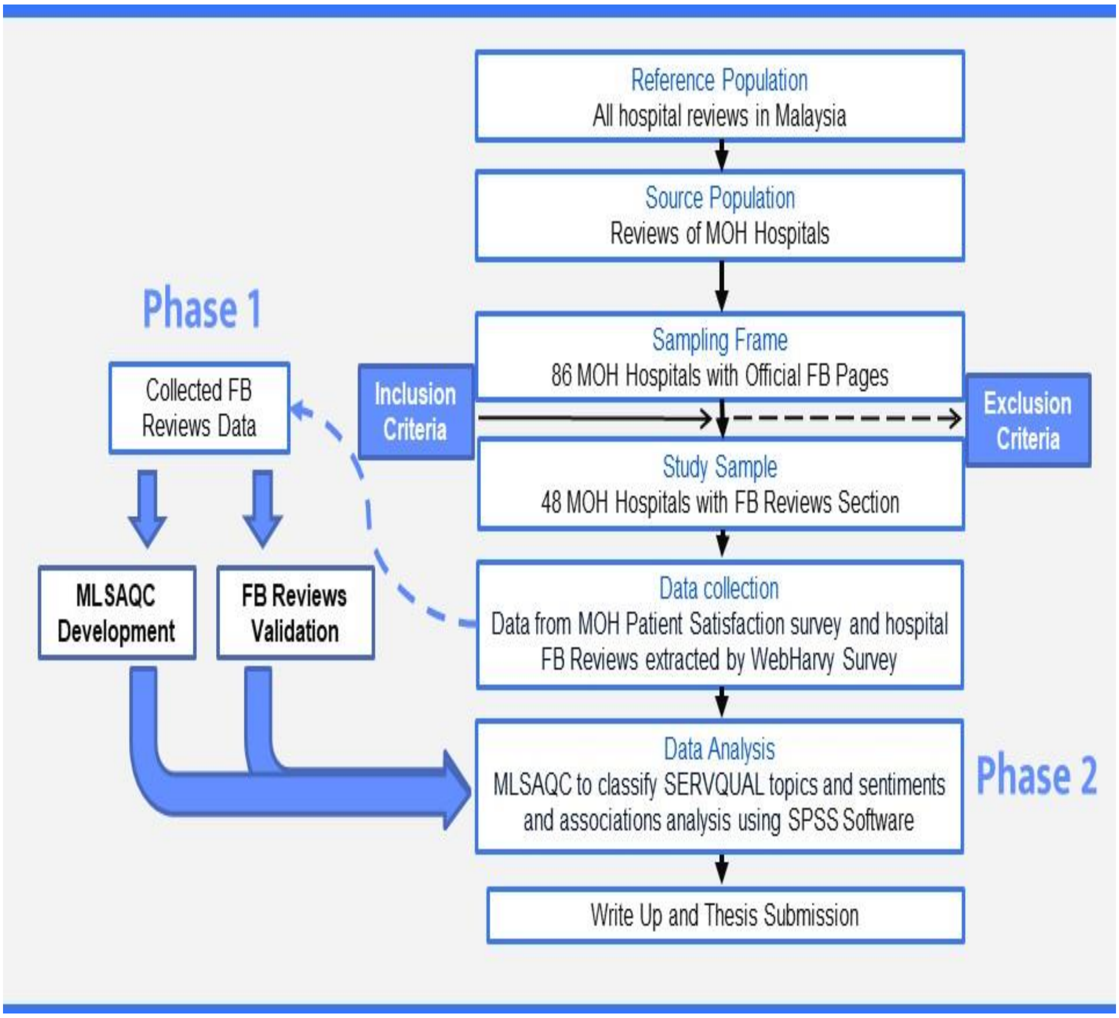

Figure 6: Study Flowchart

3.5 Ethical considerations

This study analysed primary data from the FB Reviews that was readily accessible to the public (e.g.: no privacy settings were adjusted by the researchers). Our research captured no sensitive data, and hence there was no awareness of the hospital or individual identities being assessed and publicly disclosed. All information accessed via the FB pages adheres to the Personal Data Protection Act 2010 standard. No conflict of interest existed in this study. All data was completely anonymous and stored in the encrypted Microsoft Excel and SPSS programmes. Only members of the study team have access to the data. The data was published in aggregate and did not identify individual respondents.

The study's findings may assist the Ministry of Health in monitoring hospital performance on a real-time basis. Additionally, our study's findings may motivate hospital administrations in Malaysia to develop a digital brand on social media platforms and to raise their quality-of-care standards. Furthermore, social media evaluations can have an effect on patient autonomy and self-determination in medical treatment, underlining the critical role of patient experience and satisfaction on the internet in deciding the quality of health care. Moreover, the community will benefit from FB reviews in determining where to get treatment, what to anticipate from the service, and even their impression of healthcare practitioners.

Ethical approvals were acquired through Universiti Sains Malaysia's Jawatankuasa Etika Penyelidikan (Manusia) (JEPeM), code: **USM/JEPeM/19120839** (Appendix D) and the Ministry of Health's National Medical Research Register (NMRR), code: **NMRR-19-3307-51882** (Appendix E).

CHAPTER 4: MANUSCRIPT ONE

Article

Assessing Patient-Perceived Hospital Service Quality and Sentiment in Malaysian Public Hospitals Using Machine Learning and Facebook Reviews

Afiq Izzudin A. Rahim [1], Mohd Ismail Ibrahim [1,*], Kamarul Imran Musa [1], Sook-Ling Chua [2] and Najib Majdi Yaacob [3]

[1] Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia; drafiqrahim@student.usm.my (A.I.A.R.); drkamarul@usm.my (K.I.M.)
[2] Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, Cyberjaya 63100, Selangor, Malaysia; slchua@mmu.edu.my
[3] Units of Biostatistics and Research Methodology, School of Medical Sciences, Health Campus, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia; najibmy@usm.my
* Correspondence: ismaildr@usm.my; Tel.: +60-97676621; Fax: +60-97653370

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Abstract: Social media is emerging as a new avenue for hospitals and patients to solicit input on the quality of care. However, social media data is unstructured and enormous in volume. Moreover, no empirical research on the use of social media data and perceived hospital quality of care based on patient online reviews has been performed in Malaysia. The purpose of this study was to investigate the determinants of positive sentiment expressed in hospital Facebook (FB) reviews in Malaysia, as well as the association between hospital accreditation and sentiments expressed in FB reviews. From 2017 to 2019, we retrieved comments from 48 official public hospitals' FB pages. We used machine learning to build a sentiment analyzer and service quality (SERVQUAL) classifier that automatically classifies the sentiment and SERVQUAL dimensions. We utilized logistic regression analysis to determine our goals. We evaluated a total of 1852 reviews and our machine learning sentiment analyzer detected 72.1% of positive reviews and 27.9% of negative reviews. We classified 240 reviews as tangible, 1257 reviews as trustworthy, 125 reviews as responsive, 356 reviews as assurance, and 1174 reviews as empathy using our machine learning SERVQUAL classifier. After adjusting for hospital characteristics, all SERVQUAL dimensions except Tangible were associated with positive sentiment. However, no significant relationship between hospital accreditation and online sentiment was discovered. FB reviews powered by machine learning algorithms provide valuable, real-time data that may be missed by traditional hospital quality assessments. Additionally, online patient reviews offer a hitherto untapped indication of quality that may

benefit all healthcare stakeholders. Our results confirm prior studies and support the use of FB reviews as an adjunct method for assessing the quality of hospital services in Malaysia.

Keywords: machine learning; social media; Facebook; service quality; SERVQUAL; sentiment; patient online review; accreditation; Malaysia

1. Introduction

The patient-centered approach (PCA) has become a critical component in the development and enhancement of health services and patient care. It values the important input of medical consumers in order to develop aspects of healthcare services that improve patients' and consumers' experiences. Consumers and patients have been more involved in talks among stakeholders and health care task groups in recent years. Nonetheless, with the goal of actively including health consumers in the transformation and reconstruction of quality care activities, debate persists about whether PCA methods should be adopted or if conventional organizational requirements seem to take precedence [1]. Over the past decade, quality management studies have emphasized PCA as a critical component of high-quality care delivery [2-4]. Patients may be the most trustworthy journalists when it comes to some aspects of the health care process; their perspectives should be taken into account when advocating for reforms to enhance patient safety [5]. The Scottish Health Agency is an example of a healthcare organization that has changed its emphasis to a patient-centered approach. Their health and social care policies have shifted in recent years from a hierarchical approach centered on hospitals to an integrated, co-management, and community-based approach [6].

The balance between patient demands and quality improvement programs is critical, as it influences patient safety, life and death, and long-term health [7]. A systematic analysis concluded that poor healthcare quality was the primary factor contributing to an increase in fatalities from cardiovascular disease, newborn traumas, and communicable diseases [8]. As healthcare prepares for the effect of Industrial Revolution 4.0 by becoming more patient-centered and value-driven, quality management programs must include efforts that identify and respect patients' interests, wants, and beliefs. Because such reports can only be produced by patients, it is essential to establish mechanisms to monitor patient experiences and to encourage their usage at both the individual and community level [9,10]. Furthermore, by eliciting and enhancing patient perceptions of treatment quality via PCA methods, the likelihood of medical, medication, and laboratory mistakes will be reduced [2].

Structured patient satisfaction and quality measure surveys, such as the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) and Service Quality (SERVQUAL) questionnaires, are often used to assess healthcare quality services [11-14]. SERVQUAL, HCAHPS, and other standard quality assessments are the product of years of evaluative analysis, are conducted and evaluated in a systematic manner, and can capture a significant number of patient answers per institution [14-16]. However, traditional patient or public surveys used to evaluate the quality of healthcare services are time and resource-intensive, requiring significant time between hospital admission and report disclosure, frequently resulting in a failure to identify the underlying causes of concerns, and possibly introducing response and selection bias [11,17]. Meanwhile, healthcare authorities now have an alternative to conventional patient surveys through social media [3]. There is increasing awareness that user-generated material available through social media platforms such as Facebook (FB), Twitter, and Yelp may be utilized as a rich source of data for patient experience and quality-of-care metrics [11,12,18]. By improving their early-warning capabilities for healthcare quality management, such data may be utilized to augment and expand the breadth of patient experience and health quality services [19].

Numerous studies believe that social media represents the next horizon for provider-patient communication in healthcare. In Malaysia, FB is extensively utilized, and its market share continues to rise and in 2020, FB was the country’s most popular social networking site [20]. FB reviews is a technology that allows people to provide narrative reviews on organizations’ FB pages, and the feature offers insight into how the public perceives healthcare services [21]. Few studies have been conducted in the past to evaluate FB reviews of hospital services and nursing homes and found a low to moderate correlation between FB ratings and patient satisfaction metrics from systematic surveys [18,22-24]. With an increasing number of patients seeking and publicly sharing hospital ratings and reviews on FB, data collected via the feedback channel may be objectively related to traditional patient satisfaction or quality measure surveys such as SERVQUAL, HCAHPS, Consumer Assessment of Healthcare Providers and Systems (CAHPS) Dental Plan Survey, hospital accreditation, and clinical outcomes [11,25-27].

Nonetheless, social media data are often massive in quantity, posing challenges such as data cleaning, data processing, and the creation of a well-established empirical model of social media content quality [28]. While this may be accomplished manually via human input, its validity and reliability are widely disputed. As a result, such obstacles may be addressed using trained machine learning algorithms for this approach. A machine learning method for evaluating sentiment and classifying service quality based on unstructured social media data has the potential to substantially enhance both patients' and healthcare professionals' diagnosis and treatment of a range of health-related problems [29-31].

The purpose of this paper is to ascertain the prevalence of SERVQUAL dimensions and sentiments in FB reviews of Malaysia public hospitals. Second, we want to decipher the determinants of positive sentiment in hospital FB reviews. Thirdly, we are interested in determining the relationship between hospital accreditation and sentiments expressed in hospital FB reviews. Our study contributed mainly:

- To develop a novel and systematic method for converting social media comments to SERVQUAL dimensions and analyzing online sentiments in Malaysia via supervised learning.
- To classify topics based on an established methodology for service quality; SERVQUAL that is extensively used to assess the quality of health care services, overcoming obstacles, and providing policymakers with precise action implications.
- By identify the determinants of positive sentiment as well as its relationship with hospital accreditation in Malaysia using advanced statistical analysis.
- Via real-time monitoring of hospital quality and patient perceptions of health care services through the translation of social media data.
- Through the machine learning technology that can be utilized as an early-warning system for immediate quality improvement in healthcare.

2. Literature Reviews

2.1. Social Media Data

Patients and the public are increasingly using the Internet to discuss their healthcare experiences and to compare doctors and treatments [32,33]. The digital consumer movement on social media influenced patient autonomy and self-determination in medical treatment, highlighting the essential importance of online patient experience in determining health care quality [3,34]. While many studies have examined the use of social media in hospital settings, the bulk of them examines the use of Twitter or Yelp as a social media tool for evaluating the quality of hospital services, rather than the FB platform [11,12,17,35]. This is very certainly due to a population's preference for social media in various countries.

As is the case with other social media platforms, FB ratings provide insight into the public's perception of healthcare services. Numerous studies have been conducted in the past to assess FB ratings for hospital services and found a weak to moderate correlation between FB ratings and patient satisfaction metrics from systematic surveys [36,37]. Additionally, a local study discovered a modest connection between hospital patient satisfaction surveys and online satisfaction in FB reviews [38]. Moreover, with an increasing number of patients seeking and publicly sharing hospital ratings and reviews on FB, data collected via the feedback channel may be objectively associated with other hospital quality measures such as accreditation, clinical outcome indicators, and patient safety goals [18,36,39]. Reduced readmission rates are associated with an increased probability of patients recommending the hospital and, ultimately, with better FB ratings, according to a FB study [39]. However, another research found no correlation between FB user ratings and the 30-day all-cause readmission rate or Medicare expenditure per beneficiary ratio [22]. Meanwhile, a local study found no correlation between online patient satisfaction as expressed in FB reviews and hospital accreditation [38].

2.2. SERVQUAL Dimensions

SERVQUAL is a commonly used quality assessment method for assessing service quality across a range of service settings, industries, and countries [40]. The approach enables the efficient quantification of both customer service needs and perceptions of customer service [41,42]. SERVQUAL's scale development showed five aspects of perceived quality: tangibles, reliability, responsiveness, assurance, and empathy. The 'tangibles' dimension encompasses elements of the service quality experience that are physical in nature (e.g., equipment, facilities, personnel). The characteristics of 'reliability' and 'assurance' represent customers' views of the service provider's capacity to provide the service. The former entails evaluating the service provider's capabilities in terms of reliability and accuracy, while the latter entails evaluating the service provider's characteristics such as knowledge and courtesy, which may inspire trust and confidence in the provider. The 'responsiveness' component is concerned with the service provider's perceived helpfulness and promptness. Finally, the 'empathy' component refers to how individuals perceive customized, caring service [42].

SERVQUAL dimensions have been used to assess the quality of service in hospital and healthcare settings, mainly via survey-based techniques. Several local studies have developed and validated a SERVQUAL model for assessing the quality of healthcare services in Malaysia [13,43-45]. SERVQUAL and other quality measures are the results of years of evaluation, are performed and assessed in a systematic way, and can collect many patient responses per institution [14,15]. Nonetheless, the surveys have several disadvantages, including being expensive to administer, time-consuming, requiring significant time between hospitalization and public publication of results, frequently failing to identify the underlying cause of reported problems, and being susceptible to selection and response bias [3,11,12,47]. The distinction between traditional patient surveys and real-time public opinion on healthcare services demonstrates the need for additional data sources for assessing real-time public opinion on healthcare services [46]. As a result, the internet and social media have been suggested as a new way for evaluating and monitoring the quality of healthcare services [21,47-49].

2.3. Automation of SERVQUAL and Sentiment Classification

Social media data is often enormous and poses a variety of challenges, including data cleaning, data processing, and the establishment of a theoretical model of social media content quality. While this may be conducted manually via human input, the process is time-consuming, and the method's validity and reliability are often questioned. A systematic study of patient online reviews established and suggested the use of advanced analytical techniques such as machine learning to expedite the processing of large-scale online review data [3]. Additionally, the systematic review advocated for conducting an in-depth study on the content of online reviews rather than just comparing structured data to social media ratings. Monitoring service quality through hospital social media platforms may aid all stakeholders in identifying quality aspects and reducing the need for costly and time-consuming surveys. Despite their rarity, research on FB content analysis shows a correlation between quality domains in social media evaluations and conventional quality assessments [22,36-38].

The term "topics" or "text classification" refers to the act of categorizing a collection of textual texts according to their content. Machine learning allows automated subject analysis via the use of different algorithms, which fall primarily into two categories: supervised and unsupervised learning. The distinction between these two major groups is the presence of labels in the subset of training data [50]. Apart from the use of input characteristics, supervised machine learning entails the use of predefined output attributes. The algorithms try to forecast and classify the preset attribute, and their accuracy and misclassification, as well as other performance metrics, are based on the counts of the predetermined attribute that are properly predicted or classified or not correctly predicted or classed. Manual classification is a method that is often employed in supervised learning. Numerous studies have used this technique to ascertain the topics of discussion in online patient reviews [11,17,27,30,48,51-58].

Unsupervised learning, on the other hand, is pattern recognition without the use of a target characteristic. Unsupervised algorithms discover underlying groups in unlabeled data and then label each value. Topic modeling is a method for automatically detecting themes within a given comment, with Latent Dirichlet Allocation (LDA) being the most often used method. Several studies used the method to explore themes or topics of discussion in patient online reviews [12,52,59-63] or classified tweets using the SERVQUAL dimensions [64].

Another machine learning technique is semi- or partial-supervised learning, which builds classifiers using mostly unlabeled data plus a limited number of labeled positive examples that are of interest to the users [65]. A study used the technique to develop an early warning system for adverse drug reactions (ADRs) [66], while another study used it to evaluate themes and emotions in a corpus of almost 60,000 RateMD reviews [67]. Table 1 summarizes recent research using several machine learning methods for topic classification.

Meanwhile, sentiment analysis, sometimes referred to as opinion mining, assists in determining the emotional context of free-text data. Sentiment analysis examines user expressions and connects emotions with them [31]. The analysis is advantageous for ascertaining how individuals feel about goods, activities, people, and services. Sentiment analysis has been applied in health care to assess patients' perceptions of the quality of treatment they got [29,31]. Additionally, the English National Health Service [68] highlighted the importance of sentiment analysis data as a valuable and unique source of information for patients when selecting medical services [68]. The technique used by machine learning for sentiment analysis is similar to that taken for text classification. Sentiment analysis is frequently conducted using a supervised approach and includes some manual classification methods [48,51-53,55-58,62,69]. Even if the comments are pre-labeled, knowing what the negative and positive comments are particularly discussing takes reading through all of them. Moreover, the sentiment may be evaluated using unsupervised learning techniques such as LDA or lexicon-based libraries [12,61,63,64,67]. Additionally, several research used open-source or commercial sentiment analysis tools, such as TheySay [17], TextBlob [11], SentiWordNet [65], DICTION [59], TencentNLP [46], NVivo [25], and Keras [30]. Table 1 summarizes previous works on sentiment analysis using various machine learning methods.

2.4. Topics and Sentiments in Patient Online Reviews

Prior studies indicate that patient online reviews often address topics such as waiting times, healthcare system efficiency, and interpersonal quality [11,12,52,54]. However, other topics were identified as major issues, including communication, treatment efficacy and patient safety, the environment, and hospital costs [11,46,54,70].

Meanwhile, thorough analyses of patient online reviews showed that the majority of responses were positive [3,71]. An in-depth study using supervised learning discovered that patients who received a positive rating in Health Grades had a shorter wait time [27]. A similar study discovered that although empathy, friendliness, and explanation are often mentioned in positive sentiment, negative comments showed concerns regarding appointment access, appointment wait time, and time spent with a physician [52]. Additionally, a FB reviews analysis of hospitals in the United States discovered that waiting times, treatment efficacy, communication, diagnostic quality, environmental sanitation, and cost considerations are the factors most strongly associated with patients' overall ratings [54]. Another study of patient feedback collected via Press Ganey questionnaires discovered that the most often used terms in positive patient responses are "nurse" and "doctor." However, physical factors such as "Room," reliability topics such as "discharge", and responsiveness factors such as "tests and treatments" received the most unfavorable comments [30]. According to a study conducted on Chinese social media platforms, the predominant attitude about their healthcare is negative, with the doctor–patient relation category having the greatest percentage of negative sentiment, followed by service efficiency and nurse service [46]. However, both Chinese and American patients remarked on medical treatment, bedside manner, and appreciation/recommendation in their favorable evaluations, with Chinese patients focusing more on medical treatment and American patients focusing more on the recommendation. Additionally, Chinese patients' evaluations of bedside manner focused more on physicians, while American patients' reviews focused more on staff [61]. It is unsurprising that certain topics tended to be more negative than others. Discussions about time, money, or discomfort, for example, are unlikely to be positive [11].

Previous research using the LDA method discovered that the most frequently discussed subjects in patient online feedbacks were healthcare systems, interpersonal relationships, and technical elements [12,59,64]. Negative sentiment is often associated with personnel, timeliness, and diagnostic issues, while positive sentiment is strongly associated with interpersonal and technical excellence [59]. However, a study of Yelp reviews found that positive sentiment was linked with interpersonal quality and surgical treatment, whereas negative sentiment was associated with insurance, billing, and the cost of the hospital visit [12]. Another study used the SERVQUAL model and LDA to analyze NHS tweets and discovered that the dimensions of responsiveness and assurance are often discussed in negative sentiment, while sentiment ratings for empathy are entirely positive [64].

Although many prior studies have shown the percentage of subjects or themes with positive or negative sentiment, studies of patient online reviews should go beyond basic descriptive analysis and test theory-based hypotheses in order to offer additional clinical and policy implications [3]. In recent years, we have seen an increase in studies comparing patient online reviews and sentiments to traditional patient surveys [12,17,25,27,48,54,69], clinical outcomes [11], and hospital ranking [55]. Table 1 summarizes studies that demonstrate correlations between clinical outcomes, patient surveys, or other quality indicators, and the findings from machine learning/natural language processing analyses. However, the existing body of knowledge is still restricted due to a dearth of sophisticated statistical studies and their connection to additional quality indicators. A systematic review recommended doing more empirical research with relevant hypotheses, rigorous design, and data analytics on patient online reviews [3].

2.5. Proposed Work

Our proposed work was based on the aforementioned literature reviews. Given that social media continues to grow in all directions and penetrates virtually every sector in Malaysia and Southeast Asia, it is essential to use technology to improve healthcare services. Meanwhile, FB is a behemoth among social media sites. However, only minor research on machine learning and quality metrics utilizing FB data has been conducted [54,55,69]. Given FB's popularity in Malaysia and its increasing use in healthcare, this research aims to close a gap by examining whether patient comments in FB reviews can be used in conjunction with patient satisfaction surveys and as a creative tool for assessing patient-perceived hospital quality of service. Additionally, most studies on patient online reviews have focused on populations in Western nations. Few studies have examined patient annotations among Chinese [46,61,63], Indian [55], and Korean populations [58]. Due to a lack of research involving Asian populations, we suggest that our proposed study adds value to patient online reviews from another Asian population through the Malaysian viewpoint.

Meanwhile, in terms of machine learning methods, our proposed study combines two approaches—topic classification and sentiment analysis—via the use of supervised learning. According to the research, conventional patient satisfaction surveys have a variety of disadvantages, and social media has been suggested as a possible alternative for assessing real-time patient satisfaction and mood. Additionally, a systematic review of the use of natural language processing (NLP) and machine learning (ML) to process and analyze patient experience data concluded that manual classification of free text comments remains the 'gold standard' method for analysis and is currently the only way to ensure that all pertinent patient comments are coded and analyzed [28]. Moreover, the study indicates that the patient inputs generated from free-text supplementing structured questionnaires are stable in nature, making them an attractive source of data for supervised learning. Numerous studies have used supervised machine learning to classify topics and sentiments [48,51,54-58]. Furthermore, we suggested that our machine learning topic classifier be trained using SERVQUAL dimensions. Few studies have assigned domains to classify themes in patient online reviews, such as SERVQUAL [64], CAHPS Dental Plan Survey [27], and HCAHPS [12]. The possible outcomes may be compared to conventional surveys of patient satisfaction or quality of care metrics.

Another area of focus for the development of our own machine learning is that most software products and open-source tools used in topic or sentiment classification were originally designed to identify opinions about products in non-healthcare settings or other commercial industries or to be compatible with specific healthcare systems, particularly in Western countries [29]. Therefore, it may influence the accuracy and reliability of the classification in a range of healthcare settings. Additionally, commercial software is often expensive and unsuitable for long-term usage. Thus, our research demonstrated a novel approach for developing a new classifier and sentiment analyzer for service quality problems in FB reviews of a Malaysian public hospital.

In addition, our research should go beyond simple descriptive analysis and test theory-based hypotheses to provide additional clinical and policy implications. As such, we want to employ rigorous statistical methods such as regression analysis to ascertain the determinants of positive sentiment. Previous studies used analysis of variance (ANOVA) [27], Regression analysis [11,59,60,67,69], Pearson correlation [12,55], or Spearman's rank correlation [25,55].

Furthermore, we want to compare patient online reviews with established quality measures in health care, such as the SERVQUAL, HCAHPS, hospital accreditation, and national quality indicators, among others. Previous research has discovered a moderate correlation between online patient feedback and the General Practice Patient Survey (GPPS) and the Friends and Family Test (FFT) [25]. Moreover, studies found several topics correspond to the CAHPS Dental Plan Survey [27] or HCAHPS survey [54]. Also, patients' informal comments in FB help to predict the HCAHPS survey [69] while some topics in Yelp are correlated with positive or negative reviews but are not included in the HCAHPS [12]. However, sentiments in Twitter were not associated with the HCAHPS [11] and NHS inpatient survey [17]. Additionally, there were only weak to moderate associations between topics classified from NHS Choices comments and responses from the national inpatient survey [48]. Furthermore, by improving the sentiment score, one can bring their hospital ranking to the next level [55]. The findings may be utilized to improve the quality of hospital services and to offer more information to policymakers through online patient feedback in order to help them make more informed choices. Table 2 summarizes the proposed work in this research.

Table 1. Summary of Previous Studies.

				Topic Classification			Sentiment Analysis			
Study	**Data Source**	**Population of Study**	**Number of Records**	**Supervised**	**Non-Supervised**	**Topics / Themes**	**Supervised**	**Non-Supervised**	**Other Tool**	**Assoc. ***
Lee et al, (2021)[64]	Twitter	UK	50,716		X	5	X	X		
Zaman et al, (2021)[54]	FB	USA	6581	X		7	X			X
Boylan et al (2020)[25]	NHS Choices	UK	1396			3			NVivo	X
Lin et al (2020)[27]	Health Grades	USA	204,751	X		17				X
Nawab et al, (2020)[30]	Press Ganey	USA	2830	X		13			Keras	
Hu et al (2019)[46]	WeChat, Qzone	China	29,017,055			9			Tencent NLP	
Ko et al (2019)[60]	Vitals	USA	1,560,639		X	5				
Huppertz & Otto (2018)[69]	FB	USA	57,985				X			X
Abirami & Askarunisa, (2017)[55]	Multiple sources including FB, Twitter etc.	India	1941	X		5	X			X
Doing- Harris et al (2017)[52]	Press Ganey	USA	51,235	X	X	7/30	X			
Jimenez- Zafra et al (2017)[53]	Zorgkaart Nederland, Masquemedicos	Netherland, Spain	156,975 of COPOD & 743 of COPOS				X			
James et al (2017)[59]	RateMDs	USA	3712		X	6			Diction	
Hao et al (2017)[61]	RateMDs, Haodf	USA, China	156,558 of RateMD, 57,342 of		X	10		X		

			Haodf							
Ranard el al (2016)[12]	Yelp	USA	16,862		X	50		X		X
Bahja & Lycett (2016)[62]	NHS Choice	UK	76,151		X	30	X			
Daniulaityte et al (2016)[56]	Twitter	USA	4000	X		3	X			
Hao & Zhang (2016)[63]	Haodf	China	731,264		X	10				
Hawkin et al (2016)[11]	Twitter	USA	11,602	X		10			Text Blob	X
Cole-Lewis et al (2015)[57]	Twitter	USA	17,098	X		10	X			
Jung et al (2015)[58]	Naver & Daum Web	South Korea	9450	X		6	X			
Rastegar-Mojarad et al (2015)[65]	Yelp	USA	6914	X*	X*	20			Senti WordNe t	
Yang et al (2015)[66]	MedHelp	USA	3000	X*	X*	10		X		
Greaves et al (2014)[17]	Twitter	UK	1000	X		6			TheySay	X
Wallace et al (2014)[67]	RateMDs	USA	58,110	X*	X*	3		X		X
Greaves et al (2013)[48]	NHS Choice	UK	6412	X		3	X			X
Alemi et al (2012)[51]	RateMDs	USA	955	X		9	X			

* Associations with healthcare quality measures, patient surveys, hospital ranking, etc.
COPOD = corpus of patient opinions in Dutch; COPOS = corpus of patient opinions in Spanish.
X* = semi- or partial-supervised learning

Table 2. Proposed work, its justification and comparison studies.

