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Users' intention to continue using mHealth services: A DEMATEL approach during the COVID-19 pandemic

Abstract

The coronavirus disease 2019 (COVID-19) has changed the way we use and perceive online services. This study examined the influence of service quality factors during COVID-19 on individuals' intention to continue use mHealth services. A decision-making trial and evaluation laboratory (DEMATEL) approach was used to identify and analyse the relationships between service quality and individuals' intention to continue use mHealth during the COVID-19 pandemic. Individuals' direct, indirect, and interdependent behaviours in relation to service quality and continues use of mHealth were studied. A total of 126 respondents were involved in this study. The results identified several associations between service quality factors and individuals' continuous use of mHealth. The most important factor found to influence users' decision to continuously use mHealth was assurance, followed by hedonic benefits, efficiency, reliability, and content quality. The relevant cause-and-effect relationships were identified and the direction for quality improvement was discussed. The outcomes from this study can support healthcare policy makers to swiftly and widely respond to COVID-19 challenges. The findings provide fundamental insights for healthcare organisations to promote continuous use of mHealth among people by prioritising service improvements.

Keywords: mHealth, COVID-19, service quality, continuous intention, DEMATEL

1. Introduction

The impact of COVID-19 has been reported in different sectors in developing and developed countries. The lockdown and other governmental restrictions have influenced people's information access behaviour and habit. The healthcare sector is one of the most affected sectors due to the COVID-19 pandemic, and certainly the public are the most affected ones (Davalbhakta et al., 2020; Tebeje & Klein, 2020). A number of studies have recently examined the impact of COVID-19 on people's behavioural responses and how these responses may shape their intentions to use healthcare services. This implies that the public are at the centre of the healthcare service delivery, and that health services should be transformed so that individuals can be continuously use them effectively (Kamulegeya et al., 2020; Whitelaw et al., 2020). Hospitals and healthcare service providers have been struggling to handle the increasing number of patients and to prevent nosocomial infections (Tracy et al., 2020). In addition, healthcare members are expected to maintain their performance levels during the pandemic in order to provide the necessary care to patients. In most countries, mobile health or mHealth is becoming one of the key tools for providing urgent medical helps as well as monitoring services to patients (Williams et al., 2020). The delivery of mHealth services includes infection tracing and management, reporting, and other relevant functionalities. According to Adans-Dester et al. (2020), mHelath is currently used to monitor individuals with COVID-19 symptoms. It can provide a means for the detection of virus exacerbations and the utilisation of clinical interventions when needed. mHealth is also seen as an instrument for monitoring users' real time, longitudinal, and dynamic experience of the virus (Attipoe-Dorcoo et al., 2020; Vafea et al., 2020).

However, there are few studies that have empirically examined the service quality of mHealth and its impact on individuals' continuous intention to use it for COVID-19-related treatment or monitoring. The current literature on this topic is sparse, and the existing studies (e.g., Zamberg et al., 2020) are mostly reporting the views of practitioners and healthcare professionals, with limited insight from the user perspective. In addition, there is a limited understanding of service quality provided by healthcare organisations and its impact on people's continuous use of mHealth to contain COVID-19. Our review of the literature showed a significant body of evidence to support the potential of mHealth prior to this pandemic. Despite this, the main dimensions of service quality and its relationships to the continuous intention of individuals to access mHealth services are yet to be defined. This is supported by Oliver et al. (2020) who have indicated the importance of addressing the use of mHealth in order to enable rapid deployment and scale-up of evidence based solutions.

This study aims at answering two questions: "What are the service quality factors that most impact individuals' continuous intention to use mHealth during COVID-19?" and "What are the causal relationships between these factors?" In order to answer these questions, we used a decision-making trial and evaluation laboratory (DEMATEL) approach to conceptualise the causal relationships between different service quality factors and individuals' continuous use of mHealth. The DEMATEL approach has been used by previous studies to create an impact-relation map of certain elements, and to ascertain the level of influence of each element over the other (Al-Samarraie et al., 2019; Alzahrani et al., 2018). Identifying the key factors contributing to mHealth continuous use among people can support healthcare policy makers to swiftly and widely respond to COVID-19 challenges. The study can also offer ways for healthcare organisations to encourage active use of mHealth among people by prioritising relevant service improvements to attract new users.

2. Literature Review

The COVID-19 global pandemic has dramatically affected the way we use and perceive online services. It has transformed healthcare provision and created new demands for the use of mHealth services. The fear of a potential infection in a clinical setting has led to reduction in on-site referrals (Behar et al., 2020), and increased traffic to mHealth services. The recent COVID-19 trend requires sufficient mHealth services that balances the market demands and users' needs. mHealth technology is a mobile electronic device used for creating, storing, retrieving and transmitting data in real time in healthcare provision (Oppong et al., 2018), as well as offering services such as remote monitoring, remote consultation, and personal healthcare (Akter et al., 2010; Kim et al., 2019). Significant forms of mHealth technology include mobile devices, software platforms and mHealth applications (Meng et al., 2019). In meeting the new health challenges (COVID-19), understanding service quality strikes as key for generating intention and sustained interest towards continued use of mHealth services.