Proposed Work	Justification	Comparison studies
FB as Data Source	Limited studies utilized FB data. Yet, FB is popular among patients and healthcare providers in Malaysia.	Studies that used FB data including Zaman et al. (2021) [54], Huppertz & Otto (2018) [69], and Abirami & Askarunisa, (2017)[55]
Asian as Study Population	Limited studies among Asian population	Chinese study by Hu et al. (2019) [46], Hao et al. (2017) [61] and Hao & Zhang (2016) [63], Indian study by Abirami & Askarunisa, (2017) [55], and Korean study by Jung et al. (2015) [58].
Topic and sentiment classification approach	Supervised learning via manual classification remains the 'gold standard' method for analyzing free text comments for patient online reviews.	Zaman et al. (2021), Abirami & Askarunisa, (2017), Daniulaityte et al. (2016) [56], Cole-Lewis et al. (2015) [57], Jung et al. (2015), Greaves et al. (2013) [48], and Alemi et al. (2012) [51] employed supervised learning for both topic and sentiment classifications.
SERVQUAL	Domains of a traditional survey of patient experiences (SERVQUAL) serve as a foundation for our ML topic classifier.	SERVQUAL by Lee et al. (2021) [64], CAHPS Dental Plan Survey by Lin et al. (2020) [27], and HCAHPS by Ranard et al. (2016) [12].
Advanced analytical approach	Most patient online review studies were descriptive. Hence, we aim to test the associations using advanced statistical analysis.	ANOVA by Lin et al. (2020), regression analysis by Zaman et al. (2021), Ko et al. (2019) [60], Huppertz & Otto (2018), James et al. (2017) [59], Wallace et al. (2014) [67] and Hawkin et al. (2016) [11], Pearson Correlation by Abirami & Askarunisa, (2017) and Ranald et al. (2017), Spearman's rank correlation by Boylan et al. (2020) [25], Abirami & Askarunisa, (2017) and Greaves et al. (2014) [17].

Comparison with health care quality measures	Only a few studies compared standard health care quality measures such as HCAHPS, SERVQUAL, hospital accreditation or national quality indicators, etc.	GPPS and the FFT by Boylan et al. (2020), CAHPS Dental Plan Survey by Lin et al. (2020), HCAHPS survey by Zaman et al. (2021), Ranard et al. (2016), Huppertz & Otto (2018), and Hawkin et al. (2016), hospital ranking by Abirami & Askarunisa, (2017) and NHS inpatient survey by Greaves et al. (2014) and Greaves et al. (2013).

3. Materials and Methods

3.1. Hospital Facebook Data

Between January 2017 and December 2019, this study examined data from FB reviews that were publicly available on official public hospital FB pages. We used WebHarvy software (SysNucleus, Kochi, India) to gather all 3618 FB reviews from 48 official FB pages of Malaysian public hospitals. The automated parsing software was used in previous studies for web scrapping of online reviews [72] and extended to data mining [73]. The term "official" refers to the hospital FB page as one that had the hospital's official name on the page, referenced the hospital's official name in the page's description, or connected directly to the hospital's FB page from the hospital's official website. We included only publicly accessible FB pages associated with the hospital, and all data gathered from the official FB page was retained in a pro forma checklist, such as the average number of stars the page had previously earned and the presence of complete hospital information on the page. The FB pages of hospital departments, as well as those of health organizations such as the Ministry of Health and the Institute of Medical Research, as well as those of non-governmental organization hospitals and long-term care facilities, were all excluded. All collected reviews were carefully screened, and any reviews that were deemed irrelevant due to company promotion or marketing were removed. These techniques of searching have also been used in earlier research [18,22,74]. All data was collected prior to the COVID-19 pandemic.

There are four major factors in patient online reviews that may influence sentiment in hospital FB reviews: hospital characteristics, FB characteristics, SERVQUAL dimensions, and hospital accreditation status. We quantified hospital characteristics by geographical region, urban or rural location, type of hospital (primary, secondary, or tertiary), and bed count. Additionally, factors pertaining to FB characteristics were examined, including previous FB star ratings, adequate hospital information on the hospital's FB page, and whether or not the hospital responded to or reacted to patient comments in the FB reviews section. Moreover, Empathy, Assurance, Responsiveness, Reliability, and Tangible were the SERVQUAL dimensions evaluated in this research. Meanwhile, hospital accreditation refers to the status of accreditation conferred by the Malaysian Society for Quality in Health (MSQH) to public hospitals in Malaysia that met a wide range of hospital quality characteristics. The proposed work's conceptual framework is shown in Figure 1.

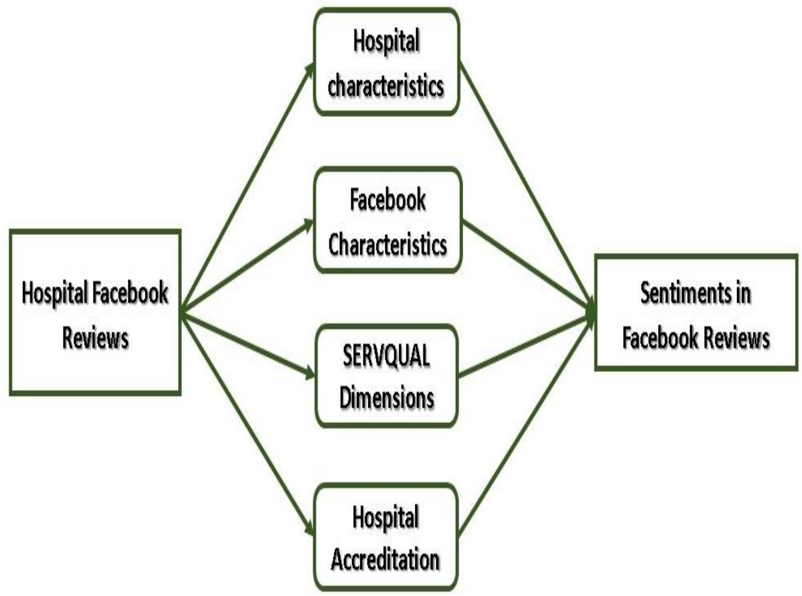

Figure 1. Conceptual framework for proposed work.

Malaysia is a multicultural country with a rich linguistic and dialectal diversity. Malay is our national language, while English is our second language. As a consequence, we gathered reviews in those languages only. After standardizing the dual-language FB data, the Malay language data were translated manually by junior doctors into English for further study.

3.2. SERVQUAL Dimensions Classification

Through manual coding, a labeled data set was created to serve as a "gold standard" for machine learning quality dimension classifiers. The word "classifier" refers to the class labels applied during the human annotation step that is attempted to be correctly labeled by machine classification models [57]. The steps of topic classification were as follow:

1. Two hospital quality managers or SERVQUAL domain experts were appointed to do an initial “open” coding on batches of 100–300 FB reviews based on the MOH SERVQUAL patient satisfaction survey in order to create the source coding standard (Appendix A1). Additionally, we supplemented descriptions in relevant dimensions using survey questions from previous SERVQUAL research.
2. Next, a randomly selected subsample of 300 FB reviews was used to assess intercoder reliability. The reliability subsample was coded independently by the raters. Cohen’s Kappa values were used to determine inter-rater agreement for each SERVQUAL dimension. The agreement between the coding of Tangible (Cohen’s = 0.885, $p < 0.001$), Empathy (Cohen’s = 0.875, $p < 0.001$), Reliability (Cohen’s = 0.736, $p < 0.001$), and Responsiveness (Cohen’s = 0.72, $p < 0.001$) characteristics from FB reviews was high, but agreement for Assurance (Cohen’s = 0.626, $p < 0.001$) was modest. Cohen’s coefficient averaged 0.769 across all dimensions.
3. Then, we utilized a sample of 900 manually labeled FB reviews to train our machine learning quality control tool.

The machine learning method analyses the properties of the individual phrases used in the FB reviews and utilizes this information to construct a topic classifier. To begin, the labeled dataset was pre-processed to remove URLs, numbers, punctuation marks, and stop words, as well as to reduce words to their simplest forms using a lemmatization method (e.g., treating as treat). Following that, we determined the weight of words using the term frequency-inverse document frequency (TF-IDF) method, which shows their importance to the documents and corpus. We next split randomly labeled data into 80% for training and 20% for testing using iterative stratification. For topic classification, a variety of multi-label classifier methods were trained, including Binary Relevance, Label Powerset, Chain Classifier, RAkEL: RAndom k-labELsets, MLkNN: Multi-Label k-Nearest Neighbor, and BRkNN: Binary Relevance k-NN. We trained three basic classifiers for each technique: Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR). The NB, SVM, and LR classification techniques are all extensively used and have been shown to perform well on text classification problems [31,75]. The classifiers with multiple labels were assessed using Python’s scikit-multilearn package [76]. Several studies have used similar methods to build their topic categorization models in this investigation [11,51,52]. Figure 2 illustrates the process of topic classification.

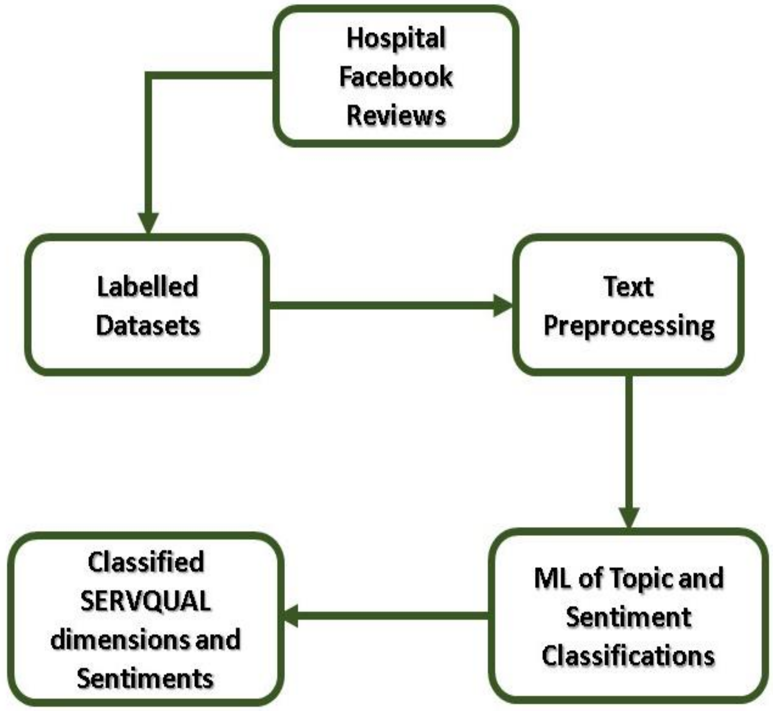

Figure 2. Machine learning development process.

We used 5-fold cross-validation for evaluating the different classifiers. The classification models' predictive performance scores varied between 0.13 and 0.25, suggesting that the models accurately categorized the reviews with an F1 value of 0.687 to 0.757. In general, when compared to other models and classifiers, the SVM model with chain classifier multilabel method has the highest accuracy (0.215) and F1-score (0.757). In addition, the hamming loss, which quantifies the percentage of erroneously predicted class labels, is more significant for topic classification models. In comparison to other models, the SVM model with chain classifier has the lowest hamming loss (0.273). As a consequence, the SVM model will be utilized to train the machine learning service quality classification, which will be trained using the Chain classifier method. The prediction performance of supervised machine learning with 5-fold cross-validation is summarized in Table 3, along with the accuracy ratings for the best classification model and multi-label classifier.

Table 3. Overall ML models performance.

Multilabel Classifier	Model	Accuracy	Recall	Precision	F1-Score	Hamming Loss
Binary Relevance	NB	0.147	0.761	0.701	0.730	0.315
	SVM	0.211	0.763	0.745	0.754	0.278
	LR	0.193	0.775	0.732	0.753	0.285
Label Powerset	NB	0.130	0.896	0.633	0.741	0.349
	SVM	0.166	0.799	0.679	0.734	0.323
	LR	0.158	0.825	0.669	0.739	0.326
Chain Classifier	NB	0.149	0.756	0.705	0.730	0.313
	SVM	0.215	0.761	0.753	0.757	0.273
	LR	0.191	0.770	0.727	0.748	0.290
RAkEL	NB	0.157	0.749	0.699	0.722	0.322
	SVM	0.186	0.764	0.724	0.743	0.295
	LR	0.180	0.765	0.726	0.745	0.293
MLkNN	N/A	0.140	0.737	0.697	0.715	0.327
BRkNN	N/A	0.157	0.648	0.732	0.687	0.330

NB = Naïve Bayes, SVM = Support Vector Machine, LR = Logistic Regression.

3.3. Outcome: Sentiment in Facebook Reviews

The study's conclusion is based on the positive or negative sentiments expressed in FB reviews. To evaluate the sentiment expressed in patient online reviews, human coding was used to generate a labeled data set that would serve as the "gold standard" for the machine learning sentiment analyzer. We enlisted the assistance of hospital quality managers familiar with patient satisfaction surveys to conduct open coding on 100–300 randomly selected FB reviews in order to generate a coding guideline (Appendix A2). Following that, an intercoder reliability assessment was conducted using a randomly chosen subsample of 300 FB reviews. The agreement between the positive (Cohen's = 0.721, $p < 0.001$) and negative (Cohen's = 0.686, $p < 0.001$) sentiment coding was satisfactory. The neutral or unidentified category of review, on the other hand, had a lower degree of agreement (Cohen's = 0.43, $p = 0.027$), which could be explained by the category's more amorphous and heterogeneous nature. Thus, both quality managers will debate and re-evaluate the group of emotions that is neutral or unidentified. If the review remains neutral or unidentified, it will be deleted, since we prefer binary sentiment classification for reviews. Earlier research has validated and demonstrated that the binary technique outperforms multiclass sentiment classification (positive, negative, neutral) in terms of accuracy, recall, and F-score performance [56,77]. Following that, we labeled and pre-processed 1393 randomly chosen data instances in preparation for machine learning training. We divided the training set into 80% for machine learning training and 20% for testing the machine learning model using stratification. Our machine learning model was trained using the Python libraries nltk, spacy, and scikit-learn using three different types of classifiers: NB: Naive Bayes, SVM: Support Vector Machine, and LR: Logistic Regression. In this research, a few methods from prior studies were used to create a sentiment analyzer [48,51,62,77]. Our method of sentiment classification is shown in Figure 2.

Again, we used 5-fold cross-validation to evaluate the effectiveness of the machine learning sentiment analysis. SVM findings outperformed other machine learning methods in terms of accuracy (0.874), precision (0.903), and F1-score (0.919). However, naive Bayes has a greater recall than other algorithms (0.999). The assessment of the model after 5-fold cross-validation is summarized in Table 4. We selected the SVM model for our machine learning sentiment analyzer due to its excellent prediction accuracy.

Table 4. Model evaluation of sentiment analyzer.

Model	Accuracy	Recall	Precision	F1-Score
NB	0.781	0.999	0.777	0.874
SVM	0.874	0.936	0.903	0.919
LR	0.843	0.992	0.833	0.906

NB = Naïve Bayes, SVM = Support Vector Machine, LR = Logistic Regression.

3.4. Comparison with Hospital Accreditation

MSQH provided us a list of accredited public hospitals in 2018 and 2019. MSQH is a not-for-profit organization that was established in collaboration with the Malaysian Ministry of Health, the Malaysian Association of Private Hospitals, and the Malaysian Medical Association. MSQH criteria are applicable to all types of hospitals that are undergoing accreditation consideration, whether public or private, big, or small. Prior to the accreditation survey, a hospital pursuing accreditation must perform a self-assessment. The evaluation is carried out by a team of surveyors, who then analyze and vote on their findings by members of the Malaysian Council for Health Care Standards. During the study period, Malaysia had 69 accredited public hospitals.

3.5. Statistical Analysis

Due to the non-normal distribution of the data, numerical data were expressed as medians (interquartile range [IQR]) while categorical variables were expressed as frequencies and percentages in our statistical analysis. The connection between positive sentiments in FB reviews was determined using binary logistic regression analysis. The relationships were adjusted for hospital characteristics (region, bed count, urban or rural location, and type of hospital) and FB page characteristics such as previous star ratings, acceptable hospital information on the FB page, and administrator reaction in the FB review area. According to a prior study, these attributes are associated with positive sentiments [11]. We analyzed the results in terms of those that were statistically significant at p-value less than 0.05. All statistical test assumptions have been validated and met. The Hosmer–Lemeshow test, as well as the area under the receiver operating characteristic (ROC) curve, were utilized to validate the model fitness of our study. The data were analyzed using SPSS software version 26 (IBM Corp, Armonk, NY, USA).

4. Results

4.1. Hospital and Facebook Characteristics

Overall, 86 (63.7%) of Malaysia's 135 public hospitals have an official FB account, with 48 (55.5%) allowing for customer input on the site. Twenty-five (52.08%) of the forty-eight hospitals that have FB reviews were accredited. Except for the western area, every region in Malaysia had at least ten hospitals that offered a FB review function: nationally, 37.5% of tertiary hospitals, 8.3% of secondary hospitals, and 54.2% of primary hospitals had FB review sections. Most of these hospitals were in urban areas and averaged 730 beds. Each hospital's FB page received an average of 15.5 (27.5) reviews, with an average previous FB star rating of 5.00. (1.65). Numerous hospitals have contact details on their FB sites and have reacted to customer feedback.

4.2. Facebook Review Characteristics and Sentiment

We analyzed 1825 FB reviews in detail. Overall, the west (50.5%) and north (21.5%) areas received the bulk of evaluations. 87.2% of all reviews came from urban hospitals, while 88.8% came from tertiary institutions. Additionally, many evaluations (61.6%) were conducted in accredited hospitals, and the median number of beds was 730. In terms of prior FB ratings, the average was 4.70 stars. Most FB reviews provide sufficient hospital information on the hospital's FB page but limited responses from the hospital administration. Most important, we had 1315 (72.1%) reviews with positive sentiment and 510 (27.9%) reviews of negative sentiment as identified by our machine learning sentiment analyzer.

4.3. SERVQUAL Dimensions

Using a machine learning tool for SERVQUAL dimensions classification, overall, we had 240 (13.2%) reviews with tangible dimension, 1257 (68.9%) reviews of reliability, 125 (6.8%) reviews of responsiveness, 356 (19.5%) reviews of assurance, and 1174 (64.3%) reviews of empathy. The summary of overall SERVQUAL domains is presented in Figure 3.

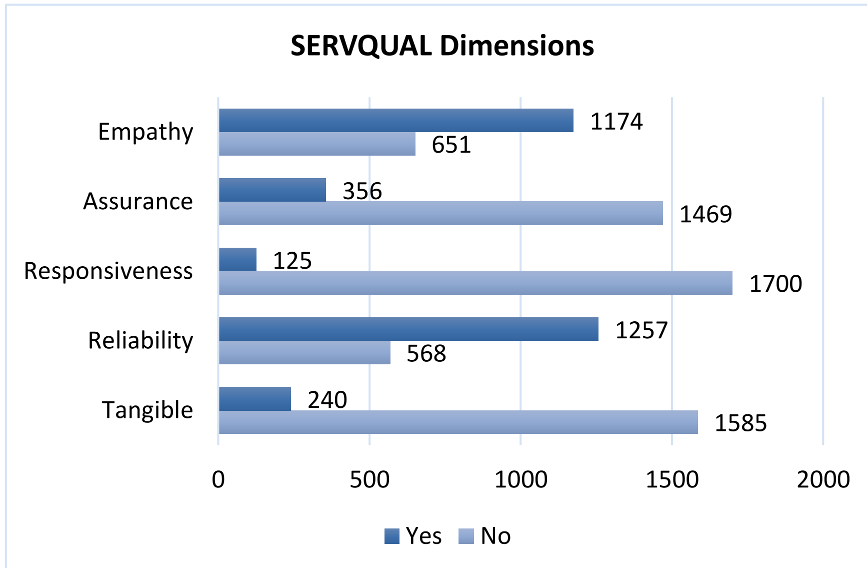

Figure 3. Overall SERVQUAL dimensions classified by machine learning.

4.4. Determinants of Positive Sentiment

Univariate analysis of hospital characteristics revealed that 10.3% of positive reviews came from the east coast, 22.4% from the north, and 52.1% from the west. Each of the three areas (East coast, OR = 1.80 (95% CI: 1.34–2.86); North, OR = 2.11 (95% CI: 1.41–3.17); and West, OR = 2.03 (95% CI: 1.41–2.92)) is associated with positive sentiment. 1162 (88.4%) of positive reviews were from hospitals situated in urban areas, indicating a strong relationship between urban location and positive sentiment, with a 43% probability (95% CI: 1.07–1.92). Additionally, we discovered a significant relationship between previous FB star ratings and positive sentiment (OR = 1.09, (95% CI: 1.01–1.17)), but not with other FB features. The features of the hospital and FB are detailed in Table 5, and their relationship with positive sentiment is addressed in Table 6.

Table 5. Characteristics of FB reviews (n = 1825).

Variables		Sentiment			
		Negative		Positive	
		n	(%)	n	(%)
Hospital Characteristics					
Region	East Coast	53	(10.4)	136	(10.3)
	North	98	(19.2)	295	(22.4)
	West	237	(46.5)	685	(52.1)
	South	63	(12.4)	115	(8.7)
	East Malaysia	59	(11.6)	84	(6.4)
Location	Rural	81	(15.9)	153	(11.6)
	Urban	429	(84.1)	1162	(88.4)
Hospital Type	Primary	43	(8.4)	82	(6.2)
	Secondary	22	(4.3)	58	(4.4)
	Tertiary	445	(87.3)	1175	(89.4)
Beds (Median, IQR)		730	(604)	704	(563)
FB Features					
Admin Response	No	463	(90.8)	1188	(90.3)
	Yes	47	(9.2)	127	(9.7)
Adequate Hospital Information	No	35	(6.9)	76	(5.8)
	Yes	475	(93.1)	1239	(94.2)
Hospital Accreditation	No	210	(41.2)	491	(37.3)
	Yes	300	(58.8)	824	(62.7)

On the other hand, 874 (66.5%) reviews were classified as reliability with a positive sentiment, 72 (5.5%) as responsiveness, 273 (20.8%) as assurance, 813 (61.8%) as empathy, and 170 (12.9%) as tangible with a positive sentiment. All SERVQUAL dimensions (Reliability, OR = 0.66 (95% CI: 0.52–0.83); Responsiveness, OR = 0.50 (95% CI: 0.35–0.72); Assurance, OR = 1.35 (95% CI: 1.03–1.77); and Empathy, OR = 0.67 (95% CI: 0.54–0.83)) were significantly associated with positive sentiment, except for the Tangible (OR = 0.93 (95% CI: 0.69–1.26)). Table 7 and Figure 4 summarize the proportion of SERVQUAL dimensions and sentiments, whereas Table 6 discusses their associations with positive sentiment.

Table 6. Determinants of positive sentiment using univariate analysis (n = 1825).

Variables		Crude OR	95% CI (Lower, Upper)	p-value *
Hospital Features				
Region	East Malaysia	Ref		
	East Coast	1.80	1.14, 2.86	0.012
	North	2.11	1.41, 3.17	<0.001
	West	2.03	1.41, 2.92	<0.001
	South	1.28	0.82, 2.02	0.282
Location of Hospital	Rural	Ref		
	Urban	1.43	1.07, 1.92	0.015
Type of Hospital	Primary	Ref		
	Secondary	1.38	0.75, 2.56	0.301
	Tertiary	1.39	0.94, 2.03	0.097
Numbers of Bed		1.00	1.00, 1.00	0.017
FB Features				
Admin Response to Review	No	Ref		
	Yes	1.05	0.74, 1.50	0.773
Adequate Hosp Info	No	Ref		
	Yes	1.20	0.79, 1.82	0.385
Previous FB Star Ratings		1.09	1.01, 1.17	0.033
SERVQUAL				
Tangible	No	Ref		
	Yes	0.93	0.69, 1.26	0.651
Reliability	No	Ref		
	Yes	0.66	0.52, 0.83	<0.001
Responsiveness	No	Ref		
	Yes	0.50	0.35, 0.72	<0.001
Assurance	No	Ref		
	Yes	1.39	1.03, 1.77	0.030
Empathy	No	Ref		
	Yes	0.67	0.54, 0.83	<0.001
Hospital Accreditation	No	Ref		
	Yes	1.18	0.95, 1.45	0.131

* Simple Logistic Regression.

Table 7. SERVQUAL dimensions in FB reviews (n = 1825).

Variables		Overall		Sentiment			
				Negative		Positive	
		n	(%)	n	(%)	n	(%)
Tangible							
	No	1585	(86.8)	440	(86.3)	1145	(87.1)
	Yes	240	(13.2)	70	(13.7)	170	(12.9)
Reliability							
	No	568	(31.1)	127	(24.9)	441	(33.5)
	Yes	1257	(68.9)	383	(75.1)	874	(66.5)
Responsiveness							
	No	1700	(93.2)	457	(89.6)	1243	(94.5)
	Yes	125	(6.8)	53	(10.4	72	(5.5)
Assurance							
	No	1469	(80.5)	427	(83.7)	1042	(79.2)
	Yes	356	(19.5)	83	(16.3)	273	(20.8)
Empathy							
	No	651	(35.7)	149	(29.2)	502	(38.2)
	Yes	1174	(64.3)	361	(70.8)	813	(61.8)

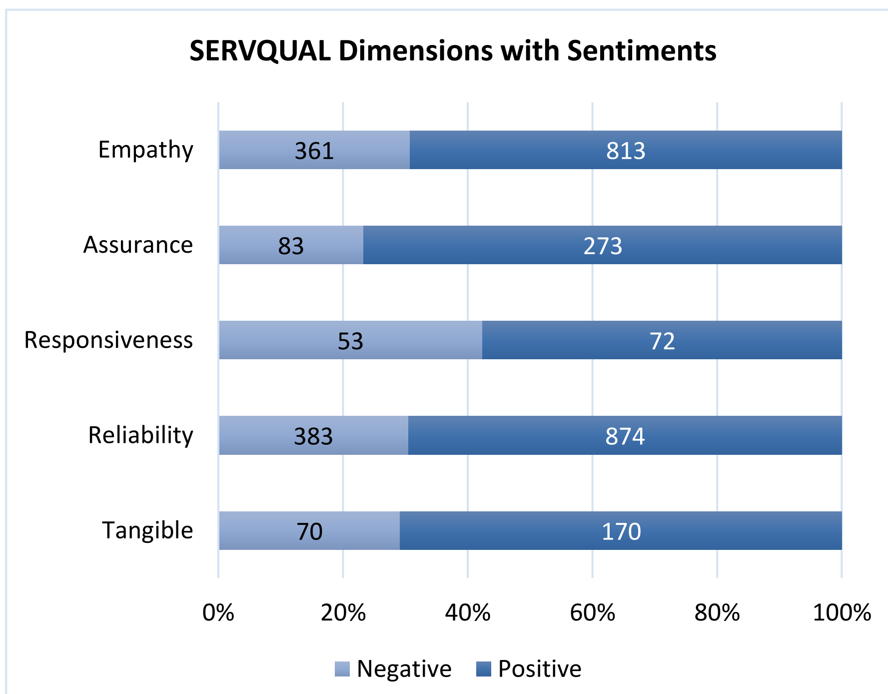

Figure 4. SERVQUAL dimensions with positive or negative sentiment.

In multivariable analysis, all significant variables or *p*-value less than 0.25 in the univariable analysis were selected in the process of model selection. We applied forward LR, backward LR, and manual selection methods using SPSS software to achieve a parsimonious model. The final model consisted of hospital location and SERVQUAL dimensions except for Tangible. A hospital located in an urban area has a 52% better chance of positive sentiment compared to a hospital in a rural area (95% CI: 1.12–2.04) when SERVQUAL dimensions were controlled. Moreover, assurance has 121% odds of positive sentiment (95% CI: 1.63–3.01) when other significant variables were adjusted. Meanwhile, with reliability, responsiveness, and empathy topics, the odds of having positive sentiment reduced by 58% (95% CI: 0.32–0.54), 51% (95% CI: 0.32–0.73), and 58% (95% CI: 0.33–0.55) respectively when location and other dimensions were controlled. The multivariate model has no interaction and multicollinearity in this study. The model was also acceptable as confirmed by the Hosmer–Lemeshow test ($p = 0.648$), 72.6% of Classification Table, and 62.3% of area under the Operating Curve (ROC) ($p < 0.001$). The multivariable analysis is described in Table 8.

Table 8. Determinants of positive sentiment using multivariate analysis ($n = 1825$).

Variable		**Adjusted OR**	**95% CI (Lower, Upper)**	***p*-value ***
Location	Rural	Ref		
	Urban	1.52	1.12, 2.04	0.007
Reliability	No	Ref		
	Yes	0.42	0.32, 0.54	<0.001
Responsive	No	Ref		
	Yes	0.49	0.32, 0.73	0.001
Assurance	No	Ref		
	Yes	2.21	1.63, 3.01	<0.001
Empathy	No	Ref		
	Yes	0.42	0.33, 0.55	<0.001

* Multiple Logistic Regression. Constant = 1.686. Forward LR, Backward LR, and Manual selection were applied. No significant interaction or multicollinearity. Hosmer–Lemeshow test = 0.648. Classification Table = 72.6%. Area under the operating curve (ROC) = 62.3% ($p < 0.001$).

4.5. Association of Hospital Accreditation and Sentiment in FB Reviews

There were 824 (62.7%) positive FB reviews and 300 (58.8%) negative FB reviews from accredited hospitals. However, there was no significant relationship between hospital accreditation and positive sentiment (Crude OR = 1.18, (95% CI: 0.95–1.45), $p = 0.131$) or when hospital characteristics were adjusted for (Adjusted OR = 0.99, (95% CI: 0.73–1.34), $p = 0.933$). The details are in Table 5, and its univariate relationship with positive sentiment is presented in Table 6.

5. Discussion

To our knowledge, this is the first research to determine how patients evaluate the quality of hospital care and sentiment via the use of FB Reviews in Malaysia and Southeast Asia. The study examined the hospital and FB characteristics of public hospitals, as well as SERVQUAL dimensions and sentiment analysis of Malaysian social media data. The research represents a critical first step in developing a technique for harnessing social media data, as well as an early effort to monitor public views of healthcare services via the use of a novel data source. Our findings indicate that social media use is increasing in Malaysia's public hospitals, with the majority now having their own FB page. The findings confirmed research conducted in Taiwan, which established that the popularity of FB prompted healthcare institutions to create their own accounts on the site [78]. However, more than half of Malaysian hospitals' FB sites lack a section dedicated to customer input. It is unknown if hospital officials disabled comments on purpose or were just unaware of the FB review feature.

5.1. Service Quality and Sentiment Analysis

This is the first study in Malaysia to develop a machine learning model for monitoring hospital quality. The findings of this study demonstrate how supervised machine learning algorithms may be used to accurately identify SERVQUAL dimensions and sentiment content in Malaysian FB reviews. Combining two elements of content analysis tasks, such as topic classification and sentiment analysis, is a novel technique, particularly in developing markets with a growing healthcare market and service provision such as Malaysia.

In terms of machine learning topic categorization, our research determined that the two most often discussed SERVQUAL dimensions were Reliability and Empathy. Previous studies indicate that waiting times, the efficiency of the healthcare system, and interpersonal quality are commonly discussed topics in patient online evaluations [11,12,52,54]. However, other topics have emerged as major issues, including communication, treatment effectiveness and patient safety, the environment, and hospital costs [11,46,54,70]. A systematic examination of patient internet evaluations corroborated the findings, revealing that these comments addressed the facility's overall health care experience, including staff friendliness, empathy, time spent with patients, and wait time [3,34].

Meanwhile, our sentiment analysis revealed that the overwhelming majority of patient evaluations are positive. The generally favorable attitude on FB corroborates prior systematic reviews showing that social media users have a positive judgment bias [3,71]. However, other studies indicate that most social media comments are associated with negative feelings [30,46,75,79]. A comprehensive study of sentiment analysis in a social media platform for health care confirmed the contradictory findings of prevalent views [29]. Furthermore, additional systematic studies indicate that the polarity of sentiments was affected by the corpus- and thesaurus-based techniques employed in the research [28,31].

Except for the tangible dimension, our in-depth analysis revealed that all service quality themes were significantly associated with positive sentiment in this study. Our study's sentiment evaluations found that reliability and empathy were highly valued. The outcome almost confirmed results from a study of NHS tweets conducted using the LDA method, which revealed their empathy is all positive, while their responsiveness and assurance were often criticized [64]. Additionally, our results corroborate previous research demonstrating a significant correlation between specific service quality topics mentioned in hospital-related social media comments and emotions [11,54]. Another study showed that patients who had a positive rating in Health Grades had a shorter wait time [27] whereas empathy, friendliness, and explanation are often mentioned in positive emotion [52]. Meanwhile, a Korean study found unfavorable sentiment about problems such as professionalism, competence, and treatment received via the use of a mixed conceptual model that included themes related to service quality [58].

Furthermore, a study showed that tangible, reliability, and responsiveness themes received more negative responses when utilizing Keras NLP software [30]. It was backed up by a large-scale analysis of China's social media platforms using Tencent NLP, which discovered that the doctor–patient connection category had the greatest percentage of negative comments, followed by service efficiency and nursing care [46]. Despite the diversity of machine learning methods, it is unsurprising that certain subjects tended to be more negative than others—discussions about time, money, or discomfort, for example, are unlikely to be positive in patient online reviews.

Taken together, our findings suggest that FB review is a one-of-a-kind tool for engaging patients and eliciting hitherto untapped feedback. This study shows that these machine learning methods are more useful and informative than the general emotion-focused terms employed in traditional sentiment analysis. To improve the quality of the healthcare system, a systematic and effective approach is required. A paper calls for systematic, comprehensive monitoring and reporting of quality-improvement efforts, as well as a strong focus on reacting to and learning from events involving the quality of treatment [80]. To enhance healthcare outcomes in Malaysia, data on patient online assessments and systematic methods for analyzing patient input must be collected. The study's approach allows policymakers to utilize public opinion about health care services on social media as a substitute for conducting and scheduling more costly national questionnaire polls. Additionally, because SERVQUAL serves as the foundation for public hospital patient satisfaction surveys in Malaysia, the conceptualization used in this study may be used in conjunction with the Ministry of Health's hospital patient satisfaction survey and as a valuable early warning system for hospital quality management. Thus, we may determine societal views and integrate them into the design of high-quality healthcare services by systematically monitoring internet comments. Furthermore, we can help health care policymakers and providers in evaluating their quality of care in real-time and changing their policies or resources to better serve their patients [81,82].

5.2. Accreditation and Sentiment Analysis

Numerous previous studies established a correlation between social media results and clinical outcomes (e.g., mortality rate or readmission rate) [17,18,22,83] as well as with other structured quality measures such as HCAHPS, patient safety metrics, etc. [3,34]. Hospital accreditation in Malaysia attests to a hospital's adherence to quality criteria, which includes treatment accessibility, appropriateness, effectiveness, and safety, as well as patient-centered activities, efficiency, and governance. The requirements place a premium on safety; an organization that fulfills all other criteria but falls short on safety will be refused accreditation [84]. After controlling for hospital factors, this study found no significant association between patient online sentiment and hospital accreditation. The result supports a previous study in Malaysia on hospital accreditation and online patient satisfaction [38]. Additionally, other study results indicated there was a weak or non-existent connection between clinical outcomes or indicators of quality of treatment [11,17,48]. The finding means that when compared to clinical results and quality metrics, sentiment in FB reviews should be evaluated with precaution. Because this research is still in its infancy with regards to the usage of FB data, robust techniques for comparing clinical outcomes or other quality criteria are required [3]. Our findings, however, suggest that there is some new data from social media that hospital administrators should closely monitor.

5.3. Implications/Recommendation

We suggest that each Malaysian public hospital create a separate or official FB page and monitor what their patients say on social media. By analyzing the emotion expressed in spontaneous tales, we may improve health care services by including factors that were previously unknown. Patient evaluations of health care services, for example, may help in identifying areas for service improvement, thus affecting health outcomes and use. In terms of public health efforts, patients' views may assist health professionals in identifying potential obstacles to population-based interventions such as vaccination. Understanding how patients respond to different treatments may help in the creation of more tailored treatment regimens. Furthermore, patient evaluations show that patients agreed to their participation in online discussions. As such, health care administrators and policymakers must recognize that the findings are unlikely to be fully representative of the hospital service population. Rather than that, this examination of service quality problems should be seen in conjunction with conventional data collecting efforts. The study's rapid identification and evaluation of certain service features are unique, and without it, healthcare organizations would have been unable to analyze massive amounts of real-time (unstructured) data.

5.4. Limitation and Future Scope

Numerous limitations exist in our study. To begin, although our study of FB reviews was prone to response and selection bias, this is also true of any conventional survey. We cannot rule out the potential of a causal relationship in our results due to the cross-sectional design of the study. Additional studies into the origins of these results would be beneficial. In addition, only 45 of 87 hospitals have FB reviews. Incorporating unofficial or unapproved FB sites for public hospitals may result in a change in public opinion. When it comes to sentiment analysis and topic classification, machine learning algorithms are only as effective as the training set used to train them. The primary limitation is that our dataset is deemed tiny in comparison to previous big data research, as social media reviews are still relatively new in Malaysia's healthcare industry and our population is small. Malaysians' use of social media, on the other hand, continues to increase year after year across all social demographic groups. As is the case in developed countries, we may anticipate a surge of social media evaluations of healthcare services. Another issue was the difficulty of manually coding social media information, especially for human coders with considerable expertise in quality management or the SERVQUAL model. This result is consistent with prior studies indicating ambiguity and a range of contextual perceptions in social media content as major issues [56,77]. Manual classification for supervised learning may become difficult as the quantity of comments on social media grows. To overcome this, a technique based on LDA may be used to discover numerous topics of discussion [85]. However, LDA has certain limitations of its own. It is expected that the produced topics are dependent on the sentiment distributions and that the generated words are conditional on the sentiment topic pairings. Thus, a weakly supervised joint sentiment-topic mode may be utilized to improve the accuracy of topic modeling by extending the maximum entropy discrimination latent Dirichlet allocation (MEDLDA) topic model [86].

Future research should focus on increasing sentiment analysis and topic classification performance, as well as on amassing a larger dataset of patient online evaluations, including those from the Malaysian private healthcare sector. Also, additional research is required to extend the method's applicability to other types of free-text material on social media. For instance, different techniques may be added to strengthen the process, such as assessing unigrams, bigrams, or larger n-grams, as well as improving contextual polarity. Likewise, future research can be conducted using deep learning neural networks, such as Deep Block Scheme, a deep learning method based on blockchain technology [87], Kmean methods, a clustering algorithm for sentiment analysis [88], or graph convolutional networks (GCNs) and auxiliary node relations for modeling multi-target sentiment classification [89]. Moreover, to improve and ensure the security, confidentiality, and privacy of hospital data that was stored in the cloud, a blockchain-based secure storage architecture called BIIoVT can be implemented [90]. Furthermore, further studies are necessary to ascertain the connection between patient online reviews and other hospital quality measures. For example, evaluating the relationship between quality dimensions derived from social media reviews and patient satisfaction as measured by prior studies [35,70]. In addition, a comparison of the labeled dataset used in this study to other dictionaries or tools used in prior studies to enhance sentiment and text classification would be beneficial [28,29]. Further, future research may include other social media platforms (e.g., Twitter, Instagram, Tik-Tok, etc.) to provide health care practitioners and academics with a more complete picture of consumer views of healthcare quality of service. Finally, this research may be repeated to assess hospital service sentiment during the COVID-19 epidemic in Malaysia.

6. Conclusions

We demonstrate how monitoring FB reviews with machine learning methods offers valuable, real-time data that is not available via conventional quality measures or surveys. According to this study, patients in Malaysia were generally satisfied with the services provided by public hospitals. With the exception of tangible, all SERVQUAL dimensions were significantly associated with positive sentiment. However, there is no association between hospital accreditation and the sentiment expressed in FB reviews. While many hospitals have their own FB pages and actively monitor them, we propose that hospital administrators and policymakers use this unique data stream to obtain a better knowledge of healthcare consumers' experiences and the quality of care they receive. If an online review is strongly associated with a certain negative element of service quality, it suggests where hospital administrators should focus their efforts on patient care improvement.

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Institutional Review Board Statement: Ethical clearance was obtained from the Ethical and Research Committee Review of Universiti Sains Malaysia, code: **USM/JEPeM/19120839.**

Informed Consent Statement: Informed consent was not applicable for the current study because it does not involve humans.

Data Availability Statement: The FB data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy and confidentiality. However, restrictions apply to the availability of hospital data. Data was obtained from MSQH and Ministry of Health and are available from the authors with the permission of both organizations.

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Conflicts of Interest: There is no conflict of interest in this study.

Appendix A

Appendix A.1. SERVQUAL Guideline

Domain	Description	FB Reviews Example
Tangible	General: The appearance of employees, equipment, and physical facilities of the hospital. Specific: The hospitals have up to date equipment. The physical facilities are visually new or outdated. The staff are well dressed, appear neat and good looking. The appearance of the physical facilities of the hospital are well maintained with the type of services provided.	"Cleanliness of the Hospital is good" "Car parking is difficult and limited" "Satisfied with the facilities. Large room, feels like a hotel." "The hospital is well maintained, and their food is delicious."
Reliability	General: Accurate, dependable, and consistent performance of the service. Specific: When the hospital promised to do something by a certain time, it does so. Hospital service is efficient and dependable. The hospital provides services at the time as promise to do so. The hospital keeps the records accurately or at online.	"My appointment scheduled at 9 a.m. but then it was postponed to 12.00 p.m. Unbelievable." "System needs to be improved especially discharge process. It took hours to settle it." "Efficient and top-quality hospital services" "Staff mistakenly collected medical record of other patient with similar name of mine"

Responsiveness	General: Willingness to provide prompt service to the patients. Specific: The hospital let patients know exactly when the services will be performed. The staff give prompt services to patients upon request. The staff are always willing to help their patients. The staff give medical attention promptly.	"My specialist took his time to explain me about my disease and how he will treat it" "They answered all my questions during the admission." "Arrived at emergency department due to road traffic accident and the medical team immediately respond to it." "I don't feel any pain throughout the minor surgery on my arm, and it was done in a flash"
Assurance	General: the staff knowledge and courtesy, ability to inspire trust, confidence, and security; also reflects on confidentiality and privacy of patients. Specific: The staff are trustworthy. Patients feel safe in their transactions with the hospitals. The staff are polite, friendly. The staff have adequate support from the hospitals to do their jobs well.	"The surgery was successful. Mr A is a competent and trusted surgeon." "I feel comfortable and safe in this hospital. Just like at home" "The staff at the front desk was rude." "The doctors and staff nurses in this hospital are skillful and well-trained"
Empathy	General: Providing convenient services and giving attention or patience of the staff to the patients' needs. Specific: The staff give patient personal attention and helpful. The staff are knowledgeable to understand patient's specific needs. The hospital has patient best interests at heart. The hospital has operating hours convenient to all the patients. Cost of treatment is affordable for patients	"Nurses are very helpful." "A staff came and offered to help my father climb stairs without we ask him. We appreciated his kindness." "They are very concerned about patient's condition and served it with their heart" "The price is affordable compared to private hospital."

Appendix A.2. Sentiment Analysis Guideline

Category	Description	FB Reviews Example
Positive	Expression of liking, approval, gratefulness (Like, love, support, thankful, etc.)	"I like this hospital. Doctors and nurses are pleasant and helpful." "Thank you for your service, Doctor and nurses."
	Positive qualities of hospital services and facilities (Clean room, efficient, fast appointment, affordable, etc.)	"The wait time was brief. The pharmacy counter did an excellent job." "The room is neat and tidy, and the food is delicious. I really like it."
	Positive qualities of staff (Polite, friendly, helpful, responsive, etc.)	"Staff are polite and kind." "Dr. B took her time explaining my health condition until I understood it. It was greatly appreciated."
	Encourage or recommend others to use	"I recommend having your baby delivered at this hospital." "I like their antenatal counselling and will recommend it to other couples. It is extremely beneficial to us."
	Positive/desirable effects of service (Successful treatment/procedures, good health outcome, etc.)	"I'd like to thank Mr A for performing bowel surgery on my father. He is now doing well." "I found the physiotherapy session to be beneficial. I'm able to walk with less pain now."
Negative	Expression of disliking or disapproval (Do not like, hate, etc.)	"I hate the security guard." He was impolite to me!" "I'm not a fan of the food service here. The food has no taste."

	Negative characteristic of hospital services or facilities (Poor maintenance, slow service, expensive, long waiting time, etc.)	“The discharge procedure was extremely slow.” “There are a limited number of parking spaces available, and getting one is difficult.” “We waited for 5 h at the out-patient clinic before seeing the doctor. This is intolerable.”
	Negative qualities of staff (Rude, not-friendly, not-helpful, slow responsive, incompetency, etc.)	“Staff nurses were rude and stubborn. I requested assistance but received no response.” “The doctor criticised us for arriving at the emergency department at 3 a.m. for treatment. We were annoyed by his attitude.”
	Negative/undesirable effects (Surgical or procedural complications, medicolegal, poor health outcome, etc.)	“My father fell in the toilet and was left alone for a few minutes. The hospital director must explain the incident to our family.” “After being admitted to this hospital two days ago, my husband’s condition has deteriorated. No one, however, can explain the situation to us”.

Neutral	Review that reports factual information/no opinion.	"Serdang Hospital is one of the Klang Valley's cardiac centres". "A Muslim-friendly hospital"
	Review as questions	"Do you have any spine surgeon in your hospital?" "How to get an appointment with your ear. Nose and throat (ENT) clinic?"
	Too ambiguous/unclear/greetings only	"Good morning." "No comment." "Let's wait and see first"

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CHAPTER 5: MANUSCRIPT TWO

Article

Facebook Reviews as a Supplemental Tool for Hospital Patient Satisfaction and Its Relationship with Hospital Accreditation in Malaysia

Afiq Izzudin A Rahim [1], Mohd Ismail Ibrahim[1]*, Kamarul Imran Musa [1], Sook-Ling Chua[2]

[1] Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia
[2] Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia.
* Correspondence: Dr Mohd Ismail Ibrahim email: ismaildr@usm.my, tel: 6097676621, fax: 6097653370

Abstract: Patient satisfaction is one indicator used to assess the impact of accreditation on patient care. However, traditional patient satisfaction surveys have a number of disadvantages, and some researchers have suggested that social media be used in their place. Social media usage is gaining popularity in healthcare organizations, but there is still a paucity of data to support it. The purpose of this study was to determine the association between online reviews and hospital patient satisfaction and the relationship between online reviews and hospital accreditation. We used a cross-sectional design with data acquired from the official Facebook (FB) pages of 48 Malaysian public hospitals, 25 of which are accredited. We collected all patient comments from FB reviews of those hospitals between 2018 and 2019. Spearman's correlation and logistic regression were used to evaluate the data. There was a significant and moderate correlation between hospital patient satisfaction and online reviews. Patient satisfaction was closely connected to urban location, tertiary hospital, and previous FB ratings. However, hospital accreditation was not found to be significantly associated with online reports of patient satisfaction. This groundbreaking study demonstrates how FB Reviews can assist hospital administrators in monitoring their institutions' quality of care in real time.

Keywords: social media; Facebook; patient satisfaction; quality of care; online review; accreditation; hospital management; clinical quality; Spearman correlation; Malaysia

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1. Introduction

Accreditation has gained global recognition as a framework for healthcare organizations to maintain quality of care. In an ideal environment, accreditation guarantees conformity with standards while promoting continuous quality improvement. Numerous kinds of healthcare accreditation exist for condition- or specialty-specific hospital and organization-level operations. The current state of knowledge about accreditation paints a mixed picture of whether it actually improves clinical processes and outcomes. A patient satisfaction score is a critical indicator of the quality of treatment and impact of accreditation in a healthcare setting [1]. Structured patient satisfaction surveys, such as the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) and SERVQUAL (which measures service quality), are frequently used for assessing customer satisfaction with specific service quality criteria [2–4]. Even though these surveys are conducted in a systematic manner and capable of capturing a significant number of patient responses in a given hospital, they are expensive to implement, time intensive, and suffer from poor response rates and other challenges [2,5]. Thus, the internet, and social media specifically, has been proposed as a method of complementing or replacing traditional methods of assessing patient satisfaction and monitoring the quality of healthcare services [6,7].

Social media platforms such as Facebook (FB) and Twitter enable patients and the general public to share healthcare experiences and participate in real-time public conversation with healthcare professionals. Interactions between healthcare practitioners and patients can result in significant changes, combining patient-centered care, the internet, and social media—creating a 'perfect storm' environment [8]. Public or private healthcare issues will be discussed on social media channels based on customer feedback. The use of data in social media research is rapidly increasing in many areas of medicine and the health sciences. The widespread use of social media and the strength of word-of-mouth advertising may assist healthcare providers in monitoring their quality of care and identifying factors associated with patient satisfaction online, while also assisting patients in deciding where to obtain services and what to expect from a given hospital [9,10].

Patient online reviews through social media have developed into a patient-driven alternative that may offer near-instant feedback on a health care provider's performance. The increasing knowledge base on the impact of online reviews on patients' health care decision-making has resulted in an increase in the number of research papers on online reviews and social media [11]. Several studies indicated that online review and social media research possess greater scientific value to explore. Few research works have examined the relationship between online review sites and hospital quality indicators [12,13] or conventional patient satisfaction surveys [6,14]. Meanwhile, other researchers examined the quality of online reviews in relation to public perceptions and sentiments [2,15–17]. However, more empirical research beyond descriptive analyses are necessary to elucidate clinical and policy significance [11].

The present field of study about the use of social media in healthcare and its impact on healthcare remains in its infancy. When compared to the exponential rise of online review usage, the number of published research was modest particularly in developing countries [18,19]. Additionally, there is limited research examining the use of social media as a complement to hospital patient satisfaction surveys, and no study has yet examined the impact of accreditation on social media [11]. Thus, we seek to determine the relationship between hospital patient satisfaction surveys and online patient satisfaction as measured by FB reviews on the official FB pages of Malaysian public hospitals. Additionally, we are interested in investigating the link, if any, between hospital accreditation and online patient satisfaction as measured by FB reviews.

2. Theoretical Background

2.1. Hospital Facebook Reviews

The global population's affinity for social media has recently prompted many healthcare organizations to use their country's most popular social media platforms as a means of online communication and interaction with the public. A nationwide study in Taiwan revealed that FB enjoys high penetration and popularity in that country, which may have been one reason for more than half of Taiwan's hospitals to establish an official FB page [20]. FB is also a vital component of social media use in Malaysia. According to a 2020 report, FB was used by 91.7% of Malaysian internet users and is expected to remain the country's most popular social networking site [21].

While FB and other social media platforms have been shown to improve health outcomes through health education and information [18,19] and have proven beneficial during public health crises [22,23], other studies have examined specific features of social media platforms such as reviews and ratings and their relationship to patient satisfaction and hospital quality indicators [11]. For instance, FB includes a review tool that enables users to write narrative evaluations and rate the performance of businesses and institutions on those organizations' FB pages. Numerous studies have discovered a low to moderate connection between FB evaluations and metrics from systematic patient satisfaction surveys [12,13,24], while another study found that clinical quality indicators such as reduced readmission rates are linked with patient recommendations and higher FB ratings [25]. According to a recent study, hospitals with an active FB page had more “likes”, a higher rate of patients willing to recommend the hospital, and a better overall satisfaction score [26]. Additional research on the patient perspective and its connection to hospital patients’ overall reviews on FB found links with many topics, including waiting times, treatment efficacy, and communication [16]. Thus, the popularity of FB among Malaysians and the FB review function provide an excellent opportunity for us to further explore its use for healthcare and the public good in Malaysia.

2.2. Hospital Accreditation Standards

Several hospital accreditation standards exist, including the Joint Commission International (JCI) standard developed in the United States, Accreditation Canada, and the Australian Council on Health Care Standards. Other standards include those established by the International Organization for Standardization, Six Sigma, Quality Awards, and the European Foundation for Quality Management. Meanwhile, Malaysia its own Malaysian Hospital Accreditation Program that is administered by the Malaysian Society for Health Quality (MSQH). A few countries or organizations have established certification systems that are adaptable to local requirements and circumstances based on mature accreditation models’ experiences [27]. For instance, in response to the global growth of Islamic medical tourism, researchers have proposed the creation of an international Islamic accreditation standard [28].

Assessing hospital accreditation standards is critical for ensuring the high quality, safety, and efficacy of healthcare services in hospitals. The efficacy of an accreditation system is contingent on the suitability, quality, and consistency of its procedures, standards, and surveyors. According to hospital administrators in Iran, decreasing the number of standards and criteria while increasing transparency may improve the accreditation process’s efficiency [29]. This finding was corroborated by a Brazilian study that identified leadership action as a key element in the certification process [30].

Apart from the standard evaluation, studies have revealed that hospital accreditation has a positive effect on organizational processes and structures, enhancing the safety and quality culture, improving patient care, and developing professionalism and staff competencies [1,31–33]. However, other research has shown that when an accreditation program was implemented in hospitals, there was no change in quality improvement, clinical treatment, or patient satisfaction [34,35]. What is most important to patients is that accreditation results in better patient care. Establishing a connection between accreditation and increased satisfaction or experience would increase patients' confidence in and likelihood of choosing a recognized hospital [36].

2.3. Hospital Patient Satisfaction

For years, academics have evaluated hospital patient satisfaction using a variety of methods and conceptual frameworks. Earlier research indicated that patients with modest expectations were most satisfied, whereas those with unrealistic expectations were least satisfied [37]. When patients' expectations matched the delivery of health services, they expressed satisfaction with those services [38]. Since those earlier efforts, the number of variables associated with patient satisfaction has grown and varies significantly in different studies [1,31,38]. However, one systematic study concluded that two powerful predictors of patient satisfaction are healthcare provider-related factors and patient-related characteristics [38]. That review found provider–related factors to be the greatest predictor of patient satisfaction across trials. Nine determinants of healthcare services were identified: technical care, interpersonal care, physical environment, accessibility, availability, financial resources, organizational features, continuity of treatment, and outcome of care. Among service-related variables, interpersonal skills and technical care characteristics had the greatest positive correlations.

Patient characteristics such as age, gender, education, socioeconomic status, marital status, race, religion, geographic characteristics, visit frequency, length of stay, health status, personality, and expectations were all investigated to determine their associations with patient satisfaction [35]. However, throughout the sample, these correlations were weak and inconsistent. As a result, the study suggested that it may be worth trying to construct patient satisfaction using quality indicators for health services and how people improve their satisfaction with health services. SERVQUAL and HCAHPS are two examples of structured surveys that are based on the quality of healthcare services. Patient satisfaction survey results can be very beneficial to both healthcare professionals and patients. They assist healthcare professionals in identifying areas of their services that may benefit from improvement. Increased patient satisfaction with healthcare services improves patient response to public hospitals [39]. According to studies, satisfied patients are more likely to adhere to their doctors' suggested treatments and carry out follow-up visits, leading to improved health outcomes and recommendations of the hospital to others [38].