Although, extant literature on digital health has provided some understanding on adoption and use of various eHealth technologies, gaps continue to exist in relation to the influence of quality of mHealth services on people's intention towards continued use. Despite the proliferation of mHealth apps, adoption and diffusion of health technologies remain an issue in contemporary research (Balapour et al., 2019; Duarte & Pinho, 2019). Thus, a study that assesses the quality of mHealth services and its effect on users' continuous intention to use them remains unclear. This is because, service quality assessed from user perspectives has tremendous value for the eHealth industry, safety and health of citizens in general (Botti & Monda, 2020; Kitsios et al., 2019). In view of this, we examined how service quality of existing mHealth applications have influenced individuals' intention to continued use of services in the era of COVID-19. Existing research has underscored the fact that the quality of any information systems is highly linked to certain critical success factors. Arguments about the inclusion of service quality for the measurement of the effectiveness of IS services have gained grounds in the literature. In the technology-enabled environment, measurement of service quality differ slightly from the generic service quality found in the marketing research domain (McKecnie et al., 2011). This is due to certain mHealth service attributes such as virtual consultation, ubiquity, accessibility, personalised nature, immediacy, flexibility, interactivity and mobility (Akter et al., 2010; Oppong et al., 2018; Rajak & Shaw, 2019), and in particular the involvement of safety and health of individual users. Also, certain difficulties regarding the use of mHealth services such as mobile devices' structural limitations and unnecessary mental efforts needed to use services (Biduski et al., 2020; Chae et al., 2002) make the need for service quality even more vital.

Previous studies on technology service quality, such as Parasuraman et al. (2005), have proposed three main dimensions of service quality: platform quality, interaction quality, and outcome quality. These dimensions were part of the E-S-QUAL (electronic service quality) and E-RecS-QUAL (electronic recovery) service quality models. The literature also revealed a number of factors that fall under the E-S-QUAL dimensions such as efficiency, system availability, fulfilment, privacy, perceived value and loyalty intentions. Other factors such as responsiveness, compensation, and contact were included in the E-RecS-QUAL model. These factors were particularly useful for determining the web-site service quality. However, its major limitation was noted in the absence of hedonic benefits and their impact on user intention. Chae et al. (2002) proposed a causal model of information quality for mobile Internet services. They found that customers assess the information quality of mobile services based on the following four key elements: 1) connection quality; 2) content quality in terms of value and usefulness; 3) interaction quality; and 4) contextual quality in terms of timeliness and access to unrestricted information regardless of time and location.

Our review showed the importance of service quality model (SERVQUAL) within the IS discipline. SERVQUAL has been widely adopted by many studies to measure and manage service quality factors such as reliability, tangibility, responsiveness, and assurance (Akter et al., 2010; Delone & McLean, 2003). In addition, the DeLone and McLean (D&M) IS success model has been found to be very useful in service quality research (Alzahrani et al., 2019; Delone & McLean, 2003, 2004). It has been applied in several empirical studies for measuring the success of IS. Akter et al. (2010) theorised a service quality model based on existing frameworks to understand specific mHealth service quality elements and users' intention to continued usage. They argued that users assess mHealth service quality from three main levels, namely: platform quality (system reliability, system efficiency, system availability, system flexibility, and system privacy), interaction quality (responsiveness and assurance) and outcome quality (functional benefits and emotional benefits). Despite the theoretical contribution of their study towards assessing quality of mHealth services, the lack of empirical findings to either confirm or reject the proposed relationships remains a challenge. Thus, the need for further research, in particular those that explore the cause and effect relationships between mHealth service quality and users' intention to continuous use.

In a recent study, Kim et al. (2019) argued that existing quality dimensions for measuring the continuous usage of mHealth services are not comprehensive enough. As a result, they proposed five elements namely: content quality (confidence, utilitarian benefits and hedonic benefits), engagement (engagement and care), privacy, reliability and usability for assessing the quality of mHealth. Though the attempt to reclassify existing dimensions into new clusters appear laudable and good for research knowledge, this study is of the view that the D&M model and other models which categorises quality dimensions into systems quality, information quality and outcome quality are still valid. They provide wholistic view of IS quality as well as a much clearer pathways for understanding the causal linkages among quality elements and users' continued intention and usage of a technology. From the foregoing, we shaped this study based on existing research, particularly the D&M IS model, to explore the various components that may potentially influences users' continuous intention to use mHealth services during the COVID-19 era. This section reviews existing literature on service quality. We follow with a discussion of the structure of service quality such as platform quality (reliability, tangibility, efficiency and content quality), interaction quality (responsiveness and assurance) and outcome quality (hedonic benefits) (see Figure 1). Lastly, we explored the interaction between perceived quality standards of mHealth services and intention to use.

2.1 Platform quality

In a mHealth context, platform quality is considered as an authentic determinant of service quality (Lotfi et al., 2020). Platform quality mostly linked to satisfaction, usage intention, and system usage. It plays a vital role in determining the technical success of the system, mainly by assessing the system quality based on certain key elements: reliability, tangibility, availability, efficiency and content.

Reliability: Our review of the literature showed that individuals' opinions on service quality are somehow based on the reliability of the IS (Kim et al., 2019; Shamdasani et al., 2008). The reliability of mHealth can be defined as the probability that a service will operate without failure for a stated period of time. Hsiao et al. (2018) and Li and Shang (2020) have indicated that the reliability of a service can be the key factor driving individuals' willingness to use the system. Mir (2019) outlined the association between the reliability of a system and the intention of users to use cloud services. Based on these, we considered examining the impact of service reliability during COVID-19 on individuals' continued usage of mHealth.

Tangibility: Our review also showed the role of tangibility in assessing the presence of physical offices, equipment, personnel and communication materials (Delone & Mclean, 2004; Kim et al., 2019). According to Meng et al. (2019), who captured tangibility as facilitating conditions, the existing support of mHealth infrastructure can influence individuals' usage intention significantly. The tangibility of mHealth services can be measured using observable characteristics such as testing options/method for COVID-19, contact tracing platforms, diagnosis and treatment plans. In a healthcare context, Aliman and Mohamad (2016) found that tangibility of care services can significantly shape individuals' behavioural intention to use technology.

Availability: Availability of a service refers to the availability of functionalities for tracing, reporting, and treating COVID-19 symptoms at anytime and anywhere. The literature showed that the replacement of bureaucratic requisition and approval process with rapid IT-based systems can potentially promote individuals' perceptions of service availability (Croom & Johnston, 2006). In a healthcare context, Spil et al. (2010) linked service availability to users' perception of the system speed, ease of use, legibility of the data, and the provided support. The relationship between service availability and continuous intention to use mHealth is yet to be understood. The availability of Internet services, the knowledge of this availability, the preference to use digital channels, and the ability and experience to do this were among the fundamental conditions for Internet usage. Many previous studies (e.g., Almaiah & Man, 2016; Askari et al., 2020; Ratanavilaikul, 2012) have addressed the importance of availability in regulating individuals' behavioural intentions.

Efficiency: Efficiency refers to the technical performance of a system (Delone & McLean, 2003; Parasuraman et al., 2005). Efficiency can be linked to individuals' perception of the system's potential to save money, time, and efforts in the provision of public service (Li & Shang, 2020). The same can be said to the role of mHealth efficiency in the context of this study. Review of the literature revealed how system efficiency can significantly influence people's usage intention of technology. For example, Sadoughi et al. (2012) found a significant relationship between system efficiency and intention to continue using the system in a healthcare setting. Yet, evidence about the impact of mHealth efficiency on individuals' continued usage is still lacking.

Content quality: Health content quality is a representation of consistency and completeness of information provided by healthcare providers (Chae et al., 2002). Previous research suggests that the extent to which health information is personalised, easy to understand and secure, can contribute to users' quality perception. This is when users develop unique feelings of importance for their health needs, which can influence their intention to use the service (Delone & McLean, 2003; Qudah & Luetsch, 2019). However, the quality of mHealth information is critical and deserve much scrutiny since human lives are involved and any potential errors could be fatal for users. The impact of information/content quality of mobile services on individuals' usage intention has been supported by many previous studies (e.g., Kim et al., 2019; Sharma & Sharma, 2019; Sohn, 2012).

2.2 Interaction quality

Interaction quality of IS services is determined by the overall support delivered by the service provider. In most instances, such support services are either outsourced, or delivered through IS department or Internet service providers (Delone & McLean, 2003). Both responsiveness and assurance have been noted in the literature as critical elements of interaction quality of e-technology (Akter et al., 2010).

Responsiveness: Responsiveness in the context of this study refers to the readiness of mHealth to respond to users' legitimate expectations regarding a set of factors related tracing, monitoring, and treating COVID-19 cases. According to Valentine (2003), it might be difficult to identify objective indicators for assessing perceived responsiveness of health systems. Thus, the responsiveness of healthcare services can be measured subjectively, by inquiring into individuals' perceptions about their experience with the health systems. We note responsiveness as a critical factor for determining users' intention and continued use of health services (Fernández-Pérez et al., 2019). This is because, users' initial access to prompt and quality care that satisfies their health needs are directly proportional to intention and continuous usage of the service.

Assurance: Assurance is aimed at providing enough organisational competence (Delone & McLean, 2003; Kim et al., 2019). In the context of this study, it refers to the ability of mHealth courtesy services to inspire trust and confidence among users. In addition, literature suggests that the site reputation in terms of products or services it offers, clear and truthful information are relevant quality measures (Parasuraman et al., 2005). In a study by Liu et al. (2019), perceived source credibility was used for understanding the extent to which mHealth service users believe information source is reliable, competent and trustworthy. According to de Kervenoael et al. (2020), assurance in the service environment is considered a fundamental constituent to long-term relationships and loyalty. This is why we believe that healthcare providers should be specialists in the type of services they offer to people. Thus, the relationship between mHealth service assurance and individuals' continuous use is worth investigation.

2.3 Outcome quality

Individuals' perceptions of system and service quality are important determinants of outcome quality. According to Akter et al. (2010), the overall benefits users accrue from using mHealth services can constitute their perception of outcome qualities. In a mHealth context, it reflects the level of completeness and accuracy of information and how they support users' health needs.

Hedonic benefits: Outcome quality was categorised into two dimensions, namely: functional (pragmatic) and emotional benefits (Akter et al., 2010; Biduski et al., 2020). Liu et al. (2019) in their study employed the term perceived enjoyment (intrinsic motivation) to represent emotional benefits a user may receive from using mHealth services. It is instructive to note their study engaged these dimensions as facilitators of the relationship between technological and psychological characteristic and usage intention. Aside from the utilitarian benefits of mHealth services, research suggests that individuals are drawn to IS due to the positive feelings or experiences (hedonic benefits) that the use of technologies arouses. Hsiao et al. (2018) indicated that individuals' perception of hedonic value may significantly influence their willingness to use technology.

Despite previous efforts to improve healthcare service quality, there seems to be a limited understanding of the relationship between the eight dimensions of service quality mentioned above and individuals' continued usage of mHealth services. Kim et al. (2019) in their study argued that poor service quality remains a major hindrance towards continued use of mHealth services. To proffer solution to this trend, critical quality factors that influence individuals' continuous intention to use mHealth services were examined in this study. As such, we proposed a number of associations between service quality and individuals' continuance intention to use mHealth services (see Table 1).