2.4. Hospital Accreditation and Patient Satisfaction Relationship

Although accreditation standards have been employed for decades and their effect on healthcare safety and quality has been widely acknowledged, attempts to assess the linkage between accreditation and patient satisfaction have produced varied results [31]. Earlier research established that accreditation was not linked with patient satisfaction [40,41] and that there was no statistically significant difference in patient satisfaction or recommendation between accredited and non-accredited hospitals [42]. This finding was supported by a study conducted in Lebanon in which the majority of patients expressed dissatisfaction with the quality of services [43], a study conducted in the United States in which no significant difference in patient satisfaction was found between accredited hospitals and other organizations [44], and an Iranian study in which an inverse relationship between patient satisfaction and quality of care was discovered [45]. However, many other studies have shown a positive correlation between accreditation and patient satisfaction in several settings, including Southeast Asia [46] and the Middle East [47,48].

2.5. Conceptual Background

Our study generally synthesized key results or conceptual frameworks from literature studies on patient satisfaction-related variables. There are four major factors (accreditation status, patient related characteristics, healthcare provider related determinants, and FB page features or engagement) that may influence patient satisfaction in hospital's FB reviews. Figure 1 illustrates the conceptual framework for this study.

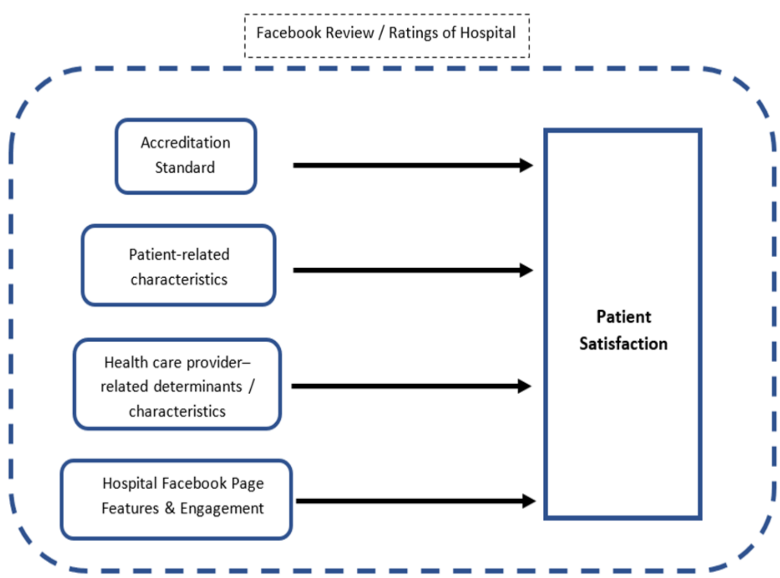

Figure 1. Conceptual framework of the study.

3. Materials and Methods

This cross-sectional study of government hospitals in Malaysia was conducted from March 2020 to May 2021 to reconcile the topic's homogeneity with the generalizability of the results. Universal sampling was employed.

3.1. Facebook Data

In the fall of 2020, we gathered data from the official FB pages of Malaysian public hospitals from 2018 to 2019. We began by using the Google search engine to browse hospital websites, using a list of all public hospitals in Malaysia obtained from the country's Ministry of Health (MOH). We looked for URLs and links to each hospital's official FB page. If the hospital's website did not have a link to an official FB page, we continued our search on FB itself. When we discovered an official hospital FB page, we validated the information by using the hospital's website's address, contacting hospital administrators, or referring to our operating definition of an official hospital FB page. These search methods have also been applied in previous studies [12,13,23].

We defined an "official" hospital FB page as one with a "verified" symbol [49], one that used the hospital's official name on the FB page, one with the hospital's official name mentioned in the FB page's description, or one with a FB page linked directly from the hospital's official website. We included only publicly accessible FB pages that were linked with the hospital, and all data acquired from the official FB page were retained in a pro forma checklist, such as the average number of stars it earned and the inclusion of complete hospital information on the page. The hospital departments' FB pages were eliminated, as were the pages of health institutions such as the MOH and the Institute of Medical Research and non-governmental organization hospitals and long-term care facilities.

3.2. Hospital Data

3.2.1. Hospital Accreditation

The MSQH provided a list of accredited public hospitals in 2018 and 2019. MSQH is a not-for-profit organization founded in cooperation with the Malaysian MOH, the Malaysian Association of Private Hospitals, and the Malaysian Medical Association. Its mission is to enhance the quality of healthcare in Malaysia by improving organizational performance and patient care. MSQH is the only accreditor in Malaysia. Its certification standards address a broad variety of quality attributes, including treatment access, appropriateness, effectiveness, and safety, along with patient-centered activities, efficiency, and governance [50]. Safety is a key component of the standards; an entity that complies with all other criteria while failing to satisfy safety requirements will be refused certification. MSQH standards apply to all kinds of hospitals undergoing consideration for accreditation, whether public or private, large, or small. A hospital seeking accreditation must perform a self-assessment prior to the accreditation survey. A team of surveyors conducts the assessment, and their report is then evaluated and voted on by members of the Malaysian Council for Health Care Standards. Malaysia had 69 certified public hospitals in both 2018 and 2019.

3.2.2. Patient Satisfaction Survey

The MOH conducts a yearly survey of patient satisfaction in all public hospitals to establish a benchmark for quality hospital services. The survey is based on the SERVQUAL questionnaire; each hospital's quality unit collects data and sends them to the MOH in Putrajaya for analysis. The survey is supplied to patients upon admission and collected prior to discharge. Satisfaction is evaluated by comparing the quality of the services to the patient's expectations. SERVQUAL is linked to customer expectations before and during service delivery and to their perceptions of service quality after it has been delivered. A positive SERVQUAL difference indicates that a patient was pleased and that his or her expectations were fulfilled. Negative SERVQUAL results, on the other hand, indicate discontent, such as when a service is not finished completely. While those data are not publicly accessible, they are available for study at the MOH's Medical Division in Putrajaya. However, due to technical issues, the MOH permitted us to examine only overall patient satisfaction data from 2018 and 2019 for each hospital, rather than the entire SERVQUAL domain. A hospital-wide patient satisfaction survey is one of the performance criteria used to assess service standards in the MSQH certification process. It serves as a proxy for determining the quality of patient-centered services and patient satisfaction [50]. There is no specific survey a hospital must conduct to ensure compliance with service standards. As a result, public hospitals often use the MOH patient satisfaction survey as part of the accreditation process [50].

3.3. Outcomes: Patient Satisfaction in Facebook Reviews

Users may employ the FB review feature to leave narrative reviews on the FB pages of organizations and companies. Since its debut in 2013, the FB review section has been included on the FB pages of many hospitals and is increasingly being used by patients and their families. FB had a five-star rating system until early 2018, when it switched to a binary approach— "Recommends" or "Does Not Recommend"—that significantly simplified the review process for FB. As with other social media platforms, FB reviews provide insights into how key stakeholders (e.g., former, and present patients, their relatives, or friends, past or current employees, and so on) perceive healthcare services. Numerous studies have already been conducted to evaluate FB reviews or ratings of hospital services and patient satisfaction or quality measurements [12,13,16]. To determine patient satisfaction, we used the WebHarvy (SysNucleus, Kochi, India) software package to collect customer recommendations in the reviews area of hospitals' FB pages between January 2018 and December 2019. We define patient satisfaction as a recommendation in the review area of a given hospital 's FB page. However, suggestions made on non-FB review sites were excluded.

3.4. Statistical Analysis

Categorical data were given as frequencies and percentages for statistical analysis, while numerical data were provided as medians (interquartile range [IQR]) due to a non-normal distribution of the data. To determine the validity of customer recommendations in FB reviews as a supplementary tool for traditional patient satisfaction surveys, we compared the degree of hospital patient satisfaction as measured by the MOH survey to the proportion of patient recommendations on the hospital's FB page. From the 2018 and 2019 datasets, we estimated the average percentage of patient satisfaction surveys and the proportion of FB recommendations for each institution. We then assessed their association using Spearman's rank correlation coefficient. Correlations below 0.2 were considered weak, those between 0.2 and 0.5 were considered moderate, and those greater than 0.5 were considered high. Later, we used binary logistic regression analysis to determine the relationship with overall customer recommendations in FB reviews. The relationships were controlled for hospital factors (region, bed count, urban or rural location, and hospital type) and FB page features such as past star ratings, acceptable hospital information on the FB page, and administrator reaction in the FB review area. Previous research indicates that these characteristics are related to patient satisfaction. The findings were discussed in terms of those that were statistically significant at $p \leq 0.05$. All statistical test assumptions were verified and fulfilled. To confirm the model fitness of our analysis, the Hosmer and Lemeshow test and the area under the operating ROC curve were used. SPSS, version 26 (IBM Corp., Armonk, NY, USA) software [51] was used to analyze the data.

4. Results

4.1. Hospital and Facebook Characteristics

In total, 86 of Malaysia's 135 public hospitals (63.7%) had an official FB page, with 48 (55.5%) allowing consumer feedback on that platform. Accreditation had been granted to 25 (52.08%) of the 48 hospitals with FB reviews. Except for the western region, each region in Malaysia had at least 10 hospitals offering a FB review function: 37.5% of tertiary hospitals, 8.3% percent of secondary hospitals, and 54.2% percent of primary hospitals nationwide had FB review sections. The majority of these hospitals were located in urban areas and had an average of 730 beds. According to the annual MOH study, the average percentage (IQR in parentheses) of patients satisfied with treatment received in public hospitals was 96.93% (3.00). The average number of reviews per hospital FB page was 15.5 (27.5), and the average previous star rating was 5.00 (1.65). Many hospitals' FB pages have contact information and responded to user reviews. The average proportion of customer recommendations in FB reviews was 80.7% (48.43). The hospitals and their FB characteristics are summarized in Table 1.

Table 1. Hospital and FB (FB) characteristics (*n* = 48).

Variable		*n* (%)	Median (IQR)
<u>Hospital Characteristics</u>			
Region			
	North	10 (20.8)	
	West	6 (12.5)	
	South	11 (22.9)	
	East Coast	10 (20.8)	
	Borneo	11 (22.9)	
Type of Hospital			
	Primary	26 (54.2)	
	Secondary	4 (8.3)	
	Tertiary	18 (37.5)	
Location			
	Rural	22 (45.8)	
	Urban	26 (54.2)	
Number of Beds			730 (563)
Average Patient Satisfaction in MOH Survey			96.93 (3.00)
Hospital with Accreditation Status			
	No	23(47.92)	
	Yes	25(52.08)	
<u>FB Characteristics</u>			
Previous FB Star Ratings			5.00 (1.65)
Number of Reviews			15.5 (27.5)
Adequate Hospital Information on FB Page			
	No	11 (22.9)	
	Yes	37 (77.1)	

Hospital Administration Replied to FB Reviews			
	No	18 (37.5)	
	Yes	30 (62.5)	
Average Proportion of Patient Recommendation from FB Review			80.7 (48.43)

4.2. Correlation of Patient Satisfaction in Facebook Reviews and from Annual Hospital Surveys

The Spearman rank correlation indicated that the average proportion of patient satisfaction from the annual MOH survey was significantly correlated to the average proportion of patient recommendations in FB reviews (r = 0.35, p = 0.02, n = 48). We consider this correlation to be moderate.

4.3. Patient Satisfaction in Facebook Reviews and Its Associations

For the purpose of analyzing patient satisfaction, a total of 2019 FB reviews were collected from 48 hospital FB pages. The majority (49.1%) came from the western region, urban hospitals (87.1%), and tertiary facilities (88.5%); 9.1% of FB reviews received individualized feedback from hospital management. Approximately 61% of the reviews involved accredited hospitals. The majority of Malaysia’s public hospitals with the FB review feature enabled were recommended in FB reviews by patients or their families (74.4%). The FB reviews and their characteristics are summarized in Table 2.

Table 2. FB reviews and their characteristics (n = 2019).

Variables		n	(%)
Hospital Characteristics			
Region			
	East Coast	219	10.8
	North	441	21.8
	West	992	49.1
	South	202	10.0
	East Malaysia	165	8.2
Location			
	Rural	261	12.9
	Urban	1758	87.1
Type of Hospital			
	Primary	136	6.7
	Secondary	96	4.8
	Tertiary	1787	88.5
Accreditation Status			
	No	783	38.8
	Yes	1236	61.2

FB Page Characteristics			
Hospital Administration Response			
	No	1836	90.9
	Yes	183	9.1
Patient Recommendation			
	No	517	25.6
	Yes	1502	74.4

4.4. Hospital Accreditation and Patient Satisfaction

Hospitals in northern (Odd ration (OR) 1.66, 95% Confident interval (CI): 1.12, 2.47), southern (OR 0.54, 95% CI: 0.34, 0.83), and eastern (OR 0.49, 95% CI: 0.32, 0.76) Malaysia exhibit significant relationships with patient satisfaction (p < 0.05). Hospitals located in urban areas (OR 1.85, 95% CI: 1.40, 2.43) and classified as tertiary (OR 1.62, 95% CI: 1.12, 2.35) were also significantly associated with patient satisfaction in FB reviews. Another significant link was with prior FB ratings (OR 1.14, 95% CI: 1.06, 1.23). There was, however, no significant association between hospital accreditation and patient satisfaction (OR 1.03, 95% CI: 0.84, 1.26). All relevant confounders and factors with p-values less than 0.25 were entered into the SPSS software during the multivariate analysis to build a final model for a confirmatory study of hospital accreditation. When geographical characteristics and previous FB ratings were controlled for, there was no significant association between hospital accreditation and patient satisfaction in FB reviews (AOR 0.95, 95% CI: 0.77, 1.17; p = 0.63). The fitness tests conducted on the models were judged to be satisfactory. Tables 3 and 4 illustrate the analysis.

Table 3. Factors associated with patient satisfaction (n = 2019).

Variables		*B*	Crude OR	95% (Lower)	CI (Upper)	*p*-Value *
Hospital Characteristics						
Region	East Coast		Ref			
	North	0.51	1.66	1.12	2.47	0.013
	West	0.03	1.03	0.73	1.44	0.877
	South	−0.61	0.54	0.34	0.83	0.004
	East Malaysia	−0.71	0.49	0.32	0.76	0.001
Location	Rural		Ref			
	Urban	0.61	1.85	1.40	2.43	<0.001
Hospital Type	Primary		Ref			
	Secondary	0.10	1.11	0.64	1.93	0.725
	Tertiary	0.48	1.62	1.12	2.35	0.014
Numbers of Bed		1.19	1.00	1.00	1.00	0.273

<u>FB Page Features</u>						
Previous FB Rating		0.13	1.14	1.06	1.23	<0.001
Adequate Hospital Information on FB Page						
	No		Ref			
	Yes	0.25	1.28	0.85	1.92	0.232
Hospital Administration Reply						
	No		Ref			
	Yes	−0.27	0.76	0.55	1.06	0.114
Hospital Accreditation Status						
	No		Ref			
	Yes	0.03	1.03	0.84	1.26	0.791

** Simple Logistic Regression.*

Table 4. Factors associated with patient satisfaction using multivariate analysis (n = 2019).

Variables		Adjusted OR	95 % CI (Lower)	95 % CI (Upper)	p-Value *
Accreditation	No	Ref			
	Yes	0.95	0.77	1.17	0.633
Hospital Location	Rural	Ref			
	Urban	1.71	1.29	2.27	<0.001
Previous FB Rating		1.11	1.03	1.20	0.014

** Multiple Logistic Regression; Constant = 0.203; Forward LR, backward LR, and manual selection were applied for the confirmatory analysis. No significant interaction or multicollinearity. Hosmer and Lemeshow Test = 0.10. Classification Table = 74.4%. Area Under the ROC Curve = 58% (p < 0.001).*

5. Discussion

This is the first study we are aware of that examines FB reviews as a tool for patient satisfaction and the impact of hospital accreditation on patient satisfaction expressed on social media platforms in Southeast Asia, and possibly across Asia.

5.1. Facebook Reviews and Patient Satisfaction Survey

Social media use is growing among Malaysia's public hospitals, the majority of which now have their own FB page. The results corroborated those of research in Taiwan demonstrating that the popularity of FB led to healthcare organizations' desire to establish their own accounts on the site [20]. However, half of the Malaysian hospitals' FB pages do not have a section for consumer feedback. It is unclear whether hospital administrators actively chose to disable feedback or were simply ignorant of the FB review function.

We discovered a moderate association between hospital patient satisfaction and consumer recommendations in FB reviews, which may offer information on service quality and patient experiences to hospital management. Previous research has shown a connection of low to moderate strength between FB ratings and HCAHPS results [13,25,52]. Additionally, some studies have discovered correlations between FB ratings and other national patient experience metrics [12,53].

Studies involving other social media platforms revealed a moderate to high correlation between social media ratings and conventional patient satisfaction surveys [3,6], although a couple of studies have shown a negative correlation between social media reviews and patient satisfaction surveys or quality indices [2,54].

It was unknown whether social media reviews were incompatible with other established patient satisfaction measures. The mixed results could be explained by the fact that we examined only public or government hospitals or by the fact that our analysis was a nationwide study, whereas previous studies examined only selected states or hospitals. The difference could also be due to our decision to compare FB reviews only to traditional patient satisfaction surveys rather than to Twitter or other social media platforms and multiple clinical quality indicators. Unquestionably, a larger study investigating the connection between social media platforms and hospital quality measures is required. However, there is currently no comparable standard assessment of patient satisfaction or experience in Malaysia's public or private hospitals. While the MOH favors the SERVQUAL questionnaire, private hospitals may develop their own surveys or use another international standard [55,56]. Thus, FB reviews may serve as a new standard of patient satisfaction in both the public and private sectors.

A reviewer's suggestion in a FB review may provide insight into satisfaction with hospital care, which may be useful to other individuals seeking information about hospital quality. FB reviews are straightforward and readily accessible, removing barriers to obtaining information about hospital quality and helping hospitals to address quality-of-service concerns and alerting them to possible patient safety issues [15,57]. As a result, a FB review may assist both consumers in making healthcare choices and hospitals in ensuring high standards of quality.

Additionally, traditional patient satisfaction surveys are costly, time consuming, have low response rates, necessitate a significant amount of time between hospitalization and public disclosure of reports, frequently fail to identify the source of perceived problems, and may introduce response and selection bias [2,5,11]. The discrepancy between the typical patient survey and other data sources demonstrates the need to use other data sources to ascertain public sentiment about healthcare services [17]. Therefore, the internet in general and social media in particular have been suggested as new tools for evaluating patient satisfaction and monitoring the quality of healthcare services [7,58].

On the other hand, social media evaluations are largely untested and uncontrolled, while conventional patient satisfaction surveys have been validated, assessed, and risk adjusted. Social media users may post information on a hospital or write a review even if they have never been a patient at that hospital. This may also indicate that social media users are leaving reviews or comments on their experiences visiting a friend or family member in the hospital, which is likely related to patient satisfaction with care. More worrisome is that users of social media platforms may post fake reviews [13,24]. To help ensure the authenticity of the data, hospitals may aid customers by posting additional quality metrics on their FB sites, using MOH quality indicators, on a rolling six-month basis. This can support the public in making educated choices and encourage the adoption of validated quality measurements.

5.2. Hospital Accreditation and Patient Satisfaction

This study provides valuable knowledge regarding patient experiences with healthcare is Southeast Asia, which has not received sufficient attention in previous research. It is a matter of concern that only a few studies have examined patient experience and the impact of accreditation in various Asian contexts, revealing healthcare objectives that vary from those found in the West [59,60].

In general, we found that, after controlling for hospital location and prior FB ratings, patient satisfaction in FB reviews were not significantly associated with whether a hospital was accredited. Previous research has shown that accreditation has little effect on the quality of treatment received by patients and may not be the most important factor affecting patient desire to recommend hospital services [35,41]. This view is supported by studies in the United States and Germany that found no difference in the ratings or recommendations of accredited and non-accredited hospitals [42,44]. Additional studies in Lebanon [43], Turkey [61], India [62], and Malaysia [63] have all echoed this result. On the other hand, some research has shown a positive relationship between accreditation and patient satisfaction [46–48].

There are many possible explanations for the inconsistency in the relationship between patient satisfaction and accreditation. While a focus on patient outcomes is unquestionably beneficial, it is possible that the accreditation process places a greater emphasis on organizational structure, patient safety, and clinical qualities [1,64,65]. The most recent systematic study discovered a link between accreditation and efficiency, effectiveness, timeliness, and safety [32]. Meanwhile, other research has shown a connection between accreditation and clinical outcome improvements such as decreased standardized mortality ratios for chronic illnesses [66,67] and other measures of service quality [68]. However, other studies have shown no correlation between accreditation and clinical outcomes [59,69].

The data provide insight into the relationship between accreditation and its process and results in various areas of the globe. While enhanced clinical procedures may result in improved patient outcomes, it is critical to evaluate hospital activities that can actually increase patient satisfaction [1,59,68]. According to a systematic review, the strongest predictors of patient satisfaction are interpersonal skills and technical care [38]. Additionally, many studies have shown that hospitals with higher clinical quality and/or those that meet accreditation performance criteria, such as reduced readmission rates, have a favorable impact on patients' overall satisfaction and are therefore highly appreciated by patients, families, and the public at large. Patient satisfaction and FB ratings both increased as a result of this appreciation [9,25].

Other factors affecting the connection between accreditation and patient satisfaction include the organization's features and accessibility, which include size, type, structure, culture, and purpose [25,60,70]. A hierarchical culture has been shown to be associated with reduced readmission rates and reducing readmission rates has a beneficial effect on patient satisfaction. In other words, hierarchical culture is strongly associated with increased patient satisfaction, as has been shown by improving FB ratings [9,25]. Additionally, we discovered a strong connection between tertiary hospital type and patient satisfaction, even though some research indicates that only medium-sized hospitals will observe an increase in the quality of their care [68,71].

Patient-related factors were associated with patient satisfaction either weakly or in a mixed fashion. Age, gender, education, socioeconomic position, relationship status, ethnicity, religion, geographic features, frequency of visits, duration of stay, health condition, personality, and expectations are all considered [38]. As proof, we discovered a significant relationship between patient satisfaction and hospital location in an urban region. However, prior research indicates that rural residents were more likely to be pleased than urban residents [38,44]. Additionally, there were little data to substantiate hospital recommendations about hospital accreditation in an urban region [42]. While hospitals situated in urban areas often offer a number of advantages in terms of resources, finances, expertise, and personnel sufficiency, they also come with higher costs and with increased expectations from patients.

Managing patient expectations is inherently challenging. Although theory holds that people are pleased when their expectations match healthcare performance, associations between expectations and satisfaction have varied in published research [38]. Healthcare practitioners, patients, and their families have higher expectations and impressions of patient safety and service quality at accredited hospitals, according to studies [71,72]. Additionally, patients admitted to non-accredited hospitals expressed greater satisfaction with laboratory work, such as professionalism, than patients admitted to accredited hospitals [48].

Moreover, we were unable to identify other patient-related factors, such as age, gender, education, socioeconomic position, relationship status, ethnicity, religion, frequency of visits, duration of stay, health condition, and personality, as key variables in this research. We did not check our reviewers' FB accounts to avoid breaching the Malaysia Personal Data Protection Act or other laws. Age has been shown to have a direct and positive effect on patient satisfaction and service quality rating [43,46]. This finding was echoed by a Malaysian government survey which discovered that, between 2018 and 2020, younger people account for the majority of social media users in Malaysia [21,73]. Other variables, such as gender, can have an effect on patient satisfaction, with male patients expressing higher levels of satisfaction [46]. However, a systematic study found inconsistent correlations with the gender factor [38]. A survey found that the majority of internet users in Malaysia are male [21,73], while a study focused on Malaysia discovered no significant difference in gender and patient satisfaction between accredited and non-accredited hospitals [63].

5.3. Implications

Our research demonstrates the value of using social media to gather input on facilities and the quality of healthcare services. Social media may offer insights for healthcare organizations that can be used as real-time early-warning signs of a potential decline in healthcare quality or poor patient experiences. It may also be possible to incorporate social media ratings into existing MOH report cards for public hospitals or use them as a supplementary tool for conventional patient satisfaction surveys. Additionally, our study extends the role of hospital administrators and public health organization in enhancing healthcare service quality beyond ongoing monitoring of social media trends for health education or crisis communications. Our findings also encourage all public hospitals in Malaysia to establish and actively engage with the online community through official FB pages, given the intangible financial and educational benefits of FB pages.

5.4. Recommendation

There is a dearth of research on the use of FB and other social media platforms in healthcare quality evaluation processes such as accreditation. Malaysia and other developing nations are notable for the slow pace at which healthcare professionals establish and use official FB pages. A particularly important area of study would be to examine the variables that promote or inhibit the adoption of official hospital FB accounts. This survey should cover all hospital employees and administrators. The information gathered should include hospital workers' and leaders' attitudes about and opinions of the creation and use of social media sites. Additionally, we recommend that hospital administrators take FB sites and their use more seriously. Because potential patients are likely to form opinions based on social media content, hospitals must approach the service quality of their operations holistically to enhance their social media presence.

Additional research should be conducted to determine how FB reviews can be integrated into external measurement systems, including how patient experience scores can be linked to FB reviews, how their ambiguity can be addressed, how data changes can be quantified, and how qualitative FB data can be interpreted and used. While previous studies have used sentiment analysis, more research should be conducted to determine how to use qualitative data beyond the quantity of positive sentiments. Additional research is needed to obtain a better understanding of the patient satisfaction viewpoint expressed on social media regarding both accredited and non-accredited hospitals. According to the findings of a Lebanese study, tangible hospital characteristics such as physical facilities and equipment have an effect on patient satisfaction [43], a result that has been confirmed by another research [45,61]. Other patient perspectives or quality domains that contribute to patient satisfaction include emergency and inpatient care, triage length, and respect for patients [59,74].

5.5. Study Limitations

While our study of FB reviews may have been subject to response and selection bias, this is true of any conventional survey. Because the study was conducted in a cross-sectional fashion, we cannot rule out the potential of a causal relationship in our results. Further study on the development of these results would be beneficial. Additionally, only 45 of 87 hospitals had FB reviews. The inclusion of unofficial FB sites for public hospitals may result in disparate patient satisfaction ratings. Additionally, since the median number of reviews was only 15, many hospitals' FB reviews were insufficient to provide a meaningful indicator of how accreditation affects a hospital's quality and how it is linked to patient satisfaction on social media. Finally, owing to regulatory and legal constraints, we were unable to examine the effects of accreditation and patient satisfaction on patient-related characteristics. The study of such factors is likely to be beneficial and may provide a richer context for the use of social media in the healthcare sector.

6. Conclusions

Despite the fact that more than half of Malaysia's public hospitals have an official FB page, only a handful allow patient feedback in the form of FB reviews. As a result, hospital managers are urged to make use of the FB review function and leverage its potential as an early-warning system and real-time monitor of hospital quality and patient care. In the present study, we discovered a modest and significant correlation between MOH patient satisfaction survey results and online patient satisfaction as determined by FB reviews. Thus, FB reviews may be used in conjunction with traditional patient satisfaction surveys. Additionally, we found that accredited hospitals did not achieve a higher level of patient satisfaction on the social media platform than non-accredited hospitals. Although this research found only a modest impact of accreditation on patient satisfaction, accreditation standards are nonetheless internationally acknowledged and should be followed consistently to ensure hospital clinical and quality services. Meanwhile, further research on patient perceptions of patient satisfaction and treatment quality would benefit the healthcare sector. Finally, more reviews are necessary to represent the community of internet users and to obtain a better understanding of the impact of hospital accreditation on online patient satisfaction.