3. Method

This study examined the associations between service quality dimensions and factors (see Figure 1) such as platform quality (reliability (F1), tangibility (F2), availability (F3), efficiency (F4), content quality (F5)), interaction quality (responsiveness (F6) and assurance (F7)), and outcome quality (hedonic benefits (F8)).

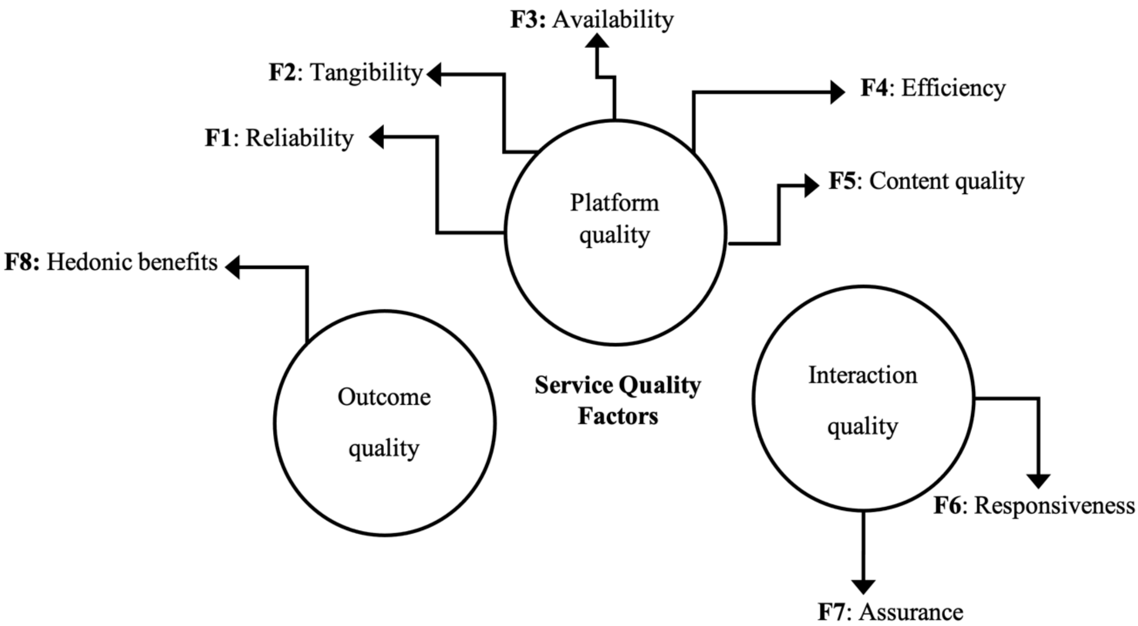

Figure 1: The proposed service quality factors

3.1 Sample and procedure

In this study, the extracted service quality factors from the literature on people's intention to use technology were used to construct a structured set of questions. We used a convenience sampling method to recruit individuals from four universities. A total of 300 invitation emails were sent individually to a pool of university students who had experience using mHealth on issues related to COVID-19 (e.g., monitoring and diagnosis). After three attempts, we were able to recruit 126 mHealth users (60 males and 66 females). Table 1 shows the main characteristics of the respondents enrolled in this study. A total of 75 respondents were within the age group 30-35 years, followed by >35 years (n: 30), 24-29 years (n: 12), and 18-23 (n: 9) respectively. The majority of respondents (n: 76) were enrolled in master's programmes, while 34 respondents were enrolled in PhD programmes.

Table 1: Sample characteristics (n:126)

Characteristics	n (%)
Gender	
Male	60 (47.6%)
Female	66 (52.4%)
Age	
18-23	9 (7.2%)
24-29	12 (9.5%)
30-35	75 (59.5%)
>35	30 (23.8%)
Education level	
Bachelor	16 (12.6%)
Master	76 (60.4%)
PhD	34 (27%)
Study disciplines	
Science	83 (66%)
Social Science	43 (34%)

The respondents were emailed a structured set of questions (Google Forms) with a guide on how to assess the level of the influence of each factor on others. A definition of each factor was provided with an example of its application in the context of this study. Table 2 summarises the main characteristics of mHealth services that the respondents used. From the table, it can be noticed that the majority of respondents used mHealth apps that were made available through the Google Play platform (n: 86), followed by iOS (n:32) and both Google and iOS (n: 8). In addition, the majority of respondents used free governmental mHealth services (n: 118). The respondents also reported that they used mHealth services in order to perform contact tracing (n: 58), view health updates (n: 37), receive health advice (n: 21), and manage health symptoms (n: 10).

Table 2: mHealth characteristics (n:126)

Characteristics	n (%)

Operating System	
iOS store only (Apple)	32 (25.4%)
Google Play only (Android)	86 (68.3%)
Both iOS and Google	8 (6.3%)
Cost	
Free	118 (93.7%)
Free for full access	3 (2.3%)
Subscription (monthly or annual)	5 (4%)
Purpose of use	
Contact tracing	58 (46%)
Health advice	21 (16.6%)
Health updates	37 (29.4)
Managing health symptoms	10 (8%)

All the respondents were asked to identify the weight/level of influence each service quality factor has on other factors (see Table 3). Here we used a scale of 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence), and 4 (very high influence). We coded all the responses individually to come out with the cause-effect relationship diagram, followed by the normalization step. The main steps used to generate the cause-effect map are discussed in the following subsection.

Table 3: The proposed pairwise relationships

Cause-effect matrix	Reliability	Tangibility	Availability	Efficiency	Content quality	Responsiveness	Assurance	Hedonic benefits
Reliability								
Tangibility								
Availability								
Efficiency								
Content quality								
Responsiveness								
Assurance								
Hedonic benefits								

Instructions for filling out the index: 0 = No influence; 1 = Very low influence; 2 = Low influence; 3 = High influence; and 4 = Very high influence.

3.2 DEMATEL method

The DEMATEL approach was originally proposed by Battelle Memorial Association in Geneva. This approach has been applied in various disciplines (e.g., management, business, education, and healthcare) to examine relationships among certain evaluation criteria (Sheng-Li et al., 2018). This approach consists of several steps that lead to the final value (see Figure 2).

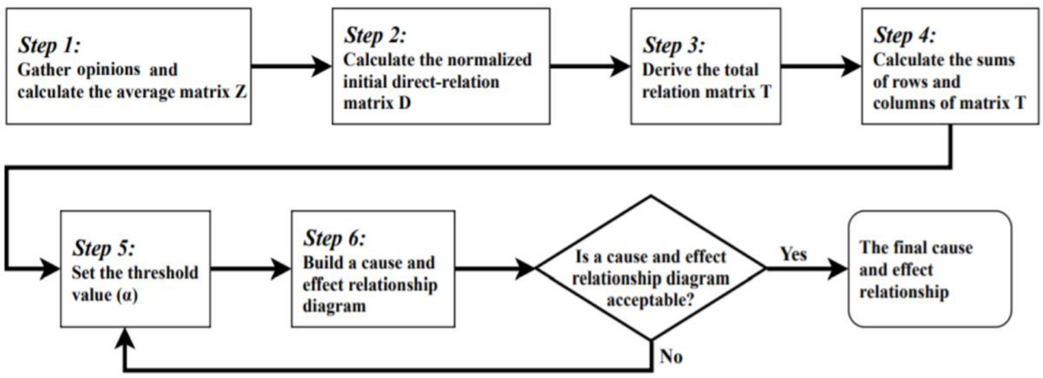

Figure 2: DEMATEL steps

Based on the literature, we were able to identify the key service quality factors that may influence individuals' continuous intention to use mHealth. These factors are outlined in Table 4.

Table 4: Service quality factors influencing continuous intention to use mHealth

Factors	Description
F1	Reliability
F2	Tangibility
F3	Availability
F4	Efficiency
F5	Content quality
F6	Responsiveness
F7	Assurance
F8	Hedonic benefits

Step 1. Calculating direct relation matrix A

After collecting responses concerning individuals' opinions about the proposed relations (see Table 5), the direct relation matrix was then calculated. This was achieved by identifying the level of influence that the element *i* in the matrix row exerts over the element *j* in the matrix column, in which a_{ij} the influence that the element *i* have on the element *j*.

Table 5: Scores of the relations

Type of relations between variables	**Influence score**
No influence	0
Very low influence	1
Low influence	2
High influence	3
Very high influence	4

The $n * n$ matrix *A* is found by averaging all scores received from individuals.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \tag{1}$$

$$a_{ij} = \frac{1}{H} \sum_{k=1}^{H} x_{ij}^{k} \tag{2}$$

Here H refers to the number of respondents in this study.

Step 2. Normalizing the direct-relation matrix

In this step, we calculated the direct relationship matrix *X* between the processed responses from the previous step by using the following formulas:

Let $$s = \max\left(max_{1 \le i \le n} \sum_{j=1}^{n} a_{ij,} \;\; max_{1 \le j \le n} \sum_{i=1}^{n} a_{ij} \right) \tag{3}$$

Then $$X = \frac{A}{s} \tag{4}$$

The sum of each row j of the matrix A is a representation of the direct effects that factor i has on other factors, here $\max\left(max_{1\leq i\leq n} \sum_{j=1}^{n} a_{ij,}\ \ max_{1\leq j\leq n} \sum_{i=1}^{n} a_{ij}\ \right)$ is used to represent the direct effects of one factor on others.

Step 3. Calculating the total-relation matrix T

Once the normalized direct-relation X was calculated, the total-relation matrix T was estimated by applying the following formula (I refers to the identity matrix):

$$X = \lim_{m \to \infty} (X + X^2 + \cdots + X^m) = \sum_{m=1}^{\infty} X^m$$

$$\begin{aligned}
\sum_{m=1}^{\infty} X^m &= (X + X^2 + \cdots + X^m) \\
&= X\,(I + X^1 + X^2\ \ldots + X^{m-1}) \\
&= X\,(\,(I - X)^{-1}(I - X)\,(I + X^1 + X^2\ \ldots + X^{m-1}) \\
&= X\,(\,(I - X)^{-1}(I - X^m)
\end{aligned}$$

$$T = X(I - X)^{-1} \qquad (5)$$

Step 4. Producing the causal diagram

The process we followed to generate the causal diagram for the impact of service quality on users' continuous intention to use mHealth was based on measuring vector R (sum of rows) and vector C (sum of columns). The causal graph was shaped by using R + C as the horizontal axis and R – C as the vertical axis. It is worth mentioning that the produced graph can help define the relationships between the factors and identification of those most important and influential (see Figure 3). The higher the value of (R + C), the higher the degree of importance of a given factor in the decision-making process.