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CHAPTER 6: MANUSCRIPT THREE

Article

Patient Satisfaction and Hospital Quality of Care Evaluation in Malaysia Using SERVQUAL and Facebook

Afiq Izzudin A. Rahim [1], Mohd Ismail Ibrahim[1*], Kamarul Imran Musa [1], Sook-Ling Chua[2,] Najib Majdi Yaacob[3]

1 Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia.
2 Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, 63100 Cyberjaya, Selangor, Malaysia.
3 Unit of Biostatistics and Research Methodology, School of Medical Sciences, Universiti Sains Malaysia, Health Campus, Kubang Kerian 16150, Kelantan, Malaysia
*Correspondence: Dr Mohd Ismail Ibrahim, email: ismaildr@usm.my, tel: 6097676621, fax: 6097653370.

Abstract: Social media sites, dubbed patient online reviews (POR), have been proposed as new methods for assessing patient satisfaction and monitoring quality of care. However, the unstructured nature of POR data derived from social media creates a number of challenges. The objectives of this research were to identify service quality (SERVQUAL) dimensions automatically from hospital Facebook (FB) Reviews using a machine learning classifier and to examine their associations with patient dissatisfaction. From January 2017 to December 2019, empirical research was conducted in which POR were gathered from Malaysian public hospital's official FB page. To find SERVQUAL dimensions in POR, a machine learning topic classification utilising supervised learning was developed and our objective was established using logistic regression analysis. We discovered 73.5 % of patients were satisfied with the public hospital service, whereas 26.5 % were dissatisfied. Also, we identified 13.2% reviews of tangible dimensions, 68.9% reliability, 6.8% responsiveness, 19.5% assurance, and 64.3% empathy. After controlling for hospital variables, all SERVQUAL dimensions except Tangible and Assurance were shown to be significantly related with patient dissatisfaction (reliability; $p<0.001$, responsiveness; $p=0.016$, and empathy; $p<0.001$). Additionally, rural hospitals have a higher probability of patient dissatisfaction ($p<0.001$). Thus, POR assisted by machine learning technologies provide a pragmatic and feasible way for capturing patient perceptions of care quality and supplementing conventional patient satisfaction surveys. Moreover, the findings offer critical

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information that will assist healthcare authorities in capitalising on POR by monitoring and evaluating the quality of services in real time.

Keywords: Patient Satisfaction, Service Quality, SERVQUAL, FB, Machine Learning, Patient Online Review, Malaysia.

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1. Introduction

The World Health Organization (WHO) stressed that substandard care wastes significant resources and jeopardises public health by degrading human capital and decreasing productivity. Thus, in addition to providing effective coverage of essential health services and financial security in each country, delivering high-quality care or service is important to achieving the Universal Health Coverage goal [1]. At the core of delivering high-quality care is a dedication to person-centered care. Communities must be engaged in the design, implementation, and ongoing evaluation of health services to ensure that they meet local health needs. Also, striking a balance between patient expectations and quality improvement initiatives is important, since it influences patient safety, survival, and long-term health [2]. According to a systematic analysis, poor healthcare quality was the main factor leading to an increase in deaths from cardiovascular disease, neonatal trauma, and communicable illnesses [3]. As healthcare prepares for Industrial Revolution 4.0 by becoming more patient-centered and value-driven, quality management systems must include efforts to understand and respect patients' interests, desires, and values. Because such reports can only be generated by patients, it is critical to create systems for monitoring patient experiences and to promote their use on an individual and communal level [4,5]. Patient perception and satisfaction have been a key component of patient-centered care since the early 1990s and have been incorporated into healthcare quality of care assessment. Healthcare administrators that aim for excellence consider patient perception while creating strategies for improving treatment quality [6].

Service quality (SERVQUAL) is a commonly used technique for evaluating the quality of service in a wide variety of service environments, sectors, and nations [7]. Because the model encompasses five dimensions: tangible, reliability, responsiveness, empathy, and assurance, it efficiently measures customer service needs and perceptions [8]. SERVQUAL, Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS), and other traditional patient satisfaction surveys are the product of years of evaluative analysis, are performed and evaluated in a methodical manner, and may evoke a wide variety of answers from patients [9,10]. However, traditional patient or public surveys used to assess the quality of healthcare services are time and resource intensive, requiring considerable time between hospital admission and report disclosure, frequently resulting in a failure to identify the underlying causes of concerns, and introducing response and selection bias [11,12]. The disconnect between conventional surveys and patient perceptions and treatment quality underscored the need of developing new data sources for assessing patient perceptions and care quality [13]. Technological innovation is essential for creating new ways for rapidly assessing the quality of services at an affordable cost. Therefore, social media platforms, which are often referred to as patient online reviews (POR), have been suggested as new ways for gauging patient satisfaction and monitoring treatment quality [14,15].

POR study revealed a very little number of studies in contrast to its exponential growth [16,17]. While it has been demonstrated that Facebook (FB) and other social media social media platforms can improve health outcomes through health education and information [18,19] and can be beneficial during public health crises [20,21], other studies have examined specific features of social media platforms such as reviews and ratings and their relationship to patient satisfaction and hospital quality measures [16]. For example, FB offers a review feature that allows users to leave narrative assessments and evaluate the performance of companies and institutions on their FB pages. Numerous studies have discovered a weak to moderate correlation between FB evaluations and traditional patient satisfaction survey metrics [22-25], while another study discovered a link between clinical quality indicators such as reduced readmission rates and higher FB ratings [26]. According to a recent research, hospitals with an active FB page had a higher number of "likes," a greater percentage of patients ready to refer the hospital, and a higher overall satisfaction score [27]. Additional study on the patient viewpoint and its relationship to hospital patients' total FB ratings discovered associations with a variety of issues, including wait times, treatment effectiveness, and communication [28]. With an increasing number of patients asking and freely sharing hospital evaluations on social media, feedback data may supplement conventional patient satisfaction surveys [14,27].

However, the unstructured nature of POR data collected from social media presents several difficulties, including data cleaning and processing. While this may be accomplished manually via human input, the process is lengthy, and the method's validity and reliability are often questioned [29]. A systematic evaluation of POR was proposed to accelerate the processing of large-scale online review data using sophisticated analytical techniques such as machine learning [16]. Consequently, a machine learning approach for classifying service quality themes or subjects based on unstructured social media data has the potential to significantly improve healthcare quality of care [30,31].

Additionally, the population's fondness for social media has led many healthcare institutions to use their country's most popular social media platforms for online communication and engagement with the public. According to a national survey conducted in Taiwan, FB has a high level of penetration and popularity in the country, which may be one of the reasons why more than half of Taiwan's hospitals have established an official FB profile [32]. FB is also a critical component of Malaysian social media use. According to a 2020 study, 91.7 percent of Malaysian internet users utilised FB, and the site is projected to continue to be the country's most popular social networking site [33]. Given the popularity of FB in our nation and its expanding usage in healthcare, we first want to assess the frequency of SERVQUAL dimensions in FB reviews of Malaysian public hospitals using a machine learning classifier and prevalence of hospital patient satisfaction. Second, we seek to establish relationships between SERVQUAL qualities and hospital patient dissatisfaction as expressed in FB Reviews. POR analyzed using a machine learning algorithm may have value in assisting all key healthcare stakeholders in making decisions to enhance the quality of care delivered in Malaysia.

2. Related Work

2.1 Patient Satisfaction

Intellectuals have been assessing hospital patient satisfaction for years, using a range of methodologies and conceptual frameworks. Earlier study showed that patients with moderate expectations reported the highest levels of satisfaction, whereas those with excessive expectations reported the lowest levels of satisfaction [34]. When patients' expectations were met in terms of health care delivery, they reported satisfaction with such services [35]. Since those early attempts, the number of factors linked with patient satisfaction has increased dramatically and varies between research [36,37]. However, one systematic review found that two significant determinants of patient satisfaction are variables affecting the healthcare provider and patient characteristics [35]. Across studies, that study found that provider-related variables were the strongest predictor of patient satisfaction. There were nine identified determinants of healthcare services: technical care, interpersonal care, physical environment, accessibility, availability, financial resources, organizational characteristics, continuity of treatment, and care result. Research that examined the physical environment in relation to patient satisfaction ratings on social media discovered that environmental variables such as parking, cleanliness, and waiting rooms all contributed to patient satisfaction [38]. Another POR research showed that comments on the efficacy of treatment, communication, and diagnostic quality are most strongly linked with patients' overall ratings [28]. A comprehensive assessment of patient satisfaction confirmed the results, revealing that interpersonal skills and technical care features had the most positive associations with service-related factors [35].

On the other hand, patient characteristics such as age, gender, education, socioeconomic status, marital status, race, religion, geographic characteristics, frequency of visits, length of stay, health status, personality, and expectations were all investigated to ascertain their associations with patient satisfaction [35]. Hospital characteristics such as location and rural regions were shown to be positively associated with patient discontent [39], even though another study found rural residents to be satisfied with healthcare services [40]. Additionally, the size and type of hospital services influenced patient satisfaction [15,41]. Previously, it was believed that people would be more unhappy with a service that dealt with a greater number of patients and a bigger office. However, in a comprehensive assessment of patient satisfaction, these associations were modest and inconsistent [35]. Therefore, the research concluded that it may be worthwhile to attempt to build patient satisfaction using health care quality indicators and how individuals increase their satisfaction with health services. SERVQUAL and HCAHPS are two examples of systematic surveys that assess healthcare quality of care. The findings of patient satisfaction surveys may be very helpful for both healthcare professionals and patients. They aid healthcare providers in finding areas in which their services might be improved. Increased patient satisfaction with healthcare services boosts public hospital responsiveness [42]. Additionally, it enables policymakers to understand patient needs and therefore create strategic plans for more effective and high-quality services. According to studies, satisfied patients are more likely to follow their physicians' recommendations for treatment and follow-up visits, resulting in better health outcomes and hospital recommendations to others [35].

2.2 Social Media Data and Machine Learning

Social media data is often massive and presents several difficulties, including data cleansing, data processing, and developing a theoretical model of social media content quality. While this may be accomplished manually via human input, the procedure is time consuming, labor intensive, and the validity and reliability of the technique are often questioned [29]. A comprehensive analysis of POR established and recommended the use of advanced analytical methods such as machine learning to accelerate the processing of huge amounts of online review data [16]. Additionally, the systematic review recommended doing an in-depth examination of the contents of online reviews rather than just comparing structured data to social media ratings. Monitoring service quality through hospital social media platforms may assist all stakeholders in detecting quality issues and minimizing the need for expensive and time-consuming surveys. Despite their rarity, research on FB content analysis demonstrates a correlation between social media quality domains and traditional hospital quality metrics [23,28,43,44].

The word "themes" or "text classification" refers to the process of grouping together a collection of textual messages according on their content. Machine learning enables automatic topic analysis via the application of various algorithms that are classified as supervised and unsupervised learning. The existence of labels in the subset of training data distinguishes these two main categories [45]. Along with input features, supervised machine learning makes use of predefined output features. The algorithms attempt to forecast and classify the predefined feature, and their accuracy and misclassification, as well as other performance metrics, are determined by the counts of the predetermined feature that are correctly predicted or classified, or that are incorrectly predicted or classified. Manual classification is a technique that is often used in supervised learning. Numerous studies have utilized this approach to deduce the topics of contention in POR [11,12,28,46-48].

On the other hand, unsupervised learning is pattern recognition that does not need the usage of a target feature. Unsupervised algorithms identify unlabeled data's underlying groupings and then label each value. Topic modelling is a technique for automatically identifying topics within a given remark, with the most often used approach being Latent Dirichlet Allocation (LDA). Numerous studies have utilized the technique to elicit information on the themes or subjects of discussion in POR [49-54].

According to prior research, POR often address issues like as appointment scheduling, wait times, the efficiency of the healthcare system, and interpersonal quality [12,28,46,50]. However, other topics such as communication, technological elements, treatment effectiveness, patient safety, environment, and hospital expenses were recognized as significant concerns [13,38,52,53]. Further study of hospitals in the United States revealed that the variables most significantly linked with patients' overall ratings or satisfaction include waiting times, treatment effectiveness, communication, diagnostic quality, environmental cleanliness, and economic concerns [28]. Comparable research utilising the Consumer Assessment of Healthcare Providers and Systems (CAHPS) Dental Plan Survey [55] and Press Ganey [56] corroborated the result. Another research discovered that the issues discussed in the dissatisfaction survey mirror the often-discussed topics of appointment access and wait time [46]. Additionally, discontent with patients is often related to personnel, punctuality, and diagnostic problems, while satisfaction is significantly related to interpersonal and technical brilliance [52]. However, Yelp review research discovered that patient satisfaction is related to interpersonal quality of surgical care, while dissatisfaction is related to insurance, billing, and the cost of the hospital visit [50]. Another study examined NHS tweets using the SERVQUAL model and found that the aspects of responsiveness and assurance are often addressed in negative narratives, while empathy is completely positive [53]. It is unsurprising that some subjects elicited more negative annotations than others, particularly comments about time, money, or pain, which are unlikely to be related to patient satisfaction [12].

2.3 Proposed Work

Given the exponential growth of social media in Malaysia and Southeast Asia, it is critical to use technology to improve healthcare services. Meanwhile, although FB is a popular social media platform, there has been very little study on machine learning and quality measures using FB data [28,57,58]. Given FB's popularity in Malaysia and its growing usage in healthcare, this research seeks to fill a void by investigating whether patient comments in FB Reviews can be categorized into SERVQUAL topics and determining their association with patient satisfaction.

Additionally, our suggested research used supervised machine learning to classify topics. Conventional patient satisfaction surveys have several disadvantages, and social media has been proposed as a potential substitute for evaluating patient satisfaction and mood in real time. According to a systematic review of the use of natural language processing (NLP) and machine learning (ML) to process and analyze patient experience data, manual classification of free text comments remains the 'gold standard' method of analysis and is currently the only way to ensure that all pertinent patient comments are coded and analyzed [29]. Additionally, the analysis shows that patient inputs produced via free-text supplements to structured questionnaires such as SERVQUAL and HCAHPS are stable in nature, making them an appealing source of data for supervised learning. Numerous studies have utilized supervised machine learning to categorize POR themes [28,47,48,57,59-61]. Moreover, we suggested that SERVQUAL dimensions be used to train our machine learning topic classifier. Previous research has classified themes or subjects in POR using structured patient questionnaires such as SERVQUAL [53,62], CAHPS Dental Plan Survey [55] and HCAHPS [50]. The potential results may be compared to those obtained via traditional surveys of patient satisfaction or treatment quality.

Nevertheless, the current body of evidence is still limited owing to a scarcity of sophisticated statistical studies linking patient satisfaction or hospital quality indicators. A systematic review suggested that more empirical research on POR be conducted using pertinent hypotheses, rigorous design, and data analytics [16]. Thus, our study should go beyond basic descriptive analysis and include the testing of theory-based hypotheses to offer additional policy implications and understanding. Previously published research has utilized analysis of variance (ANOVA) [55], various regression analytical tests [12,52,54,58], Pearson correlation [50,57] or Spearman's rank correlation [57,63]. As such, we want to examine variables related with patient dissatisfaction using rigorous statistical techniques such as regression analysis.

3. Materials and Methods

This research was cross-sectional in design and took place between March 2020 and May 2021. To achieve an equilibrium between subject homogeneity and generalizability of the findings, this research comprised only government hospitals. We utilized universal sampling as our sample technique.

3.1 Facebook Data

We used WebHarvy Scraping Software (SysNucleus, Kochi, India) to gather data on FB Reviews from official FB pages of public hospitals in Malaysia from January 2017 to December 2019. First, we checked for any webpage link of public hospital website via Ministry of Health official website. We will look for a link to the hospital's official FB page inside the hospital's web page. If there was no link to the hospital's official FB page on the hospital's website, we continued our search on the FB platform. When we discovered an official hospital FB page, we confirmed the information by utilizing the hospital's official website's URL, contacting hospital officials, or using our operational definition for a legitimate hospital FB page. We defined an 'official hospital FB page' as one with a ‘verified tick' [64] or one with the hospital's official name (RASMI in the Malay language) included in the FB page's name: or in description site. All data gathered from the official FB page was kept in a pro forma checklist. The FB accounts of hospital departments, health institutions/agencies (such as the Ministry of Health (MOH) or the Institute of Medical Research), non-governmental organizations (NGOs) and long-term care facilities were omitted. These methods of searching have been used in previous studies as well [23,24,64]. Malaysia is a multilingual country with a rich variety of languages and dialects. Malay is our national language, while English is our second language. Therefore, we gathered reviews in those languages only. To guarantee that our data language is appropriate and standardized for analysis, we had a group of junior doctors examine and correct any spelling and grammatical errors in online reviews written in Malay and English. Then, data in Malay language were manually translated into English for further research by junior doctors. All data were kept in a local database that was encrypted and accessible only to the researcher team.

3.2 Machine Learning Topics Classification

To serve as a "gold standard" for machine learning classifiers, a labeled data set was generated through manual coding. The categorization was based on the five-dimensional SERVQUAL theoretical notion [8,65]. (1) tangible: the appearance of physical facilities, equipment, and healthcare personnel; (2) reliability: the ability to perform the promised services accurately and reliably; (3) responsiveness: the willingness to assist the customer and provide prompt service; (4) assurance: the employee's knowledge and courtesy, as well as their ability to inspire trust and confidence; and (5) empathy: the ability to empathize with the customer. Two hospital quality managers or SERVQUAL domain experts were assigned to perform initial "open" coding on batches of three hundred FB reviews based on the MOH SERVQUAL patient satisfaction survey and other SERVQUAL surveys from previous studies aimed at establishing the source of the coding standard. Intercoder reliability was then determined using a randomly chosen subsample of three hundred FB reviews. The raters separately coded the reliability subsample. Inter-rater agreement was determined using Cohen's Kappa (k) values for each SERVQUAL dimension. The agreement between the coding of Tangible (Cohen's k= 0.885, $p<0.001$), Empathy (Cohen's k= 0.875, $p<0.001$), Reliability (Cohen's k= 0.736, $p<0.001$), and Responsiveness (Cohen's k= 0.72, $p<0.001$) was high, but the agreement for Assurance (Cohen's k= 0.626, $p<0.001$) was moderate. Cohen's k coefficient was 0.769 on average in all dimensions. Then, we trained our machine learning classifier on a sample of nine hundred manually labelled FB reviews.

The machine learning technique analyses the characteristics of the individual phrases used in the FB reviews and uses this data to build a topic classifier. First, the labeled dataset was pre-processed to remove URLs, numerals, punctuation marks, stop words and simplifying words using a lemmatization technique (e.g., treating as a treat). Following that, we calculated the weights of terms using the Term Frequency-Inverse Document Frequency (TF-IDF) approach, which demonstrates their significance to the documents and corpus. Figure 1 explains the Natural Language Processing (NLP) techniques used in the text preprocessing phase.

We then used iterative stratification to divide randomly labelled data into 80% for training and 20% for testing. Several multi-label classifier techniques were trained for topic classification, including Binary Relevance, Label Powerset, Classifier Chains, RAkEL: Random k-labELsets, MLkNN: Multi-label k-Nearest Neighbor, and BRkNN: Binary Relevance k-NN. For each method, we trained three main classifiers: Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression (LR). These classifiers are all widely used methods and have been shown to perform well on text classification tasks [29,31,66]. Multiple label classifiers were evaluated using the scikit-multilearn module in Python [67]. Finally, we evaluated the various classifiers using 5-fold cross-validation.

Figure 1: Text Pre-processing using Natural Language Processing (NLP) Techniques

5-fold cross-validation revealed that the machine learning algorithms' F1-score performance varied between 0.69 and 0.76, suggesting that the models accurately classified the reviews. When different models and classifiers are compared, it is shown that the SVM model with classifier chains multi-label method has the highest accuracy (0.215) and F1-score (0.757). Additionally, the model has the lowest hamming loss (0.273). Hamming loss is a key performance metric in topic classification models since it measures the percentage of erroneous projected class labels. As a consequence, we trained our machine learning classifier using the chains classifier technique on the SVM model. The performance metrics for supervised machine learning with 5-fold cross-validation are summarized in Table 1. The proposed methodology general architecture is depicted in Figure 2.

Table 1: Overall ML models performance with 5-fold cross-validation

Multilabel Classifier	**Model**	**Accuracy**	**Recall**	**Precision**	**F1-score**	**Hamming loss**
Binary Relevance	NB	0.147	0.761	0.701	0.730	0.315
	SVM	0.211	0.763	0.745	0.754	0.278
	LR	0.193	0.775	0.732	0.753	0.285
Label Powerset	NB	0.130	0.896	0.633	0.741	0.349
	SVM	0.166	0.799	0.679	0.734	0.323
	LR	0.158	0.825	0.669	0.739	0.326
Chains Classifier	NB	0.149	0.756	0.705	0.730	0.313
	SVM	0.215	0.761	0.753	0.757	0.273
	LR	0.191	0.770	0.727	0.748	0.290
RAkEL	NB	0.157	0.749	0.699	0.722	0.322
	SVM	0.186	0.764	0.724	0.743	0.295
	LR	0.180	0.765	0.726	0.745	0.293
MLkNN	N/A	0.140	0.737	0.697	0.715	0.327
BRkNN	N/A	0.157	0.648	0.732	0.687	0.330

NB: Naive Bayes, SVM: Support Vector Machine, LR: Logistic Regression

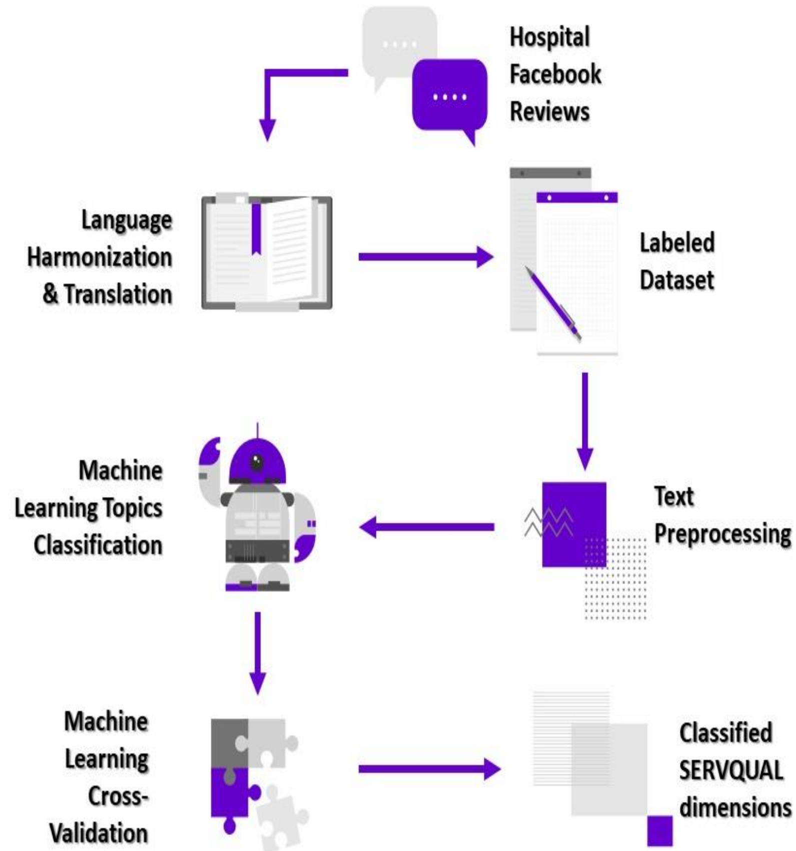

Figure 2: General Architecture of Proposed Methodology in this Study

3.3 Outcome: Patient Dissatisfaction

FB Reviews is a feature that allows people to leave narrative reviews on organizations and companies' FB profiles. Since its debut in 2013, the FB Reviews section has been included into the FB pages of many hospitals. Patients and their relatives have gradually begun to make use of it. Previously, FB utilized a five-star rating system until early 2018, when it switched to a binary rating system named "Recommends" or "Doesn't Recommend." This simplified the review process for users. As is the case with other social media platforms, FB ratings provide insight on how people feel about healthcare services. We collected customer recommendations from hospital FB pages to determine patient satisfaction. Our research characterized patient dissatisfaction as non-recommendation in the FB Review section, and patient satisfaction as recommendation. Any recommendation made outside of the FB Reviews area was ignored.

3.4 Statistical Analysis

Due to the non-normal distribution of the data, we used medians (interquartile range [IQR]) for numerical data and frequencies and percentages for categorical variables in our statistical analysis. Binary logistic regression analysis was used to evaluate the associations between patient dissatisfaction and multiple factors. Confounding variables included hospital characteristics (region, bed count, urban or rural location, and type of hospital), as well as FB page characteristics such as previous star ratings, acceptable hospital information on the FB page, and administrator reaction in the FB review area. These characteristics, according to previous research, are linked with patient satisfaction [12]. We examined the data to determine whether findings were statistically significant with a p value less than 0.05. All statistical tests have been verified and found to be valid. To verify the model fitness of our research, we used the Hosmer and Lemeshow tests, as well as the area under the receiver operating characteristic (ROC) curve. SPSS software version 26 was used to analyze the data (IBM Corp, Armonk, NY, USA).

4. Results

4.1 Hospital and Facebook Characteristics

In Malaysia, 63.7% of the 135 public hospitals have a FB page, with 48 of them accepting customer feedback through FB Reviews. Except for the western part of Malaysia, every region has at least 10 hospitals with a FB review function: 37.5% of tertiary hospitals, 8.3% of secondary hospitals, and 54.2% of primary hospitals all have FB review sections. The majority of these hospitals were located in cities, with an average of 730 beds. The average number of reviews on each hospital's FB page was 15.5 (27.5), with a previous star rating of 5.00. (1.65).

4.2 Facebook Reviews and Patient Satisfaction

We collected a total of 3025 FB reviews, with 1200 being used for machine learning training and the rest for association analysis. More FB reviews are seen at hospitals in the western (50.5%) and northern (21.5%) areas. Furthermore, urban hospitals account for 87.2% of all assessments, tertiary institutions for 88.8%, and the median bed count is 730. The average previous star rating on FB in terms of FB characteristics was 4.70. (1.5). The majority of FB reviews provide sufficient information about the hospital yet receive little to no response from hospital management. Most notably, this study discovered that 73.5% were satisfied with the public hospital service, whereas 26.5% were dissatisfied. Table 2 describes hospital FB reviews characteristics.

4.3 Classification of SERVQUAL Dimensions

Using the machine learning topics classification, we had 13.2% reviews with a tangible dimension, 68.9% reviews of reliability, 6.8% reviews of responsiveness, 19.5 % reviews of assurance, and 64.3% reviews of empathy. The overall SERVQUAL dimensions were presented in Figure 3.

Table 2: Hospital FB Review Characteristics (n = 1825)

Variable		**n**	**(%)**	**Median**	**(IQR)**
Hospital Features					
Region	East Coast	189	(10.4)		
	North	393	(21.5)		
	West	922	(50.5)		
	South	178	(9.8)		
	East Malaysia	143	(7.8)		
Location	Rural	234	(12.8)		
	Urban	1591	(87.2)		
Hospital Type	Primary	125	(6.8)		
	Secondary	80	(4.4)		
	Tertiary	1620	(88.8)		
Beds				730	(563)
FB Features					
Previous FB Star Ratings				4.70	(1.5)
Admin Response	No	1651	(90.5)		
	Yes	174	(9.5)		
Adequate Hospital Information	No	1651	(90.5)		
	Yes	174	(9.5)		
Patient Satisfaction	Dissatisfied	483	(26.5)		
	Satisfied	1342	(73.5)		

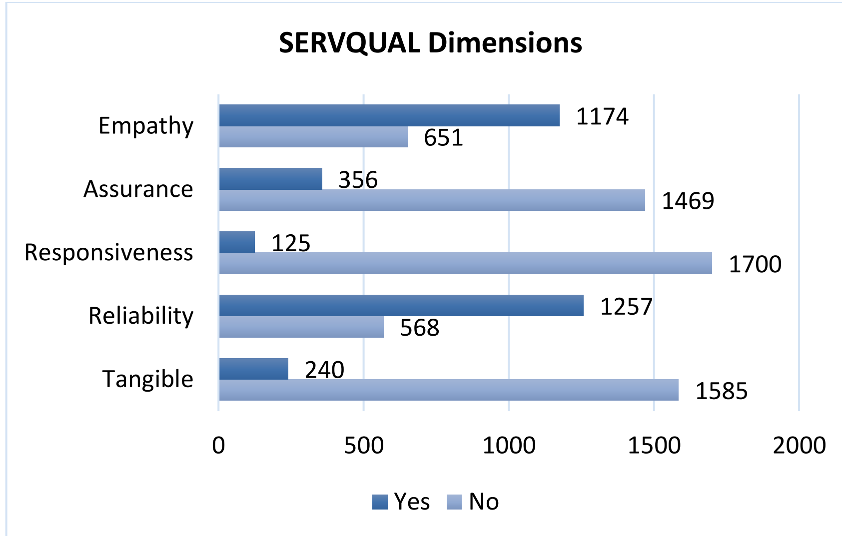

Figure 3: SERVQUAL dimensions classified by machine learning classifier (n=1825).