In addition, the value of R – C is a representation of the general nature of each relation. If the value of each relation is greater than 0, it dominates over other values, if it is negative, it is dominated by other variables. Also, the location of the result on the scatterplot in the causal-effect plot can be used to determine whether a given variable is a cause or an effect (Aldowah et al., 2019).

$$R = [r_i]_{n*1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n*1} \qquad (6)$$

$$C = [c_i]_{n*1} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1*n} \tag{7}$$

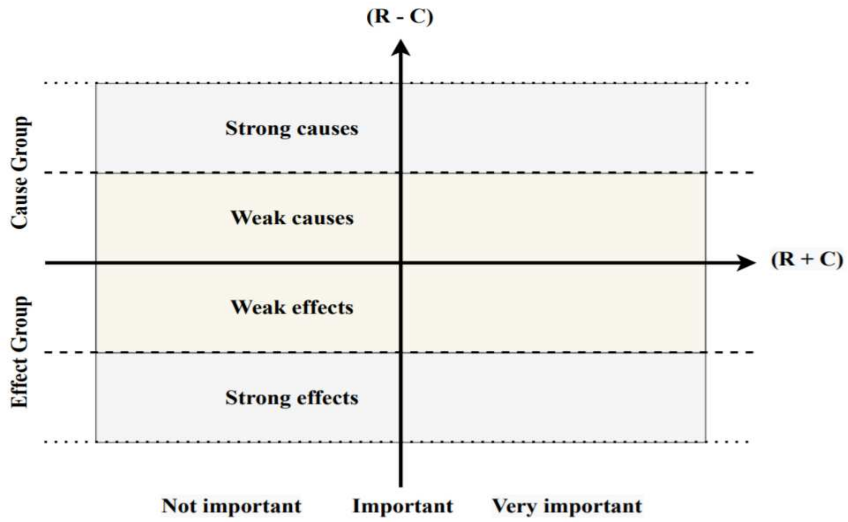

Figure 3: The causal graph

Step 5. Setting up the threshold value (α) and obtaining the causal-relation map

The process of understanding structural relations within variables was explored in this study by keeping the complexity of the whole causal-relation map at a manageable level. Here, we set the threshold value (α) in order to filter out negligible effects in matrix T. Only the factors whose effect in matrix T that are greater than the threshold value were shown in an inner dependence matrix. We identified the total threshold value by adding the mean (0.68) and the SD (0.09) of the elements in total matrix T, α = 0.77 (see Table 6-8).

Table 6: Averaged cause-effect matrix

Averaged Cause-effect matrix	F1	F2	F3	F4	F5	F6	F7	F8
F1	0.00	2.34	4.00	3.23	2.31	2.79	3.51	3.11
F2	2.11	0.00	3.12	2.67	2.75	2.20	3.10	2.90

F3	3.53	3.10	0.00	3.42	2.87	2.74	3.42	3.75
F4	2.90	2.76	3.54	0.00	3.57	2.50	3.63	2.78
F5	3.10	2.89	3.78	2.67	0.00	2.78	3.10	3.40
F6	2.10	2.53	3.10	2.78	2.31	0.00	2.10	2.56
F7	3.56	3.86	3.94	3.64	3.10	2.90	0.00	3.50
F8	3.56	3.42	3.90	2.40	2.30	3.56	3.57	0.00

Table 7: Normalized cause-effect matrix

Normalized Cause-effect matrix	F1	F2	F3	F4	F5	F6	F7	F8
F1	0.00	0.09	0.16	0.13	0.09	0.11	0.14	0.12
F2	0.08	0.00	0.12	0.11	0.11	0.09	0.12	0.11
F3	0.14	0.12	0.00	0.13	0.11	0.11	0.13	0.15
F4	0.11	0.11	0.14	0.00	0.14	0.10	0.14	0.11
F5	0.12	0.11	0.15	0.11	0.00	0.11	0.12	0.13
F6	0.08	0.10	0.12	0.11	0.09	0.00	0.08	0.10
F7	0.14	0.15	0.16	0.14	0.12	0.11	0.00	0.14
F8	0.14	0.13	0.15	0.09	0.09	0.14	0.14	0.00

Table 8: Total cause-effect matrix

Total Cause-effect matrix	F1	F2	F3	F4	F5	F6	F7	F8
F1	0.58	0.67	0.82	0.69	0.62	0.64	0.74	0.72
F2	0.60	0.52	0.72	0.61	0.58	0.57	0.66	0.65
F3	0.74	0.72	0.73	0.73	0.67	0.67	0.77	0.77
F4	0.69	0.69	0.82	0.59	0.67	0.64	0.75	0.72
F5	0.70	0.69	0.83	0.68	0.54	0.65	0.74	0.73
F6	0.56	0.57	0.68	0.58	0.53	0.45	0.59	0.60
F7	0.78	0.79	0.91	0.78	0.71	0.71	0.70	0.81
F8	0.73	0.73	0.85	0.69	0.65	0.69	0.77	0.64

4. Results and Discussion

The role of certain quality dimensions in stimulating users' continuance intention to use mHealth services has been rarely investigated, especially in the age of pandemic. Our review of the literature shed light on 8 service quality factors that may influence patients' continuous intention to use mHealth, which categorized under– platform quality (reliability, tangibility, availability, efficiency, and content quality), interaction quality (responsiveness and assurance), and outcome quality (hedonic benefits). After identifying the total cause-effect matrix, we were able to calculate the relationships between factors by calculating the row values (R) and column values (C) as shown in Table 9. According to Figure 4, this study found a potential impact of certain factors on individuals' continuous intention to use mHealth. In addition, a number of associations were identified between the study factors. Our results reported the main (prominent) factors of continuous intention to use mHealth and the main relationships amongst these factors. In Figure 4, the interrelated lines between the factors were used as an indication of the relationship from the influencing factor to the affected one, whereas the two-way arrows (double-sided) was used to represent the mutual influence between these factors.

Table 9: The resulted relations between factors

Factors	**R**	**C**	**R + C**	**R - C**	**Group**
F1	5.48	5.38	10.86	0.10	Cause
F2	4.91	5.37	10.28	-0.47	Effect
F3	5.81	6.36	12.18	-0.55	Effect
F4	5.57	5.35	10.92	0.22	Cause
F5	5.56	4.97	10.53	0.59	Cause
F6	4.55	5.03	9.57	-0.48	Effect
F7	6.17	5.72	11.90	0.45	Cause
F8	5.76	5.63	11.38	0.13	Cause

According to Fontela and Gabus (1976), a full interpretation of how the cause factors group can influence the effect factors group should be reported. This study found that the main service quality factors associated with the continuous intention of users to use mHealth during COVID-19 were assurance (F7), hedonic benefits (F8), efficiency (F4), reliability (F1), and content quality (F5), with values of 11.90, 11.38, 10.92, 10.53, and 10.86, respectively. A key point is that if any of the factors are not associated with any other factors, it means that their cause/effect is independent from other factors. Based on this, the factor with least effect was responsiveness (F6), with a value of -0.48. In addition, our results showed that the main net causers in this study were assurance (F7), efficiency (F4), reliability (F1), and content quality (F5), whereas factors related to efficiency (F4), reliability (F1), availability (F3), and tangibility (F2) were the net receiver based on the value of difference (r–c, presented in Table 8). Other factors, such as assurance (F7), hedonic benefits (F8), and availability (F3), were net causers and receivers.

Our DEMATEL map shown in Figure 4 indicated that the substantial causal factor of individuals' continuous intention to use mHealth during the COVID-19 pandemic was assurance of mHealth quality. Consequently, more attention should be given by healthcare decision makers to this dimension. This finding is supported by the recent calls in the literature on the importance of quality assurance of diagnostic tests, drugs, and vaccines and their role in stimulating people's use of technology (Newton et al., 2020). Interestingly, this study found that assurance, hedonic benefits and availability of service were interchangeability influencing users' decision to continuously use mHealth for COVID-related updates and emergencies. The literature showed few insights about the association between mHealth quality assurance, availability of service, and its hedonic value. This can be linked to the previously employed methods, which lack the absence of depth examinations of causality between factors in a context-specific manner. The assurance of service quality was found to have a direct relation with the efficiency of mHealth services. A number of studies (e.g., Mantas, 2012; Salihu et al., 2019) have addressed the role of quality assurance in increasing the efficiency of a service. Rinke et al. (2017) indicated that both quality assurance and efficiency are important in expanding the care system and services. However, our review showed limited evidence on how this relationship influences individuals' continuous intention to utilise health-related technologies. In fact, most previous studies on service quality have investigated how efficiency and quality assurance are associated with individuals' satisfaction (e.g., Salihu & Metin, 2017; Xhema et al., 2018) and intention to use services (e.g., Aliman & Mohamad, 2016). Therefore, this finding offers new evidence on the nature of quality assurance in increasing mHealth efficiency during the COVID-

19 pandemic. The direct relationship between assurance and the reliability of mHealth was found to influence users' continuous use of the service. This finding is in agreement with Meharia (2012) who reported the potential of mobile assurance and reliability in predicting the intention to use a service. Quality assurance and the tangibility of a service was found to significantly contribute to the continuous intention of people to use mHealth. This finding is supported by the work of Jaiswal and Saba (2015) who reported significant correlation between assurance and tangibility in the use of e-services. Although many previous studies have investigated quality assurance in different contexts, there is still a need for more research about its role in stimulating individuals' use of technology (Choi & Ahn, 2010). Healthcare providers should use effective strategies– by improving skills through continuous integration of relevant functionalities– to attract and sustain individuals for a lifelong relationship.

Our results also showed the impact of hedonic benefits on individuals' intention to continuously use mHealth services during the pandemic. This is in line with previous studies (e.g., Aguiar Castillo et al., 2018; Ayeh et al., 2013) which have shown a positive relationship between the perceived hedonic benefits and intention to use a system. Chiu et al. (2014) assume that hedonic benefits are sub-goals that can drive individuals to attain higher goals. Thus, users are more likely to continue use mHealth services in the future when they develop a positive perception about the service. The same can be mirrored to the impact of efficiency on the continuous intention to use mHealth. This is supported by the literature (e.g., Khatoon et al., 2020; Sadoughi et al., 2012; Tang et al., 2014) in which efficiency of a service was found to compliment users' intention to use e-services. Therefore, to provide the necessary services to users, service providers may need to improve their service efficiency by continuous adoption of innovative technologies (Lin, 2008). The DEMATEL map also showed a direct relationship between efficiency and availability of mHealth. This relationship depends on the accessibility of the service and time of access.

The reliability of a service was found to significantly influence users' continuous intention to use mHealth during COVID-19 pandemic. This is in line with previous efforts, such as Kim et al. (2015) and Sulistyowati et al. (2020), which indicated the value of service reliability on users' use of available resources and the variability of service attributes. The perception of users to mHealth may also change based on their perception of improvement in reliability and availability. This association was found in this study to favour one's continuous use of mHealth services. Meanwhile, this study found a significant influence of content quality on users' use of mHealth during the pandemic. The literature revealed a number of evidence in relation to this impact. For example, Alshurideh et al. (2019) and Calisir et al. (2014) have discussed the positive impact of content quality on users' use of e-services, mainly through knowledge integration. This led some studies (e.g., Kim, 2016) to propose managing the platform's content periodically, so to offer a process of learning and knowledge integration to users. From these, it can be said that service quality factors may differently influence the continuous intention of people to use mHealth during the COVID-19 pandemic. Our findings also revealed new relations between service quality determinants and individuals' use of mHealth.