4.4 Factors Associated with Patient Dissatisfaction

To assist MOH and key stakeholders in identifying areas for improvement, we utilised binary logistic regression with patient dissatisfaction as the primary outcome. When compared to East Malaysia, a univariate study of hospital variables indicated that the three regions were related with patient dissatisfaction: West Coast (Crude OR = 2.11, 95% CI: 1.35-3.30; p = 0.001), East Coast (Crude OR = 0.63; 95% CI: 0.41-0.96; p = 0.031), and South (Crude OR = 2.38; 95% CI: 1.49-3.80; p = 0.001). In addition, patient dissatisfaction was linked to rural hospitals (Crude OR = 1.87; 95% CI:1.40-2.49; p < 0.001) and tertiary hospitals (Crude OR = 0.65; 95% CI:0.44-0.96; p = 0.030). Moreover, we discovered a relationship between previous FB star ratings and patient dissatisfaction (Crude OR = 0.86; 95% CI:0.80-0.93; p < 0.001). Reliability (Crude OR = 1.52; 95 % CI:1.20-1.92; p = 0.001), Responsiveness (Crude OR = 2.10; 95% CI:1.45-3.04; p = 0.001), and Empathy (Crude OR = 1.57; 95% CI:1.25-1.97; p = 0.001) were all significantly associated with patient dissatisfaction. The univariate study of hospital and FB features, as well as SERVQUAL in relation to patient dissatisfaction, is summarized in Table 3.

In multivariate analysis, variables with a p-value less than 0.25 in univariate analysis were chosen throughout the model selection phase. Forward LR, backward LR, and manual selection methods were used to create a parsimonious model. The final model included hospital location and SERVQUAL dimensions other than Tangible and Assurance. When chosen SERVQUAL dimensions were controlled, hospitals situated in rural areas had a 100% higher likelihood of patient dissatisfaction compared to hospitals located in urban areas (95% CI:1.49-2.68; $p < 0.001$). Most importantly, when other variables are adjusted, reliability has a 2.13 times higher likelihood of patient dissatisfaction (95% CI:1.63-2.78; $p < 0.001$), responsiveness has a 61% higher likelihood of patient dissatisfaction (95% CI:1.09-2.38; $p = 0.016$), and empathy has a 2.08 times higher likelihood of patient dissatisfaction (95% CI:1.63-2.69; $p < 0.001$). There is no interaction and multicollinearity in the multivariate model. The model's fitness was also satisfactory, as verified by the Hosmer and Lemeshow Test ($p = 0.875$), 73.5% of the Classification Table, and 61.7% of the area under the receiver operating characteristic (ROC) curve ($p < 0.001$). Table 4 details the multivariate analysis.

Table 3: Factors Associated with Patient Dissatisfaction in Univariable Analysis (n=1825)

Variables		**Crude OR**	**95% (Lower,**	**CI Upper)**	**p-value***
Hospital Features					
Region	East Malaysia	Ref			
	East Coast	0.63	0.41	0.96	0.031
	North	1.08	0.75	1.55	0.695
	West	2.11	1.35	3.30	0.001
	South	2.38	1.49	3.80	<0.001
Location	Urban	Ref			
	Rural	1.87	1.40	2.49	<0.001
Hospital Type	Primary	Ref			
	Secondary	0.97	0.54	1.76	0.924
	Tertiary	0.65	0.44	0.96	0.030
Beds		1.00	1.00	1.00	0.275
FB Features					
Admin Response to Review	No	Ref			
	Yes	1.24	0.88	1.75	0.210
Adequate Hosp Info	No	Ref			
	Yes	0.80	0.53	1.22	0.306
FB Star Ratings		0.86	0.80	0.93	<0.001
SERVQUAL					
Tangible	No	Ref			
	Yes	1.25	0.93	1.69	0.137
Reliability	No	Ref			
	Yes	1.52	1.20	1.92	0.001

Responsiveness	No	Ref			
	Yes	2.10	1.45	3.04	<0.001
Assurance	No	Ref			
	Yes	0.96	0.74	1.25	0.766
Empathy	No	Ref			
	Yes	1.57	1.25	1.97	<0.001

**Simple Logistic Regression*

Table 4: Factors Associated with Patient Dissatisfaction in Multivariable Analysis (n=1825)

Variable		**Adjusted OR**	**Adjusted (Lower,**	**95% CI Upper)**	**p-value***
Location	Urban	Ref			
	Rural	2.00	1.49	2.68	<0.001
Reliability	No	Ref			
	Yes	2.13	1.63	2.78	<0.001
Responsive	No	Ref			
	Yes	1.61	1.09	2.38	0.016
Empathy	No	Ref			
	Yes	2.08	1.61	2.69	<0.001

*Multiple Logistic Regression
Constant = -2.180
Forward LR, Backward LR and Manual selection methods were applied
No significant interaction or multicollinearity.
Hosmer and Lemeshow Test = 0.875
Classification Table = 73.5%
Area Under the Operating Curve (ROC) = 61.7% (p<0.001)

5. Discussion

POR influences patient preferences, emphasizing the critical role of patient-centered health care and changing the system. The research is a critical first step in developing a strategy for utilizing social media data in Malaysia, as well as a first effort to monitor public views of healthcare services using a novel data source. This is the first study to use automated computer methods to assess topics from online hospital evaluations and to characterize the content of narrative online hospital reviews in Malaysia. According to the machine learning classifier, the SERVQUAL dimension with the greatest frequency was reliability, followed by empathy. The reliability dimension is often concerned with appointment scheduling, punctuality, the healthcare system's efficacy, and the capability to keep accurate data.

Meanwhile, the problem of empathy relates specifically to staff attention and helpfulness, an understanding of patient requirements, convenient hospital hours, and a commitment to the patient's best interests. Our findings supported previous studies indicating that online reviews often emphasize time promise, healthcare system efficiency, and interpersonal quality [11,12,28,46,50]. However, additional topics were identified in the POR as major concerns, including communication, therapeutic effectiveness and patient safety, the environment, and hospital costs [13,38,52,53]. Moreover, most online patients reported satisfaction with the treatments provided by Malaysian hospitals. The findings supported comprehensive studies of patient online evaluations, which showed that the majority of patients were satisfied with their healthcare providers and would recommend them to family and friends [16,68].

Patient satisfaction surveys assist health care workers in identifying opportunities for service improvement. Also, it enables authorities to understand patient needs and create strategic plans for more effective and high-quality services [35]. This study found that hospital characteristics such as location in the western and southern regions, as well as rural locations, were associated with patient dissatisfaction. This was supported by African research [39], despite the fact that an Asian survey found rural residents to be generally satisfied with healthcare services [40]. Additionally, the size and type of hospital services had an effect on patient satisfaction [15,41]. Previously, it was believed that people would be more unhappy with a service that dealt with a greater number of patients and a bigger practice. However, we found a negative correlation between tertiary center and patient dissatisfaction, suggesting that our patients were pleased with the service given by bigger types of hospitals, owing to the comprehensive healthcare services provided to them.

Interpersonal skills (empathy) were shown to be a major factor in increased patient satisfaction [35,69,70]. In this study, the empathy component was shown to be positively associated with patient dissatisfaction. The finding was confirmed by a social media study performed in China [13] and research conducted on the NHS Choices website [71], both of which revealed further negative comments regarding the doctor-patient connection, nurse service, roughness, and apathy. Moreover, a comparative study of POR in China and the United States found that the majority of complaints addressed the doctor's or hospital staff's bedside demeanor [51]. However, data from NHS Twitter show that patients express a high degree of satisfaction with the empathy component of healthcare [53]. Physicians and nurses were assessed on their interactions with patients and their family or friends, including their friendliness, honesty, concern, compassion, empathy, kindness, civility, and respect for patient preferences [35,70]. Patients who are satisfied with physicians' affective behaviors are more likely to recommend them to others, according to research performed at a Scottish NHS trust [72].

Another area in which Malaysian public hospitals might improve was their reliability. We found a positive and statistically significant relationship between reliability and patient dissatisfaction in public hospitals. It is unsurprising that the majority of patient complaints or dissatisfaction voiced through POR on time commitment, appointment or follow-up access, and service inefficiencies [12,13,28,46,51]. Patient satisfaction was positively linked with ease of access to the hospital, convenient location, a streamlined admission and discharge procedure, and an efficient appointment system [35]. According to one research, scheduling convenience and adequate follow-up may help reduce patient dissatisfaction [54]. Additionally, local research has shown that the "lean" strategy may be effectively utilized to improve hospital reliability [73].

Responsiveness is defined as the willingness of healthcare professionals and providers to assist and give timely service to clients. Between responsiveness and patient dissatisfaction, we found a positive and statistically significant connection. Similar findings have been reported in earlier local research [74,75] as well as in international SERVQUAL studies [10,76]. Also, experimental research of the perceived SERVQUAL model using tweets from the NHS UK found that people express their dissatisfaction with responsiveness more than with other elements [53]. Patient satisfaction was shown to be positively linked with reduced wait times and quick treatment in a systematic study [35]. A comprehensive study showed that a wait time of more than 17 minutes decreases the probability of obtaining a good rating status [54].

Although our study discovered no significant connections between assurance and tangible dimensions and patient dissatisfaction, it is worth highlighting the dimensions' predictive value in POR. The quality of technical care is closely related to elements of assurance such as human competency, professionalism, and confidentiality [35]. Moreover, it pertains to the services' compliance with clinical diagnostic and treatment standards and recommendations. Numerous studies have found an association between assurance-related topics and patient satisfaction, including treatment effectiveness, diagnostic quality, and treatment side effects, utilizing theme analysis of social media data [28,77]. Meanwhile, study comparing POR in China and the United States found that both nations' citizens are dissatisfied with medical treatment [51]. Previously, it was thought that those who felt they had been treated unfairly were less satisfied with health care services. However, since some patients were unable to evaluate the technical quality of therapy due to their limited comprehension, they may have replaced their judgement for the sense of how nice and caring health professionals were toward them [35].

The physical environment is another important factor influencing patient satisfaction. Patient satisfaction was expected to be related to the pleasantness of the environment, cleanliness, noise level, food service, toilet comfort, clarity of signs and instructions, layout of equipment and facilities, and parking. Few studies have shown that patient satisfaction is influenced by attractive facilities, environmental cleanliness, and design-related factors [28,38,40,46]. However, further research showed that patients were unhappy with aspects of the hospital atmosphere based on their online assessments [46,53,61,69]. Malaysia's government has spent millions of ringgits in a series of Malaysia Plans aimed at enhancing public hospital facilities and services and building new hospitals [78]. As a result, hospital clients appreciate the upgraded and improvement of public hospital assets on social media.

Our findings have a number of implications for many aspects of hospital quality of care. To begin, we can monitor and evaluate our quality-of-care metrics and patient satisfaction in real time by using hospital FB reviews and machine learning algorithms. The method used in this study enables policymakers to make use of social media data rather than more expensive national questionnaire surveys. Moreover, there is no comparable open-standard research of patient satisfaction in Malaysia's public and private sectors. While the Ministry of Health prefers the SERVQUAL questionnaire, private hospitals may develop their own or adhere to an international standard. As a result, FB reviews may serve as a new barometer of patient satisfaction in each of these domains. Additionally, FB reviews are straightforward and accessible, reducing obstacles to obtaining information about hospital quality and helping hospitals in addressing quality-of-service problems while also alerting hospitals to possible patient safety concerns. While social media ratings are untested and unregulated, traditional patient satisfaction surveys have been validated and tested. By including additional hospital quality metrics on hospital FB pages and critical information such as the official status of the FB site and the exact FB addresses, the validity of FB data will be increased [23].

Furthermore, we highlighted three SERVQUAL characteristics, namely reliability, responsiveness, and empathy, that need additional attention and improvement on the part of Malaysian healthcare authorities. Enhancing interpersonal skills training, especially for medical students, ongoing training for health professionals in the workplace, and lean model adaption will substantially enhance the quality of treatment that is now lacking [79,80]. However, health authorities must realize that the findings are unlikely to be representative of the whole population served by hospitals. Rather than that, this study of service quality issues should be seen as a complement to more traditional data collection efforts and as an effective early warning system for hospital quality management.

5.1 Future works and Limitations

Future study should concentrate on improving the efficacy of machine learning classifiers and collecting a bigger dataset of POR, including those from the Malaysian private sector. Second, further research is required to establish the relationship between POR and other hospital quality or clinical outcome measures, as earlier studies have done [11,12,43,63,81]. Additionally, future research may incorporate additional social media platforms (e.g., Twitter, Instagram, Tik-Tok, etc.) with specific adjustments such as a focus on the youth population (targeted audience), common public health topics discussed on social media platforms (depression, vaccination, cyberbullying, etc.), as well as identifying popular hashtags related to public health issues. The data collected from various social media platforms may offer healthcare agencies with a unique viewpoint on patients and may be utilized as a real-time public health surveillance system.

Our research has a number of limitations. Due to the cross-sectional nature of the research, we cannot rule out the possibility of a causal connection in our findings. Moreover, almost one-third of public hospitals posted feedback on FB. Incorporating unauthorized FB pages for public hospitals may have a contrasting impact. Additionally, our dataset is considered small-scale in comparison to other POR research, due to Malaysia's small size population and the relatively recent adoption of POR in the Malaysian healthcare sector. Malaysians, on the other hand, have a high rate of internet usage, which continues to grow year after year. Thus, in the next years, we may expect a surge of POR about healthcare services. Also, the time needed for content analysis and manual coding was the main limitation. Comprehensive reading and classification of datasets remains the gold standard for building machine learning-based topic classifiers and the only way to ensure that all essential comments are coded [29]. However, it is time consuming, and in text classification, increasing the diversity of comments lowers the ability of the machine learning system to properly recognize the remark. However, if social media input becomes more prevalent, manual coding may become problematic owing to time constraints, and topic modelling may be a viable alternative. Topic modelling using Latent Dirichlet Allocation (LDA) may aid in determining how well the results fit the themes chosen by domain experts, and this unsupervised approach allows the identification of previously undiscovered topics [82].

6. Conclusions

Patient online reviews offer healthcare authorities with a practical, low-cost, and accessible way of collecting information about the quality of care they deliver. Healthcare officials have long considered how to include POR into citizen-government engagement and policymaking in order to create evidence-based reporting. Despite scholars' focus on the potential for POR data to assist in decision-making, methods for realizing this potential have been very restricted, often fragmentary, and non-standardized. We suggested a systematic method for integrating POR data in order to analyze and monitor patient perceptions of the service quality at Malaysian public hospitals in this article. Automatically classifying FB reviews into SERVQUAL dimensions using machine learning minimizes human interference and selection bias in the study. We verified classification performance, emphasized the criticality of collecting reliable quality of care topic sets using the SERVQUAL model, and used it to grasp the context of FB reviews. Despite the fact that the majority of POR were satisfied with the hospital service in this study, we highlighted SERVQUAL dimensions of reliability, responsiveness, and empathy as areas for quality-of-care improvement in Malaysian public hospitals. Additionally, public hospital service in rural areas was associated with patient dissatisfaction. The results provide important insights that will aid healthcare officials and authorities in capitalizing on the opportunities of POR by monitoring and assessing services' quality in order to make rapid improvements. Furthermore, the findings of traditional patient satisfaction surveys may be routinely supplemented with data from POR to continually improve and create high-quality healthcare services.

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CHAPTER 7: CONCLUSION

7.1 Overall Conclusion

POR provide healthcare authorities with a convenient, low-cost, and easily accessible method of gathering information about the quality of treatment they provide. Officials in healthcare have long studied how to include POR in citizen-government participation and policymaking in order to provide evidence-based reporting. Despite researchers' emphasis on the potential for POR data to aid decision-making, techniques for realising this promise have been very limited, often incomplete, and non-standardized. In this study, we proposed a systematic technique for combining POR data for the purpose of analysing and monitoring patient perceptions of service quality at Malaysian public hospitals. The study's human involvement and selection bias are minimised by automatically categorising FB reviews into SERVQUAL dimensions and positive or negative sentiment using ML. We validated classification performance, emphasised the need to gather accurate quality of care topic sets, and demonstrated how to apply the SERVQUAL model to comprehend the context of FB reviews. Despite the fact that the majority of POR were satisfied with hospital services in this survey, we identified the SERVQUAL dimensions of reliability, responsiveness, and empathy as opportunities for improvement in Malaysian public hospitals' quality of care. Additionally, we show that, with the exception of the tangible dimension, all SERVQUAL dimensions were significantly associated with positive sentiment.

There is, however, no association between hospital accreditation and the sentiment conveyed in FB Reviews or between accredited hospitals and patient satisfaction on the social media platform. Additionally, we identified a slight but substantial link between the findings of the MOH's patient satisfaction survey and online patient satisfaction as measured by FB Recommendations.

While many hospitals maintain and actively monitor their own FB pages, we recommend that hospital managers and policymakers use this unique data stream to get a better understanding of healthcare customers' experiences and the quality of treatment they receive. If an online review is highly related to a particular poor aspect of SERVQUAL dimension, it indicates where hospital management should direct their efforts toward improving patient care. The findings give critical information that will assist healthcare administrators and authorities in capitalising on POR potential by monitoring and reviewing the quality of services in order to make speedy adjustments. Additionally, standard patient satisfaction surveys may be frequently complemented with POR data to continuously enhance and develop high-quality healthcare services.

7.2 Strength and Weakness

To begin with, although our analysis of FB reviews was susceptible to response and selection bias, any traditional survey is similar as well. Due to the cross-sectional design of the research, we cannot rule out the possibility of a causal relationship between our findings. Additional research into the mechanisms behind these findings would be desirable. Also, only 45 out of 87 hospitals have reviews on FB. Thus, by incorporating unofficial or unapproved FB pages for public hospitals, public opinion may be swayed.

Additionally, ML-based sentiment analysis and topic classification approaches are only as good as the numbers of training set used to guide them. The key restriction is that our dataset is considered small in contrast to other big data studies, owing to the fact that social media reviews are still relatively new in Malaysia's healthcare business and our population is small. Nonetheless, social media usage continues to expand in Malaysia on an annual basis across all sociodemographic groups (MCMC, 2020). Thus, as is the case in industrialised nations, we may anticipate an avalanche of consumer evaluations of healthcare services on social media.

Apart from that, supervised learning is time-consuming due to the need for human coding. Nonetheless, it is advantageous for analysing patient online evaluations, which are often encountered in structured surveys like SERVQUAL and HCAHSP (Daniulaityte *et al*., 2016; Huppertz and Otto, 2018; Lee *et al*., 2021). Manual classification for supervised learning may become impossible as the number of comments on social media grows. To address this, a topic modelling technique based on latent Dirichlet allocation (LDA) may be effective in establishing how closely the results match what domain experts have determined the subjects to be, as well as in uncovering previously unidentified topics (Kherwa and Bansal, 2018). However, LDA has certain inherent restrictions. It is envisaged that the generated topics will be influenced by the sentiment distributions and that the generated words will be dependent on the sentiment topic pairings. Thus, by expanding the maximum entropy discrimination latent Dirichlet allocation (MEDLDA) topic model with a weakly supervised joint sentiment-topic mode, it is possible to increase the accuracy of topic modelling (Kalaivaani and Thangarajan, 2019).

While our ML classifiers performed well, the human coding approach used in our research included the possibility of selection bias. We sought the support of two hospital quality managers who are familiar with SERVQUAL domains and patient satisfaction surveys in order to minimise bias. Additionally, extra bias may occur since social media evaluations are often made by younger individuals who live in urban areas. However, this bias was offset by the inclusion of reviews from rural public hospitals.

7.3 Recommendation

There is a scarcity of study on the use of FB and other social media platforms in quality assessment procedures in healthcare, such as accreditation. Malaysia and other developing countries are noted for the lag in the establishment and usage of official FB accounts by healthcare professionals. A critical topic of research would be to determine the factors that contribute to or limit the adoption of official hospital FB profiles. This survey should be sent to all hospital staff and management. The data should include hospital employees' and leaders' views about and opinions on the establishment and usage of social media platforms. Additionally, we urge that hospital managers adopt a more proactive approach to FB pages and their usage. Due to the likelihood that prospective patients may develop views based on social media material, hospitals must approach SERVQUAL dimensions holistically in order to improve their social media presence. For example, patient assessments of health care services may aid in identifying areas for service improvement, hence improving health outcomes and use.

In terms of public health activities, patients' perspectives may aid clinicians in identifying possible barriers to population-based interventions such as immunization.

Additionally, patient ratings or reviews indicate that patients consented to participate in online conversations. Nevertheless, health care executives and policymakers must acknowledge that the results are unlikely to be completely representative of the hospital service population. Besides, this evaluation of SERVQUAL dimensions through FB Reviews should be considered alongside more traditional data collection activities. The study's quick identification and assessment of certain service aspects using a machine learning tool is unique, and without it, healthcare organizations would have been unable to examine huge volumes of unstructured real-time data.

Furthermore, future study should concentrate on improving the efficacy of sentiment analysis and topic classification, as well as on gathering a wider collection of patient online assessments, including those from the Malaysian private sector. Also, additional study is necessary to demonstrate the method's applicability to other forms of free-text content on social media. For example, additional procedures such as analysing unigrams, bigrams, or bigger n-grams, as well as strengthening contextual polarity, may be introduced to enhance the process.

Similarly, future research can be conducted using deep learning neural networks, such as Deep Block Scheme, a method for deep learning based on block-chain technology (Singh *et al*., 2021a), Kmean methods, a sentiment analysis clustering algorithm (Wu *et al*., 2019), or graph convolutional networks (GCNs) and auxiliary node relations for modelling multi-target sentiment classification (Feng *et al*., 2020). Moreover, a blockchain-based secure storage architecture called BIIoVT may be developed to enhance and protect the security, confidentiality, and privacy of hospital data stored in the cloud (Singh *et al*., 2021b).

Secondly, additional research is essential to determine the relationship between POR and other hospital quality criteria. For instance, examining the link between quality parameters generated from social media evaluations and hospital clinical outcomes (Alkazemi *et al*., 2020; Chakraborty and Church, 2020). Moreover, it would be good to compare the labelled dataset used in this research to other dictionaries or tools used in previous studies to improve sentiment and text classification (Gohil *et al*., 2018; Khanbhai *et al*., 2021). Likewise, future study may include other social media platforms (e.g., Twitter, Instagram, Tik-Tok, and others) in order to offer public health professionals, agencies and academics with a more comprehensive picture of consumer perceptions over healthcare quality of service in Malaysia.

7.4 Reflection

To begin, prior to the research project, I was unfamiliar with ML, yet I never doubted its promise in healthcare. Through intensive readings, learning, and application of ML subjects in my study, my understanding of the subject has grown significantly, and I can anticipate that the future of healthcare will be dominated by cutting-edge technology. We have already seen a few public health programmes that include ML or artificial intelligence and successfully complete a variety of duties.

Additionally, managing large amounts of data is not a simple operation. The ability to effectively clean and analyse large amounts of data is critical for developing accurate models. The ability will come in handy later in my job. Moreover, my networking grew outside the healthcare community during the creation of ML models. Our local data and computer scientists are willing to contribute and interested to collaborate in future research in healthcare.

Furthermore, the outcomes of this research open up a new vista for assessing the quality of care through social media reviews. Our research may have prompted hospital managers and officials from ministry of health to explore the feasibility of using social media for public health interventions and campaigns.

In sum, the dissertation provided me with unique experiences and abilities that have helped me develop into a competent and visionary public health specialist.

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APPENDICES

Appendix A: Proforma

No.	Variables	Data
	Hospital Characteristics	
1	Hospital Name	
2	State	
3	Region	
4	Urban or Rural Hospital	
5	Type of Hospital	
6	Numbers of Bed	
7	Accreditation Status	
	FB Characteristics	
8	Previous FB Ratings	
9	Numbers of FB Review	
10	Adequate Hospital Information on FB Page	
11	Hospital Administration Replied to FB Reviews	

12	FB Review	
13	Date of Reviews	
14	FB Recommendation	

Appendix B: SERVQUAL Guideline

Domain	Description	FB Reviews Example
Tangible	General: The appearance of employees, equipment, and physical facilities of the hospital. Specific: The hospitals have up to date equipment. The physical facilities are visually new or outdated. The staff are well dressed, appear neat and good looking. The appearance of the physical facilities of the hospital are well maintained with the type of services provided.	"Cleanliness of the Hospital is good" "Car parking is difficult and limited" "Satisfied with the facilities. Large room, feels like a hotel." "The hospital is well maintained, and their food is delicious."
Reliability	General: Accurate, dependable, and consistent performance of the service. Specific: When the hospital promised to do something by a certain time, it does so. Hospital service is efficient and dependable. The hospital provides services at the time as promise to do so. The hospital keeps the records accurately or at online.	"My appointment scheduled at 9 a.m. but then it was postponed to 12.00 p.m. Unbelievable." "System needs to be improved especially discharge process. It took hours to settle it." "Efficient and top-quality hospital services" "Staff mistakenly collected medical record of other patient with similar name of mine"
Responsiveness	General: Willingness to provide prompt service to the patients. Specific: The hospital let patients know exactly when the services will be performed. The staff give prompt services to patients upon request. The staff are always willing to help their patients. The staff give medical attention promptly.	"My specialist took his time to explain me about my disease and how he will treat it" "They answered all my questions during the admission." "Arrived at emergency department due to road traffic accident and the medical team immediately respond to it." "I don't feel any pain throughout the minor surgery on my arm, and it was done in a flash"

Assurance	General: the staff knowledge and courtesy, ability to inspire trust, confidence, and security; also reflects on confidentiality and privacy of patients. Specific: The staff are trustworthy. Patients feel safe in their transactions with the hospitals. The staff are polite, friendly. The staff have adequate support from the hospitals to do their jobs well.	"The surgery was successful. Mr A is a competent and trusted surgeon." "I feel comfortable and safe in this hospital. Just like at home" "The staff at the front desk was rude." "The doctors and staff nurses in this hospital are skillful and well-trained"
Empathy	General: Providing convenient services and giving attention or patience of the staff to the patients' needs. Specific: The staff give patient personal attention and helpful. The staff are knowledgeable to understand patient's specific needs. The hospital has patient best interests at heart. The hospital has operating hours convenient to all the patients. Cost of treatment is affordable for patients	"Nurses are very helpful." "A staff came and offered to help my father climb stairs without we ask him. We appreciated his kindness." "They are very concerned about patient's condition and served it with their heart" "The price is affordable compared to private hospital."

Appendix C: Sentiment Analysis Guideline

Category	Description	FB Reviews Example
Positive	Expression of liking, approval, gratefulness (Like, love, support, thankful, etc.)	"I like this hospital. Doctors and nurses are pleasant and helpful." "Thank you for your service, Doctor and nurses."
	Positive qualities of hospital services and facilities (Clean room, efficient, fast appointment, affordable, etc.)	"The wait time was brief. The pharmacy counter did an excellent job." "The room is neat and tidy, and the food is delicious. I really like it."
	Positive qualities of staff (Polite, friendly, helpful, responsive, etc.)	"Staff are polite and kind." "Dr. B took her time explaining my health condition until I understood it. It was greatly appreciated."
	Encourage or recommend others to use	"I recommend having your baby delivered at this hospital." "I like their antenatal counselling and will recommend it to other couples. It is extremely beneficial to us."
	Positive/desirable effects of service (Successful treatment/procedures, good health outcome, etc.)	"I'd like to thank Mr A for performing bowel surgery on my father. He is now doing well." "I found the physiotherapy session to be beneficial. I'm able to walk with less pain now."
Negative	Expression of disliking or disapproval (Do not like, hate, etc.)	"I hate the security guard." He was impolite to me!" "I'm not a fan of the food service here. The food has no taste."
	Negative characteristic of hospital services or facilities (Poor maintenance, slow service, expensive, long waiting time, etc.)	"The discharge procedure was extremely slow." "There are a limited number of parking spaces available, and getting one is difficult." "We waited for 5 h at the out-patient clinic before seeing the doctor. This is intolerable."