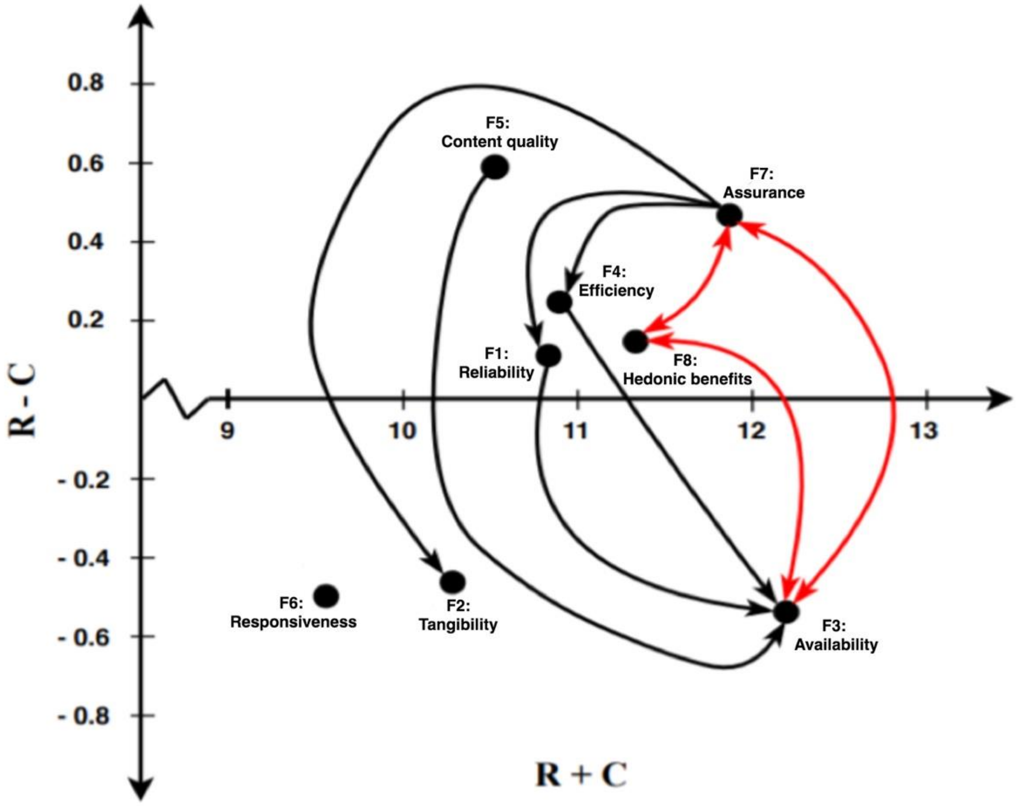

Figure 4: The DEMATEL map

5. Implications

The identified relationships between different service quality factors can enable health decision makers and government to identify the most influential factors on the use of mHealth, thus taking early measures to increase the efficiency of their quality of service. From a theoretical perspective, this study adds to previous models on service quality (e.g., E-RecS-QUAL, E-S-QUAL, and SERVQUAL) in that it identified the core and secondary factors of users' perceptions toward the current mHealth services. This study also reveals new associations between service quality determinants and individuals' use of healthcare technologies. For example, the association between quality assurance and users' intention to use mHealth services extends the D&M model and addresses some of the issues that may affect the general quality of healthcare services. From a practical perspective, understanding the relationships between certain service quality factors of mHealth can help health decision makers to respond appropriately to challenges posed by COVID-19. For example, health decision makers can pay more attention to the assurance of service quality by ensuring their services are free of breach of confidentiality, when one needs it, especially in emergency situations.

6. Limitations and Future Directions

Despite the listed implications, there are still some unavoidable limitations that needs further investigation. For example, this study was limited to certain service quality factors (platform, interaction, and outcome). In addition, empathy was not an important aspect in this study because the interaction between users and healthcare specialist through mHealth do not offer individualized, caring-based interventions for patients. We also faced some difficulties in recruiting a large and representative sample of individuals with experience in using mHealth apps for tracing, reporting, and treating COVID-19. The findings from this study might not be generalized to the general population since the participants were representatives of educated young adults. Therefore, scholars in the future may further recruit a more diverse and heterogeneous sample of individuals to provide an in-depth understanding of the various relationships between the identified service quality factors. Meanwhile, future works may pay more attention to possible interrelationships between individuals' demographic background and their perceptions of mHealth service quality. This may involve applying other data collection and analysis methods to find the causal relations of other different factors that were not included in this work.

7. Conclusion

This study used the DEMATEL approach to reveal new relationships between the different service quality factors affecting users' continuous intention to use mHealth during the COVID-19 pandemic. The results showed that five core factors can potentially influence individuals' use of mHealth services, these were: assurance, hedonic benefits, efficiency, reliability, and content quality. While other factors such as availability and tangibility were found to be primarily associated with the core factors. The study also revealed new associations between these factors and people's use of mHealth services. The assurance and availability of mHealth services were found to be very important in shaping individuals' use of health technologies during COVID-19. These findings add new knowledge to the literature about how service quality can influence users' use of health technologies during the time of crisis.

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