	Negative qualities of staff (Rude, not-friendly, not-helpful, slow responsive, incompetency, etc.)	“Staff nurses were rude and stubborn. I requested assistance but received no response.” “The doctor criticised us for arriving at the emergency department at 3 a.m. for treatment. We were annoyed by his attitude.”
	Negative/undesirable effects (Surgical or procedural complications, medicolegal, poor health outcome, etc.)	“My father fell in the toilet and was left alone for a few minutes. The hospital director must explain the incident to our family.” “After being admitted to this hospital two days ago, my husband’s condition has deteriorated. No one, however, can explain the situation to us”.
Neutral	Review that reports factual information/no opinion.	“Serdang Hospital is one of the Klang Valley’s cardiac centres”. “A Muslim-friendly hospital”
	Review as questions	“Do you have any spine surgeon in your hospital?” “How to get an appointment with your ear. Nose and throat (ENT) clinic?”
	Too ambiguous/unclear/greetings only	“Good morning.” “No comment.” “Let’s wait and see first”

Appendix D: Ethical approval from USM Research and Ethics Committee (JePEM)

Appendix E: Ethical approval from the Ministry of Health's National Medical Research Register (NMRR)

Appendix F: FRGS 2020 Offer Letter

Appendix G: Manuscript 4 – Hospital Facebook Reviews Analysis Using a Machine Learning Sentiment Analyzer and Quality Classifier

Jawatankuasa Etika
Penyelidikan Manusia USM (JEPeM)

Human Research Ethics Committee USM (HREC)

Universiti Sains Malaysia
Kampus Kesihatan
16150 Kubang Kerian, Kelantan, Malaysia.
Tel. : +609 - 767 3000/2354/2362
Fax. : + 609 - 767 2351
Email : jepem@usm.my
Laman Web : www.jepem.kk.usm.my
www.usm.my

6th May 2020

Dr. Afiq Izzudin A. Rahim
Department of Community Medicine
School of Medical Sciences
Universiti Sains Malaysia
16150 Kubang Kerian, Kelantan.

JEPeM Code : USM/JEPeM/19120839
Protocol Title : Development of Machine Learning Sentiment Analyzer and Quality Classifier (MILSAQC) and its Application in Analyzing Hospital Patients Satisfaction from Facebook Review.

Dear Dr.,

We wish to inform you that your study protocol has been reviewed and is hereby granted approval for implementation by the Jawatankuasa Etika Penyelidikan Manusia Universiti Sains Malaysia (JEPeM-USM). Your study has been assigned study protocol code **USM/JEPeM/19120839**, which should be used for all communication to the JEPeM-USM related to this study. This ethical clearance is valid from **6th May 2020** until **5th May 2021.**

Study Site: Hospital's Reviews in Malaysia.

The following researchers also involve in this study:
1. Assoc. Prof. Dr. Mohd Ismail Ibrahim
2. Assoc. Prof. Dr. Kamarul Imran Musa
3. Dr. Chua Sook Ling @ Landa Chua
4. Miss Nor Asida Shafii

The following documents have been approved for use in the study.
1. Research Proposal

In addition to the abovementioned documents, the following technical document was included in the review on which this approval was based:
1. Proforma Checklist

Attached document is the list of members of JEPeM-USM present during the full board meeting reviewing your protocol.

While the study is in progress, we request you to submit to us the following documents:
1. Application for renewal of ethical approval 60 days before the expiration date of this approval through submission of **JEPeM-USM FORM 3(B) 2019: Continuing Review Application Form.**
2. Any changes in the protocol, especially those that may adversely affect the safety of the participants during the conduct of the trial including changes in personnel, must be submitted or reported using **JEPeM-USM FORM 3(A) 2019: Study Protocol Amendment Submission Form.**
3. Revisions in the informed consent form using the **JEPeM-USM FORM 3(A) 2019: Study Protocol Amendment Submission Form.**
4. Reports of adverse events including from other study sites (national, international) using the **JEPeM-USM FORM 3(G) 2019: Adverse Events Report.**

5. Notice of early termination of the study and reasons for such using **JEPeM-USM FORM 3(E) 2019.**
6. Any event which may have ethical significance.
7. Any information which is needed by the JEPeM-USM to do ongoing review.
8. Notice of time of completion of the study using **JEPeM-USM FORM 3(C) 2019: Final Report Form.**

Please note that forms may be downloaded from the JEPeM-USM website: **www.jepem.kk.usm.my**

Jawatankuasa Etika Penyelidikan (Manusia), JEPeM-USM is in compliance with the Declaration of Helsinki, International Conference on Harmonization (ICH) Guidelines, Good Clinical Practice (GCP) Standards, Council for International Organizations of Medical Sciences (CIOMS) Guidelines, World Health Organization (WHO) Standards and Operational Guidance for Ethics Review of Health-Related Research and Surveying and Evaluating Ethical Review Practices, EC/IRB Standard Operating Procedures (SOPs), and Local Regulations and Standards in Ethical Review.

Thank you.

Sincerely,

PROF. DR. HANS AMIN VAN ROSTENBERGHE
Chairperson
Jawatankuasa Etika Penyelidikan (Manusia) JEPeM
Universiti Sains Malaysia

JAWATANKUASA ETIKA & PENYELIDIKAN PERUBATAN
(*Medical Research & Ethics Committee*)
KEMENTERIAN KESIHATAN MALAYSIA
d/a Kompleks Institut Kesihatan Negara
Blok A, No 1, Jalan Setia Murni U13/52,
Seksyen U13, Bandar Setia Alam,
40170 Shah Alam, Selangor.
Tel: 03-3362 8888/8205

Ref : KKM/NIHSEC/ P20- 1081 (4)
Date: 18- June- 2020

DR AFIQ IZZUDIN BIN A RAHIM
UNIVERSITI SAINS MALAYSIA (USM), HEALTH CAMPUS

Dear Sir/ Mdm,

ETHICS INITIAL APPROVAL: NMRR-20-781-54336 (IIR)
FACEBOOK REVIEW AS AN ADDITIONAL HOSPITAL PATIENT SATISFACTION TOOL

This letter is made in reference to the above matter.

2. The Medical Research and Ethics Committee (MREC), Ministry of Health Malaysia (MOH) has provided ethical approval for this study. Please take note that all records and data are to be kept strictly **CONFIDENTIAL** and can only be used for the purpose of this study. All precautions are to be taken to maintain data confidentiality. Permission from the District Health Officer / Hospital Administrator / Hospital Director and all relevant heads of departments / units where the study will be carried out must be obtained prior to the study. You are required to follow and comply with their decision and all other relevant regulations, including the Access to Biological and Benefit Sharing Act 2017.

3. The investigators and study sites involved in this study are:

MULTIMEDIA UNIVERSITY (MMU)-CYBERJAYA CAMPUS
Dr Afiq Izzudin Bin A Rahim (Penyelidik Utama)
Dr Chua Sook Ling

UNIVERSITI SAINS MALAYSIA (USM), HEALTH CAMPUS
Associate Professor Kamarul Imran Musa
Dr Afiq Izzudin Bin A Rahim (Penyelidik Utama)
Dr Mohd Ismail Bin Ibrahim

4. The following study documents have been received and reviewed with reference to the above study:

Documents received and reviewed with reference to the above study: 1. Study Protocol Version 2.1, dated 27.5.2020 2. Study Clinical Report Form (CRF) / Data Collection Form Version 2, dated 27.5.2020 3. Investigator's documents : Declaration of Conflict of Interest (COI), IA-HOD-IA, and CV: a) Dr Chua Sook Ling b) Associate Professor Kamarul Imran Musa c) Dr Afiq Izzudin Bin A Rahim (Penyelidik Utama) d) Dr Mohd Ismail Bin Ibrahim

5. Please note that ethical approval is valid until **17-June -2021**. The following are to be reported upon receiving ethical approval. Required forms can be obtained from the Medical Research Ethics Committee (MREC) website (**http://www.nih.gov.my/mrec**).

i. **Continuing Review Form** has to be submitted to MREC within 2 month (60 days) prior to the expiry of ethical approval.

ii. **Study Final Report** upon study completion to the MREC.
iii. Ethical approval is required in the case of **amendments / changes** to the **study documents/ study sites/ study team**. MREC reserves the right to withdraw ethical approval if changes to study documents are not completely declared.

6. This study involves the following methods:

   i. Secondary Data

7. Please take note that the reference number for this letter must be stated in all correspondence related to this study to facilitate the process.

Comments (if any): **NIL**

<u>Project Sites:</u>
MULTIMEDIA UNIVERSITY (MMU)-CYBERJAYA CAMPUS
UNIVERSITI SAINS MALAYSIA (USM), HEALTH CAMPUS

Decision by Medical Research & Ethics Committee:
(√) Approved
(   ) Disapproved

Date of Approval : 18- June-2020

DR HJH SALINA ABDUL AZIZ
Chairperson
Medical Research & Ethics Committee
Ministry of Health Malaysia
MMC No: 27117

NA/Approval2020/Mrecshare

Bahagian Penyelidikan dan Inovasi
Division of Research and Innovation
Pejabat Pengurusan dan Kreativiti Penyelidikan
Research Creativity and Management Office

Canselori II

Aras 2, Canselori II, Bangunan E42
Universiti Sains Malaysia
11800 USM Pulau Pinang, Malaysia
T : (6)04 653 6527/6525
F : (6)04 653 6553/6554
L : www.research.usm.my
www.usm.my

Tarikh: 14 Disember 2020

Profesor Madya Dr. Mohd Ismail Ibrahim
Pusat Pengajian Sains Perubatan
Universiti Sains Malaysia
Kampus Kesihatan
16150 Kubang Kerian
Kelantan

YBrs. Profesor Madya Dr. Mohd Ismail Ibrahim,

KEPUTUSAN PERMOHONAN SKIM GERAN PENYELIDIKAN FUNDAMENTAL (FRGS) FASA 1/2020

Saya dengan hormatnya merujuk kepada perkara di atas.

2. Diucapkan tahniah di atas kejayaan YBrs. Profesor Madya Dr. memperolehi FRGS Fasa 1/2020 seperti berikut. Selaras dengan penerimaan peruntukan daripada Kementerian Pengajian Tinggi (KPT), bersama-sama ini dimajukan kod akaun untuk tindakan pihak YBrs. Profesor Madya Dr. selanjutnya.

Penyelidik Utama	Profesor Madya Dr. Mohd Ismail Ibrahim	PTJ	Pusat Pengajian Sains Perubatan
Penyelidik Bersama	1. Profesor Madya Dr. Kamarul Imran Musa 2. Chua Sook Ling @ Landa Chua 3. Dr. Najib Majdi Bin Yaacob	PTJ	1. Universiti Sains Malaysia 2. Multimedia University 3. Universiti Sains Malaysia
Tajuk Projek	***Elucidating the Machine Learning Sentiment Analyzer And Quality Classifier (MLSAQC) And Its Application in Analysing Hospital Patient Satisfaction from Facebook Review***		
Kod Akaun	203.PPSP.6171293	Jumlah Peruntukan	RM 76,400.00
Tempoh Projek	2 Tahun		
Tarikh Mula	1 November 2020	Tarikh Tamat	31 Oktober 2022
Catatan	- **Perbelanjaan Geran Penyelidikan Fundamental (FRGS)** adalah secara kawalan vot. Penyelidik mestilah membuat perancangan dan pebelanjaan mengikut jumlah agihan vot yang diluluskan dan perlu mematuhi prosedur dan peraturan kewangan semasa Universiti. Sebarang permohonan/keperluan untuk pindaan vot perlu mendapat kelulusan RCMO dan dipertimbangkan/dibenarkan **setahun sekali sahaja**. - Semua pembelian, penempatan, pemantauan dan penyelenggaraan aset/inventori yang diluluskan merupakan **hak USM** dan tanggungjawab Ketua Penyelidk. Pengurusan dan pengawasannya diletakkan di bawah tanggungjawab PTJ setelah geran tamat. Universiti berhak untuk mengagihkan semula aset/inventori ini jika diperlukan.		

3. YBrs. Profesor Madya Dr. perlu memastikan output/hasil penyelidikan projek ini seperti yang dinyatakan/ditetapkan di dalam permohonan yang telah diluluskan oleh Kementerian (*revised proposal*). Butiran adalah seperti berikut:

Output/Hasil Penyelidikan	
Bilangan penerbitan	3
Bilangan bakat	1 Sarjana

KEPUTUSAN PERMOHONAN SKIM GERAN PENYELIDIKAN FUNDAMENTAL (FRGS) FASA 1/2020

4. Bersama-sama ini dikemukakan perincian agihan untuk perhatian dan tindakan pihak YBrs. Profesor Madya Dr. selanjutnya.

5. Untuk makluman YBrs. Profesor Madya Dr. laporan kemajuan perlu dihantar pada setiap enam (6) bulan sekali dan laporan akhir dalam tempoh tiga (3) bulan selepas tamat tempoh geran. Sekiranya YBrs. Profesor Madya Dr. gagal menghantar laporan kemajuan/akhir dalam masa yang ditetapkan, semua akaun geran YBrs. Profesor Madya Dr. yang masih berstatus aktif akan **dibekukan** serta-merta tanpa notifikasi dan hanya akan diaktifkan semula setelah laporan yang berkaitan diterima. Untuk makluman juga, berkemungkinan YBrs. Profesor Madya Dr. akan **disenarai hitam** dan secara tidak langsung akan mempengaruhi peluang YBrs. Profesor Madya Dr. untuk mendapat geran pada masa hadapan.

Sekian, terima kasih.

"BERKHIDMAT UNTUK NEGARA"

Saya Yang Menjalankan Amanah,

(U. SEETA A/P UTHAYA KUMAR)
Penolong Pendaftar Kanan
Pejabat Pengurusan dan Kreativiti Penyelidikan

s.k. Pengarah
Pejabat Pengurusan & Kreativiti Penyelidikan
Universiti Sains Malaysia

Dekan
Pusat Pengajian Sains Perubatan
Universiti Sains Malaysia
Kampus Kesihatan
16150 Kubang Kerian
Kelantan

Timbalan Bendahari
Jabatan Bendahari
Universiti Sains Malaysia
Kampus Kesihatan
16150 Kubang Kerian
Kelantan Darul Naim

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Geran FRGS FASA 1/2020 - Surat Tawaran

healthcare

Article

Hospital Facebook Reviews Analysis Using a Machine Learning Sentiment Analyzer and Quality Classifier

Afiq Izzudin A. Rahim [1], Mohd Ismail Ibrahim [1,*,†], Sook-Ling Chua [2,*,†] and Kamarul Imran Musa [1]

[1] Department of Community Medicine, School of Medical Science, Universiti Sains Malaysia, Kubang Kerian, Kota Bharu 16150, Kelantan, Malaysia; drafiqrahim@student.usm.my (A.I.A.R.); drkamarul@usm.my (K.I.M.)
[2] Faculty of Computing and Informatics, Multimedia University, Persiaran Multimedia, Cyberjaya 63100, Selangor, Malaysia
* Correspondence: ismaildr@usm.my (M.I.I.); slchua@mmu.edu.my (S.-L.C.)
† Both authors play significant contribution as corresponding authors in the development of the study and writing the manuscript.

Abstract: While experts have recognised the significance and necessity of social media integration in healthcare, no systematic method has been devised in Malaysia or Southeast Asia to include social media input into the hospital quality improvement process. The goal of this work is to explain how to develop a machine learning system for classifying Facebook reviews of public hospitals in Malaysia by using service quality (SERVQUAL) dimensions and sentiment analysis. We developed a Machine Learning Quality Classifier (MLQC) based on the SERVQUAL model and a Machine Learning Sentiment Analyzer (MLSA) by manually annotated multiple batches of randomly chosen reviews. Logistic regression (LR), naive Bayes (NB), support vector machine (SVM), and other methods were used to train the classifiers. The performance of each classifier was tested using 5-fold cross validation. For topic classification, the average F1-score was between 0.687 and 0.757 for all models. In a 5-fold cross validation of each SERVQUAL dimension and in sentiment analysis, SVM consistently outperformed other methods. The study demonstrates how to use supervised learning to automatically identify SERVQUAL domains and sentiments from patient experiences on a hospital's Facebook page. Malaysian healthcare providers can gather and assess data on patient care via the use of these content analysis technology to improve hospital quality of care.

Keywords: health informatics; machine learning; topic classification; sentiment analysis; Facebook; SERVQUAL; Malaysia

check for updates

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1. Introduction

Public health professionals need accurate and up-to-date data from a range of sociodemographic categories to develop effective quality management systems for healthcare services and policy activities. Patient satisfaction is a critical indicator of the quality of care provided in a hospital environment [1–3]. By recognising and comprehending the elements that influence patient perceptions, healthcare practitioners may more effectively meet or surpass patient demand for high-quality treatment [4].

To assess patient satisfaction with various aspects of service quality, patient satisfaction surveys such as the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) and service quality (SERVQUAL) questionnaires are frequently used [5–8]. These surveys are the product of years of assessment, are methodical in their administration and review, and may gather many patients' replies per institution [9–11]. Nonetheless, they are expensive to administer, time-consuming, have low response rates, require considerable time between hospitalisation and public publication of results, frequently fail to identify the underlying cause of reported problems, and are subject to selection and response bias [5,6,12,13]. The discrepancy between the traditional patient survey and other data sources highlighted the need to use other data sources to assess public opinion on healthcare services [14]. As a result, the internet and social media have been recommended as potential substitutes for assessing patient satisfaction and evaluating the quality of healthcare services [15,16].

There is increasing recognition that user-generated information available via social media platforms such as Facebook, Twitter, and Yelp may be a significant source of data for patient experience and quality-of-care measures [17,18]. This data may be used to enhance and broaden the breadth of patient experience and health quality services by strengthening their early warning monitoring capabilities for healthcare quality management [19,20]. However, social media presents a slew of problems for data collection and analysis in online settings relevant to healthcare research. To begin, conversations on social media platforms may devolve into a range of subjects, not all of which are necessarily linked to healthcare [5]. Second, in contrast to the structured data contained in electronic medical records or clinical notes written by healthcare providers, patient feedback on social media is frequently expressed in unstructured text, necessitating the detection and extraction of interpretable factors for improved comprehension [21]. Third, it is often necessary to infer the quality of the users' therapy or clinical results from their evaluations [13].

While this may be achieved manually through human input, such processes are often inefficient and time-consuming [22,23]. Another option is to use crowdsourcing to expedite the process, but this can be quite costly (domain experts, for example, are expensive in terms of expertise and time, and the cost typically varies according to the number of tasks assigned), and in some cases, privacy concerns require sharing such data with contractors and consultants. Automated approaches, often based on machine learning (ML), are being progressively used to overcome these barriers.

In Malaysia, an annual patient satisfaction survey is conducted using the SERVQUAL method in public clinics and hospitals [24,25]. However, as previously said, it has several disadvantages. To continually enhance the quality of service and patient satisfaction, machine learning algorithms must be developed to augment traditional outcomes and support healthcare stakeholders in making timely choices. The purpose of this study is to design and assess the performance of machine learning quality classifiers (MLQC) and machine learning sentiment analyzers (MLSA) in automatically identifying SERVQUAL dimensions and sentiments in Facebook reviews of Malaysian public hospitals.

2. Related Works

2.1. SERVQUAL and Social Media

The SERVQUAL model is a widely used approach for evaluating the quality of service in a variety of service contexts, sectors, and nations [26]. The technique makes it simple to assess both customer service requirements and customer service perceptions [27,28]. The creation of the SERVQUAL scale revealed five dimensions of perceived quality: tangibles, reliability, responsiveness, assurance, and empathy. The "tangibles" dimension encompasses all physical aspects of the service quality experience (e.g., equipment, facilities, personnel). The terms "reliability" and "assurance" refer to consumers' perceptions of a service provider's ability to provide the service. The former involves assessing the service provider's reliability and accuracy, while the latter involves assessing the service provider's attributes such as knowledge and courtesy, which may inspire trust and confidence in the provider. The "responsiveness" component is concerned with the perceived helpfulness and promptness of the service provider. Finally, the component referred to as "empathy" pertains to how individuals perceive personalised, caring service [28].

The SERVQUAL model has been used to evaluate service quality in hospitals and healthcare settings, mostly using survey-based methods. Numerous studies conducted in Malaysia have established and validated the SERVQUAL model for measuring the quality of healthcare services [24,25,29,30]. SERQUAL and other quality measures are the product of years of assessment, are conducted and analysed in a systematic manner, and have the potential to gather many patient answers per institution [9,31]. Nonetheless, the surveys have several drawbacks, including being costly to administer, time-consuming, requiring significant time between hospitalisation and public publication of results, frequently failing to identify the underlying cause of reported problems, and being subject to selection and response bias [5,6,13]. The contrast between typical patient surveys and real-time public opinion about healthcare services highlights the need for additional data sources for analysing real-time public opinion about healthcare services [14]. Therefore, the internet and social media platforms have been proposed as a new method of reviewing and monitoring the quality of healthcare services [12,15,16,32].

However, social media data is often massive and presents a range of challenges, including data cleaning, data processing, and developing a theoretical model of social media content quality. While this may be accomplished manually by human input, the process is lengthy, and the method's validity and reliability are often questioned. A systematic review of patient online reviews established and recommended the use of advanced analytical methods such as machine learning to accelerate the processing of vast amounts of online review data [13]. Monitoring service quality using hospital social media platforms may assist all stakeholders in recognising quality issues and minimising the need for expensive and time-consuming surveys. Despite their uncommon, research on Facebook content analysis demonstrates a link between social media quality categories and traditional quality assessments [33–36].

2.2. Machine Learning, Sentiment Analysis, and Topic Classification

Apart from finance and marketing, machine learning has been used in clinical medicine and healthcare improvement on a regular basis. Machine learning has been used in patient care [37], stroke prediction [38], cardiology [39], and personal health investigations [40]. Additionally, machine learning is used to quantify patient experience input, which is often achieved by sentiment analysis and text classification [22,41]. Social media sentiment analysis is advantageous for assessing how people feel about goods, events, people, and services. It employs word patterns to determine if a statement in patient feedback is a complaint or a compliment. This automated process helps healthcare organisations by delivering findings faster than a human strategy would [42]. Meanwhile, topic or text analysis is a technique for analysing vast amounts of unstructured data in order to elucidate the text's primary subjects [43]. Social media data had the same enormous potential for researching health quality issues or themes as a validated and established traditional survey [33,44].

The two most commonly used approaches for text and sentiment analysis were supervised and unsupervised learning [22]. The approach that was most often employed was supervised learning, which involves manually categorising a subset of data according to themes and sentiment [45]. Comprehensive reading of all comments included inside the dataset continues to be the "gold standard" approach for free text comment analysis, since it is the only way to assure that all relevant comments are coded and analysed [22]. In supervised learning, the most often used classifiers are SVM and NB, both of which consistently exhibit high classification performance. In structured patient surveys, a supervised approach is often used to analyse online reviews [5,46,47]. On the other hand, topic modelling is an unsupervised machine learning technique that makes use of Latent Dirichlet Allocation (LDA) to automatically identify topics within a given remark [48]. LDA is a text generation model based on the premise that the words in a document represent a collection of latent themes (each word relates to a specific subject). Apart from identifying the most discussed themes in individual comments, a topic model may be utilised to find fresh insights within the free text. Consequently, this technique is often used to analyse unstructured social media comments [49–51].

Metrics like accuracy, sensitivity, recall, specificity, precision, hamming loss, and the F-measure may be used to assess machine learning performance. The model's F1 score indicates its quality [52]. In a machine learning performance evaluation of cancer treatment experience, the SVM algorithm had the highest overall sensitivity (78%), accuracy (83.5%), and overall f-score of 80% in sentiment analysis [53]. As shown in the RateMD website research, sentiment analysis using the NB classifier has a positive score of 0.94 and a negative score of 0.68, with an average score of 0.825 for text classification [46]. Meanwhile, a study of patient satisfaction at the Utah Health Care System discovered a sentiment score of 0.84 and a text score of 0.74 when the NB classifier was used [43]. Another research indicated that using the NB algorithm, patient tweets from the English National Health Service (NHS) had a sentiment score of 0.89, a theme score of 0.85 for dignity and respect, and a text classification score of 0.84 for cleanliness [47]. However, a machine learning sentiment analysis of Facebook comments using the SVM approach obtained an F1 score of 0.87 [54], equal to an average of 0.89 and 0.84 in topic classification studies of NHS tweets [5,55]. The findings indicate that SVM and NB may be used interchangeably as preferable classifiers in a supervised setting since they outperformed other classifiers in sentiment analysis and text classification.

3. Materials and Methods

3.1. Facebook Data Collection

This research analysed data collected from Facebook reviews that were publicly accessible on official hospital Facebook pages between January 2017 and March 2018. We collected all 1793 Facebook reviews from 48 official Facebook pages of public hospitals in Malaysia. WebHarvy software (SysNucleus, Kochi, India) was used to extract the data. All collected reviews were manually checked and any irrelevant reviews, such as business promotion or marketing, or reviews from hospital departments' Facebook pages or from the pages of health institutions or agencies such as the Ministry of Health (MOH), the Institute of Medical Research (IMR), non-governmental organisations (NGOs), and long-term care facilities were excluded. Malaysia is a multiracial nation with a diverse range of languages and dialects. Our national language is Malay, while English is our second language. As a result, we collected reviews exclusively in those languages. After harmonising the dual-language Facebook data into a standard language, the Malay language data was translated into English manually by local junior doctors to ensure appropriate translation.

3.2. Development of Machine Learning Quality Classifier (MLQC)

Manual coding was employed to create a labelled data set that would serve as a "gold standard" for machine learning quality classifiers (MLQC). The term "classifier" refers to the class labels applied during the manual annotation phase that the machine classification models attempt to accurately label [33]. To begin, two hospital quality managers or SERVQUAL model specialists were hired to perform a preliminary "open" coding on multiple batches of 100–300 Facebook reviews based on the MOH SERVQUAL patient satisfaction survey to establish the source coding guidelines (Appendix A Table A1). We also used the survey items of other SEVRQUAL studies to enhance the descriptions in the corresponding dimensions. Then, a random subsample of 300 Facebook reviews was chosen to test intercoder reliability. The raters separately coded the reliability subsample using Microsoft Excel. For each SERVQUAL dimension, Cohen's Kappa values were utilised to determine in-ter-rater agreement. Coding of Tangible (Cohen's = 0.885, $p < 0.001$), Empathy (Cohen's = 0.875, $p < 0.001$), Reliability (Cohen's = 0.736, $p < 0.001$), and Responsiveness (Cohen's = 0.72, $p < 0.001$) characteristics from Facebook evaluations exhibited high agreement, but agreement for Assurance (Cohen's = 0.626, $p < 0.001$) was modest. Cohen's coefficient was 0.769 on average for all dimensions. The sample of 900 manually labelled Facebook reviews were used to train our MLQC tool.

The machine learning technique examines the characteristics of the individual phrases used in the Facebook reviews and uses this data to build a quality domain classifier. Firstly, the labelled dataset was preprocessed by eliminating URLs, numerals, punctuation marks, and stop words, as well as by reducing words to their base forms using a lemmatization technique (e.g., treating as treat). Following that, we utilised the term frequency-inverse document frequency (TF-IDF) technique to determine the weight of terms, which indicates their significance to the documents and corpus. For each term t(i) in a Facebook review j, the TF-IDF score was computed as $w(i, j) = tf(i, j) \times idf(i)$. The term frequency $tf(i, j)$

refers to the number of times a term t(i) appears in a Facebook review j. The idf(i) is the inverse document frequency, which equal to log(N/df(i)) where N denotes the total number of Facebook reviews in the dataset and df(i) is the number of Facebook reviews that include term t(i). Each Facebook review is expressed as a feature vector, with each item representing the feature's TF-IDF score.

Different multi-label techniques were trained for topic classification, including Binary Relevance, Label Powerset, Classifier chain, RAkEL: RAndom k-labELsets, ML-KNN: Multi-label k-Nearest Neighbor, and BRkNN: Binary Relevance k-NN. These multi-label techniques are applied to transform multi-label problems into one or more single-label problems. With such a transformation, it allows us to apply single-label classifiers. For each technique, we trained three base classifiers: Naive Bayes (NB), Support Vector Machine (SVM), and Logistic Regression [1]. NB, SVM, and LR are all widely used classification methods that have been demonstrated to perform well on text classification tasks [42,52]. To ensure that all the quality labels are included in the training and test sets, we have applied iterative stratification sampling. The multi-label classifiers were evaluated using the Python software via the scikit-multilearn library [56]. There were studies that applied a similar approach to topic classification models [5,12,43,46,53]. The process of topic classification is summarised in Figure 1.

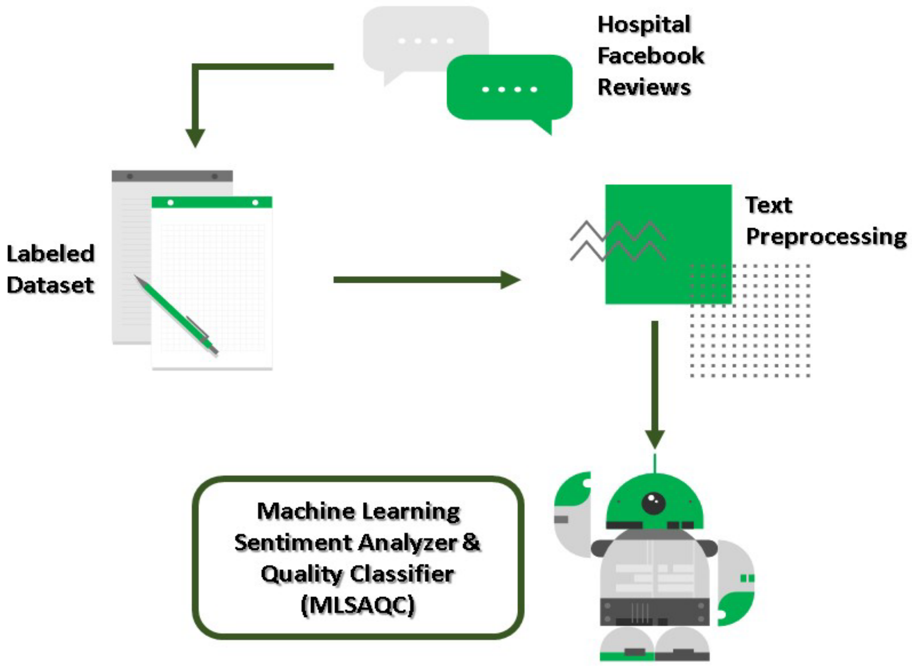

Figure 1. Machine Learning Development Process.

3.3. Development of Machine Learning Sentiment Analyzer (MLSA)

As with topic classification, we created a labelled data set for our machine learning sentiment analyzer (MLSA) using a manual coding approach. Again, our hospital quality managers, who are well-versed in-patient satisfaction surveys, were appointed to do open coding on 100–300 randomly selected Facebook reviews to generate a coding guideline (Table A2). After that, a randomly selected subsample of 300 Facebook reviews was used to assess intercoder reliability. The agreement between the coding of positive (Co-hen's = 0.721, $p < 0.001$) and negative sentiment (Cohen's = 0.686, $p < 0.001$) was satisfactory. However, the neutral or unidentified category of review had a lower degree of agreement (Cohen's = 0.43, $p = 0.027$), which might be explained by the more amorphous and heterogeneous nature of this category. Thus, both quality managers will discuss and re-evaluate the neutral or unidentifiable group of sentiments. If the review stays neutral or unidentified, it will be eliminated, as we prefer to classify reviews using binary sentiment. In an earlier study, the binary technique has been verified and demonstrated to have superior accuracy, recall, and F-score performance when compared to multiclass sentiment classification (positive, negative, neutral) [57]. Following that, 1393 randomly selected data instances were tagged and preprocessed in preparation for machine learning training. For sentiment analysis, the training data is selected using a stratified sampling technique whereby 80% of reviews in each class are selected for training. Our machine learning model was trained using the Python software packages nltk, spacy, and scikit-learn based on three base classifiers: NB, SVM, and LR. A few techniques from previous studies were applied for sentiment analyzer development in this study [12,46,53,55]. Figure 1 illustrates the process of sentiment classification.

3.4. Machine Learning Performance Evaluation

A frequently used approach for the evaluation of classification algorithms is 5-fold cross validation, which minimises the bias in estimation of classifier performance [22,52]. This technique uses the labelled dataset for training and testing. Cross-validation applies to equal-sized selections of the manually labelled data set. The cross-validation procedure is rerun five times (the folds). Test data is always kept as a single subset, while the other four subsamples are utilised as training data. Once the results of 5 different folds are obtained, an average is computed for accuracy, precision, recall, and F-score. Precision is expressed as the ratio of accurately classified positive instances divided by the number of examples the model classifies as positive. Recall, often referred to as sensitivity, is the number of identified positive examples divided by the number of true positive examples in the manually coded data. The harmonic mean of precision and recall scores is an F-score. The higher the F1 score, the superior, with zero representing the worst conceivable result and one representing the finest possible result [22].

4. Results

4.1. Performance of Machine Learning Quality Classifier (MLQC)

The number of SERVQUAL domains in our training and testing sets is shown in Figure 2. Empathy has the most records, whereas tangible has the fewest. Table 1 summarises the prediction performance from the supervised machine learning, including the accuracy ratings for the highest performing classification model and multi-label classifier. Predictive performance ratings for classification models ranged between 0.13 and 0.25, indicating that the models correctly classified the reviews with an F1 value of 0.687 to 0.757. In comparison to other models and classifiers, overall, the SVM model with the classifier chain method has the highest accuracy (0.215) and F1-score (0.757). However, more importantly for the topic classification model is the hamming loss, which measures the fraction of class labels that are incorrectly predicted. The SVM model with a classifier chain has the lowest hamming loss (0.273) compared to other models. Meanwhile, SVM with the binary relevance method was the second best, after SVM with the classifier chain. All models were evaluated by 5-fold cross validation.

While our overall average accuracy was lower than that of prior supervised machine learning studies, the performance metrics for each SERVQUAL dimension demonstrated high predictive accuracy and an F1-score. The accuracy range for the tangible dimension was 0.635–0.740, the reliability dimension was 0.657–0.718, responsiveness was 0.536–0.718, assurance was 0.574–0.691, and empathy was 0.718–0.785. The F1-scores for tangible dimensions ranged from 0.388 to 0.624, dependability dimensions from 0.766 to 0.810, responsiveness from 0.404 to 0.655, assurance from 0.643 to 0.701, and empathy from 0.821 to 0.877.

Further examination of the Tangible dimension revealed that both the SVM model for binary relevance and the classifier chain had the highest F1-score (0.587). LR with binary relevance has the highest F1 score for the dimensions of reliability (0.823) and assurance (0.7232), while NB with label powerset has the highest score for responsiveness (0.633) and LR with label powerset has the highest score for empathy (0.886). However, only SVM with a classifier chain has a consistent high performance of an F1 score in all SERVQUAL dimensions. Therefore, the SVM model was used to train the machine learning quality topic classifier (MLQC) using the classifier chain technique. Table 2 summarises the performance metrics for each SERVQUAL dimension following 5-fold cross validation.

Figure 2. The number of records in training and test datasets for each SERQUAL domain.

Table 1. Performance of ML models based on 5-fold cross validation.

Multilabel Classifier	Model	Accuracy	Recall	Precision	F1-Score	Hamming Loss
Binary Relevance	NB	0.147	0.761	0.701	0.730	0.315
	SVM	0.211	0.763	0.745	0.754	0.278
	LR	0.193	0.775	0.732	0.753	0.285
Label Powerset	NB	0.130	0.896	0.633	0.741	0.349
	SVM	0.166	0.799	0.679	0.734	0.323
	LR	0.158	0.825	0.669	0.739	0.326
Classifier chain	NB	0.149	0.756	0.705	0.730	0.313
	SVM	0.215	0.761	0.753	0.757	0.273
	LR	0.191	0.770	0.727	0.748	0.290
RakEL	NB	0.157	0.749	0.699	0.722	0.322
	SVM	0.186	0.764	0.724	0.743	0.295
	LR	0.180	0.765	0.726	0.745	0.293
MLkNN	N/A	0.140	0.737	0.697	0.715	0.327
BRkNN	N/A	0.157	0.648	0.732	0.687	0.330

4.2. Performance of Machine Learning Sentiment Analyzer (MLSA)

Figure 3 shows number of records split into positive and negative sentiment in this study. Overall, our binary sentiment classification revealed that SVM results outperform other machine learning techniques in terms of accuracy (0.874), precision (0.903), and F1-score (0.919) although NB has a higher recall (0.999). Meanwhile using hold out method, the SVM model still has the highest accuracy (90%) and F1 score of positive (93%) and negative (77%) sentiment compared to other ML models. Therefore, due to the high predictive accuracy and F1 score of the SVM model, we chose it for our machine learning sentiment analyzer (MLSA). Table 3 summarises the model evaluation following 5-fold cross validation and Table 4 describes results from hold out method.

Table 2. Performance metrics for each SERVQUAL dimension of MLQC following 5-fold cross validation.

Multi-Label	Base Classifier	Metrics	Tangible	Reliability	Responsive	Assurance	Empathy
Binary relevance	NB	Accuracy	0.675	0.690	0.636	0.643	0.782
		Recall	0.271	0.998	0.390	0.797	1.000
		Precision	0.765	0.689	0.665	0.603	0.782
		F1-score	0.399	0.815	0.485	0.681	0.878
	SVM	Accuracy	0.716	0.736	0.640	0.730	0.786
		Recall	0.511	0.885	0.514	0.730	0.951
		Precision	0.692	0.765	0.619	0.719	0.809
		F1-score	0.587	0.820	0.558	0.721	0.874
	LR	Accuracy	0.680	0.715	0.657	0.733	0.792
		Recall	0.369	0.970	0.464	0.764	0.999
		Precision	0.678	0.716	0.675	0.711	0.791
		F1-score	0.474	0.823	0.546	0.732	0.883
Label powerset	NB	Accuracy	0.661	0.692	0.554	0.566	0.782
		Recall	0.497	0.998	0.876	0.941	0.999
		Precision	0.612	0.690	0.506	0.529	0.783
		F1-score	0.531	0.816	0.633	0.675	0.878
	SVM	Accuracy	0.666	0.685	0.610	0.636	0.787
		Recall	0.471	0.884	0.688	0.816	0.948
		Precision	0.618	0.720	0.553	0.590	0.812
		F1-score	0.527	0.793	0.610	0.682	0.874
	LR	Accuracy	0.642	0.702	0.614	0.612	0.802
		Recall	0.429	0.941	0.738	0.825	0.980
		Precision	0.576	0.714	0.555	0.567	0.808
		F1-score	0.487	0.812	0.629	0.670	0.886
Classifier chain	NB	Accuracy	0.675	0.690	0.635	0.652	0.782
		Recall	0.271	0.997	0.371	0.786	1.000
		Precision	0.765	0.689	0.675	0.619	0.782
		F1-score	0.399	0.814	0.473	0.684	0.878
	SVM	Accuracy	0.716	0.731	0.651	0.737	0.799
		Recall	0.511	0.873	0.538	0.730	0.938
		Precision	0.692	0.766	0.630	0.727	0.829
		F1-score	0.587	0.816	0.577	0.726	0.879
	LR	Accuracy	0.680	0.716	0.644	0.716	0.794
		Recall	0.369	0.961	0.546	0.706	0.977
		Precision	0.678	0.719	0.617	0.713	0.803
		F1-score	0.474	0.822	0.576	0.704	0.881
RakEL	NB	Accuracy	0.639	0.692	0.628	0.648	0.782
		Recall	0.173	0.995	0.506	0.714	1.000
		Precision	0.689	0.691	0.651	0.630	0.782
		F1-score	0.274	0.815	0.521	0.657	0.878
	SVM	Accuracy	0.717	0.707	0.630	0.688	0.785
		Recall	0.494	0.900	0.522	0.719	0.952
		Precision	0.708	0.733	0.598	0.666	0.807
		F1-score	0.580	0.808	0.555	0.688	0.874
	LR	Accuracy	0.675	0.718	0.650	0.693	0.799
		Recall	0.396	0.931	0.521	0.721	0.983
		Precision	0.654	0.732	0.641	0.679	0.804
		F1-score	0.491	0.819	0.563	0.693	0.884
MLkNN	N/A	Accuracy	0.648	0.688	0.629	0.641	0.761
	N/A	Recall	0.493	0.829	0.530	0.683	0.936
	N/A	Precision	0.565	0.745	0.600	0.616	0.795
	N/A	F1-score	0.526	0.783	0.554	0.645	0.859
BRkNN	N/A	Accuracy	0.640	0.690	0.641	0.631	0.750
	N/A	Recall	0.292	0.860	0.376	0.529	0.878
	N/A	Precision	0.614	0.734	0.689	0.645	0.817
	N/A	F1-score	0.388	0.790	0.479	0.580	0.844

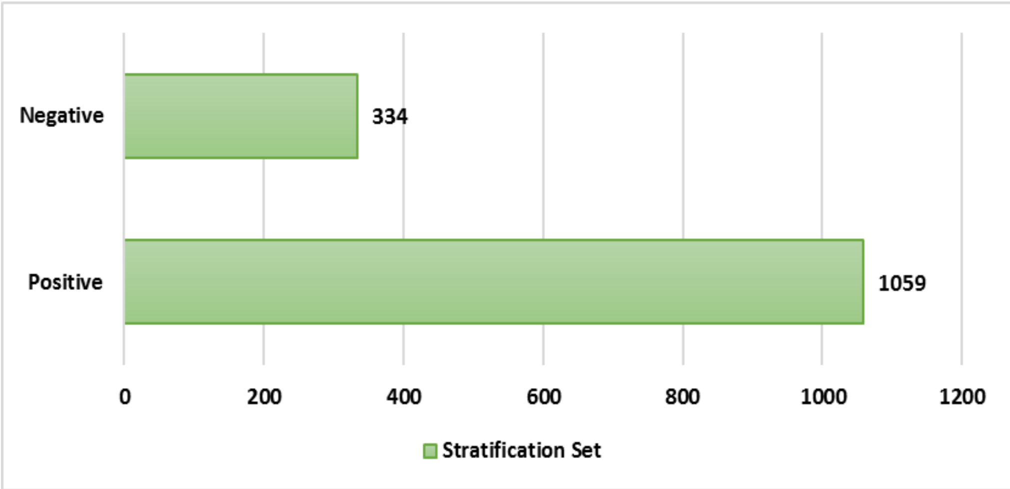

Figure 3. Number of Records used in Sentiment Analysis (n = 1393).

Table 3. Performance metrics of MLSA with 5-fold cross validation.

Model	Accuracy	Recall	Precision	F1-Score
NB	0.7810	0.9988	0.7769	0.8740
SVM	0.8743	0.9363	0.9028	0.9189
LR	0.8429	0.9917	0.8334	0.9057

Table 4. Performance metrics of MLSA with hold out method.

Model		Accuracy	Recall	Precision	F1-Score
NB	Negative	81%	19%	100%	33%
	Positive		100%	80%	89%
SVM	Negative	90%	73%	82%	77%
	Positive		95%	92%	93%
LR	Negative	87%	49%	92%	64%
	Positive		99%	86%	92%

5. Discussion

This is the first research to date in Malaysia to build a machine learning model for hospital quality of care monitoring. The results of this research show how supervised machine learning algorithms may be utilised to correctly classify SERVQUAL quality domain and sentiment-related content in Malaysian Facebook reviews. In this research, we demonstrate that SVM models with classifier chains outperform other models. Our findings almost replicated the performance of SVMs in classifying themes in a variety of experiments that used supervised machine learning and human classification. According to the RateMD research, SVM performance for staff-related topics was 0.85, whereas our score for empathy (like staff-related topics) was 0.88 using the same model [46]. According to an NHS Choice study, the subject of dignity and respect received an average score of 0.8, whereas cleanliness received an average score of 0.84 [47]. By comparison, the assurance dimension was 0.73 and the tangible dimension was 0.59 in our study. Nonetheless, their findings were validated just once or twice, as opposed to our 5-fold cross validation. Meanwhile, the overall performance of SVM-based topic classification in NHS Twitter research after 10-fold validation was 0.89, whereas our overall SVM model performed at 0.76 [5]. The benefits of having a large amount of data for analysis and a limited number of subjects for categorization are critical in determining the success of machine learning models. In comparison to the NB and LR models, our MLSA employing SVM model has a 0.92 accuracy after 5-fold validation, as well as the highest accuracy and F1 score in the holdout method, with 93% of positive and 77% of negative sentiment. In contrast to the

RateMD research, they obtained 89% of positive and 64% of negative sentiments using SVM, whereas 94% of positive and 68% of negative sentiments were obtained using the NB model [46]. Additionally, the F1 score of sentiment analysis using the SVM model was between 0.80–0.87 in earlier research [43,47,53–55,58], indicating a higher F1-score in our work.

Combining two aspects of content analysis tasks, such as topic classification and sentiment analysis, is a new technique, especially in emerging countries with an expanding healthcare market and services. These findings suggest a mechanism for utilising the massive amounts of text on social media, and that further exploration of the information contained in free-text comments may be critical for understanding patient experience, supplementing traditional survey methods, and improving hospital quality management [13,52]. Another critical issue is that manual classification techniques will continue to be the de facto standard method for supervised machine learning analysis of patient online reviews [22]. Health is a complicated topic with a plethora of medical jargon, and each medical word has a distinct meaning. Health literacy and the presence of numerous languages complicate language analysis. As a result, thorough scanning of all comments is the only method to guarantee that all relevant opinions are coded and analysed correctly. This shows that machine learning-based language analysis is only as good as the training set used to guide it [12]. As a result, the experience and knowledge of coders or independent reviewers are critical for ensuring excellent machine learning performance using supervised learning [45,57,59]. Also, our research confirmed results from earlier comparable studies that SVM was the most commonly used classifier in supervised learning, followed by NB. SVM and NB have been extensively used for text and sentiment classification because they continuously perform well [22,42].

The study's methodology allows policymakers to use social media sentiment about health care services as a substitute for conducting and scheduling more costly national questionnaire surveys. Also, because SERVQUAL serves as the foundation for public hospital patient satisfaction surveys in Malaysia, the conceptualization used in this study may serve as a supplement to the Ministry of Health's hospital patient satisfaction survey and as a valuable early warning system for hospital quality management. Thus, via systematic monitoring of internet comments, we may discover societal views and integrate them into the design of high-quality healthcare services [19,20]. Furthermore, a systematic and effective strategy is needed to enhance the quality of the healthcare system. The proposal incorporates systematic, thorough monitoring and reporting of quality improvement initiatives, as well as a priority for responding to and learning from quality-of-care incidents [60]. To improve healthcare outcomes in Malaysia, it is necessary to collect data on patient online evaluations and to use systematic methods for evaluating patient feedback. However, they take a significant amount of time between hospital admission and report disclosure, often fail to identify the underlying causes of issues, and may introduce response and selection bias [5,13,47]. The difference between the traditional patient survey and other data sources underscored the significance of using alternative data sources to evaluate patient perceptions and views about healthcare services and to understand real-time patient management. Therefore, social media platforms are a good alternative for assessing patient satisfaction and evaluating the quality of healthcare services [16,32].

Future Works and Limitations

Future studies should concentrate on improving sentiment analysis and topic classifier performance, as well as on collecting a bigger dataset of patient online reviews, including those from the private sector. Likewise, additional study is needed to expand the method's application to other kinds of free-text content on social media. For example, various methods may be included to bolster the process, such as the assessment of unigrams, bigrams, or high n-grams, as well as the refining of contextual polarity [22]. Additionally, in future studies, neural network classifiers, deep learning algorithms, and Bert-based models will be explored and compared [23,38,52]. For example, a Deep Learning model built on Bidirectional Long-Short-Term Memory (LSTM) layers may be used to utilise cutting-edge vector representations of data, such as Word Embeddings [61]. Then, we can compare the outcomes of classical machine learning and deep learning approaches as performed in the previous study [62]. Also, it would be useful to compare the labelled dataset in this research to other dictionaries or tools used in previous studies to improve sentiment and text classification [41,63]. We are also interested in exploring other sampling methods to address the imbalanced data between the positive and negative reviews [64].

Numerous limitations apply to our research. Although supervised learning is time-consuming due to the human coding needed, it is useful for analysing patient online reviews that are often seen in structured surveys such as SERVQUAL and HCAHSP [54,57,63]. Owing to the increasing number of comments on social media, manual coding for supervised learning may become impractical due to time limitations. To address it, a topic modelling method based on latent Dirichlet allocation (LDA) may be beneficial in determining how closely the findings match what people with domain expertise have decided the subjects to be, as well as identifying new topics not previously recognised by humans [48]. Additionally, sentiment analysis and topic classification methods based on machine learning are only as successful as the training set used to guide them. However, our dataset is considered limited in contrast to other machine learning studies, because the use of social media reviews in the healthcare sector in Malaysia is still relatively new and Malaysia has a small population compared to the population studied in other similar research. Nonetheless, social media use in Malaysia continues to grow every year across all sociodemographic categories [65]. Thus, as is the situation in developed countries, we may expect an avalanche of social media user reviews of healthcare services. While our machine learning classifiers performed well, our study's manual coding method presented the potential for selection bias. To reduce bias, we enlisted the assistance of two hospital quality managers who are acquainted with SERVQUAL domains and patient satisfaction surveys. Moreover, additional bias may exist since social media evaluations are usually produced by younger, wealthier people who reside in urban regions, although this prejudice was mitigated by including reviews from rural public hospitals.

6. Conclusions

By incorporating a manual coding approach into our supervised machine learning framework (MLSAQC), we proposed a strategy for auto-classification of SERVQUAL domains and sentiments on public hospital Facebook pages in Malaysia. The MLSAQC application will help healthcare providers by doing high-quality research, monitoring, and alerting them in real time to supplement other standard patient quality of care measurements in Malaysia.

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Institutional Review Board Statement: Ethical clearance was obtained from the Ethical and Research Committee Review of Universiti Sains Malaysia [22], code: USM/JEPeM/19120839.

Informed Consent Statement: Informed consent was not applicable for the current study because it does not involve humans.

Data Availability Statement: The Facebook data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy and confidentiality. However, restrictions apply to the availability of hospital data. The data is available from the authors with permission of Ministry of Health.

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Conflicts of Interest: There is no conflict of interest in this study.

Appendix A

Table A1. SERVQUAL Guideline.

Domain	Description	Facebook Reviews Example
Tangible	General: The appearance of employees, equipment, and physical facilities of the hospital. Specific: The hospitals have up to date equipment. The physical facilities are visually new or outdated. The staffs are well dressed, appear neat and good looking. The appearance of the physical facilities of the hospital are well maintained with the type of services provided.	"Cleanliness of the Hospital is good" "Car parking is difficult and limited" "Satisfied with the facilities. Large room, feels like a hotel." "The hospital is well maintained, and their food is delicious."
Reliability	General: Accurate, dependable, and consistent performance of the service. Specific: When the hospital promised to do something by a certain time, it does so. Hospital service is efficient and dependable. The hospital provides services at the time as promise to do so. The hospital keeps the records accurately or at online.	"My appointment scheduled at 9 am but then it was postponed to 12.00 pm. Unbelievable." "System needs to be improved especially discharge process. It took hours to settle it." "Efficient and top-quality hospital services" "Staff mistakenly collected medical record of other patient with similar name of mine"
Responsiveness	General: Willingness to provide prompt service to the patients. Specific: The hospital let patients know exactly when the services will be performed. The staffs give prompt services to patients upon request. The staffs are always willing to help their patients. The staffs give medical attention promptly.	"My specialist took his time to explain me about my disease and how he will treat it" "They answered all my questions during the admission." "Arrived at emergency department due to road traffic accident and the medical team immediately respond to it." "I don't feel any pain throughout the minor surgery on my arm, and it was done in a flash"
Assurance	General: the staff knowledge and courtesy, ability to inspire trust, confidence, and security. Also reflects on confidentiality and privacy of patients. Specific: The staffs are trustworthy. Patients feel safe in their transactions with the hospitals. The staffs are polite, friendly. The staffs have adequate support from the hospitals to do their jobs well.	"The surgery was successful. Mr A is a competent and trusted surgeon." "I feel comfortable and safe in this hospital. Just like at home" "The staff at the front desk was rude." "The doctors and staff nurses in this hospital are skillful and well-trained"
Empathy	General: Providing convenient services and giving attention or patience of the staffs to the patients' needs. Specific: The staffs give patient personal attention and helpful. The staffs are knowledgeable to understand patient's specific needs. The hospital has patient best interests at heart. The hospital has operating hours convenient to all the patients. Cost of treatment is affordable for patients	"Nurses are very helpful." "A staff came and offered to help my father climb stairs without we ask him. We appreciated his kindness." "They are very concerned about patient's condition and served it with their heart" "The price is affordable compared to private hospital."

Table A2. Sentiment Analysis Guideline.

Category	Description	Facebook Reviews Example
Positive	Expression of liking, approval, gratefulness (Like, love, support, thankful etc.)	"I like this hospital. Doctors and nurses are pleasant and helpful." "Thank you for your service, Doctor and nurses."
	Positive qualities of hospital services and facilities (Clean room, efficient, fast appointment, affordable etc.)	"The wait time was brief. The pharmacy counter did an excellent job." "The room is neat and tidy, and the food is delicious. I really like it."
	Positive qualities of staff (Polite, friendly, helpful, responsive etc.)	"Staff are polite and kind." "Dr. B took her time explaining my health condition until I understood it. It was greatly appreciated."
	Encourage or recommend others to use	"I recommend having your baby delivered at this hospital." "I like their antenatal counselling and will recommend it to other couples. It is extremely beneficial to us."
	Positive/desirable effects of service (Successful treatment/procedures, good health outcome etc.)	"I'd like to thank Mr A for performing bowel surgery on my father. He is now doing well." "I found the physiotherapy session to be beneficial. I'm able to walk with less pain now."
Negative	Expression of disliking or disapproval (Do not like, hate etc.)	"I hate the security guard." He was impolite to me!" "I'm not a fan of the food service here. The food has no taste."
	Negative characteristic of hospital services or facilities (Poor maintenance, slow service, expensive, long waiting time etc.)	"The discharge procedure was extremely slow." "There are a limited number of parking spaces available, and getting one is difficult." "We waited for 5 h at the out-patient clinic before seeing the doctor. This is intolerable."
	Negative qualities of staff (Rude, not-friendly, not-helpful, slow responsive, incompetency etc.)	"Staff nurses were rude and stubborn. I requested assistance but received no response." "The doctor criticised us for arriving at the emergency department at 3 a.m. for treatment. We were annoyed by his attitude."
	Negative/undesirable effects (Surgical or procedural complications, medicolegal, poor health outcome etc.)	"My father fell in the toilet and was left alone for a few minutes. The hospital director must explain the incident to our family." "After being admitted to this hospital two days ago, my husband's condition has deteriorated. No one, however, can explain the situation to us."
Neutral	Review that reports factual information/no opinion.	"Serdang Hospital is one of the Klang Valley's cardiac centres." "A Muslim-friendly hospital"
	Review as questions	"Do you have any spine surgeon in your hospital?" "How to get an appointment with your ear. Nose and throat (ENT) clinic?"
	Too ambiguous/unclear/Greetings only	"Good morning." "No comment." "Let's wait and see first"

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