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Exploring the resistance to e-health services in Nigeria: an integrative model based upon the theory of planned behavior and stimulus-organism-response

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Despite the evident advantages of electronic health services (eHS), there is a noticeable opposition to their acceptance, which has raised a crucial question about why people, particularly in developing nations, oppose the acceptance of eHS. This study was designed to obtain a comprehensive understanding of the factors that influence the rigid opposition to eHS by integrating two theoretical models: the Stimulus-Organism-Response theory and the Theory of Planned Behavior. In our detailed survey, 543 respondents over 18 years old from various regions of Nigeria participated. We evaluated the proposed model using partial least squares structural equation modeling (PLS-SEM). The findings indicated that lower health literacy was associated with a greater opposition to using eHS. In addition, communication and choice overload and perceived risk contributed to a negative attitude toward eHS. Subjective norms played a significant role in influencing the intention not to use eHS, which highlights social pressure's effect. Further, a greater perception of behavioral control reduced the intention not to use eHS. Ultimately, the intention not to use eHS affected eHS rejection behavior significantly, which makes resistance to it a substantial problem. This research unveils factors that contribute to this behavior and provides insights for policymakers in the health field, with the goal to improve people's acceptance of eHS. Further research is recommended in different geographical samples and contexts to gain a better understanding of the factors related to eHS rejection behavior.

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Introduction

Information and communication technology (ICT) has sparked a seismic upheaval in the global healthcare industry over the past two decades (AlBar and Hoque, 2019). According to the World Health Assembly (2005), electronic health (*e-health*) involves the effective and secure delivery of healthcare support using modern ICT. This includes healthcare services, health monitoring, health-related literature, health education, and advancement of knowledge and research. In the ever-evolving global healthcare landscape, ICT's transformative potential has captured our collective imagination. From telemedicine to artificial intelligence-powered diagnostics, e-health services (eHS) promise to reshape healthcare delivery by making it more accessible, efficient, and cost-effective. Notably, wealthy countries such as Saudi Arabia have invested heavily in e-health systems to reduce costs and enhance treatment quality (AlBar and Hoque, 2019). Similarly, developing nations are becoming more aware of the way that e-health can improve healthcare access, price, and quality (Blaya, Fraser, and Holt, 2010).

e-Health's numerous benefits include quicker access to healthcare facilities, excellent communication between healthcare stakeholders, patient safety (Atinga et al., 2020), care coordination, precise diagnosis and treatment (Ossebaard and Van Gemert-Pijnen, 2016), and disease prevention (Walle et al., 2023). eHS's use allows swift access to healthcare information, which encompasses patient and administrative records, diagnosis, and treatment profiles (Teviu et al., 2012). Integrating ICT empowers medical professionals to capture, save, retrieve, analyze, and communicate vast amounts of healthcare data across different care sites (Norman, Aikins, and Binka, 2011). e-Health has enhanced cost-effectiveness by expanding telemonitoring, encouraging wellness, and providing health education across care sectors (Pomerleau, 2008).

Despite these assurances, numerous obstacles persist in eHS's widespread acceptance, particularly in underdeveloped countries (Yusif et al., 2020). A prior study by AlBar and Hoque (2019) also concurred that despite eHS's benefits, their acceptance has faced challenges in various countries for different reasons. Nigeria initiated plans to implement eHS in 2015 (Aririguzoh et al., 2021). However, the road to their widespread acceptance in developing nations such as Nigeria is far from straight. Understanding why patients do not accept using eHS is a significant challenge (Talwar et al., 2023). Information gathered from Walle et al. (2023), Aririguzoh et al. (2021), Norman, Aikins, and Binka (2011), Wilson et al. (2021), and de Veer et al. (2015) previous studies indicated that several variables interact to determine whether people accept or reject these disruptive technologies. While some hurdles are context-specific, others are universal. Therefore, it is crucial to analyze the particular dynamics in Nigeria and other developing nations. Individual factors play a pivotal role in the intention not to use eHS (Mekonnen et al., 2021). The level of education, fear, and anxiety are fundamental components and often decisive factors in one's acceptance of e-health (Wilson et al., 2021). A study in Saudi Arabia (AlBar and Hoque, 2019) reported that perceived behavioral control (PBC) had no significant influence on people's acceptance of eHS, which contradicts the conventional TPB. It is essential to investigate whether PBC could contribute to the intention not to use eHS. Cognitive overload induced by excessive communication and information can be another substantial barrier. The abundance of choices often makes it difficult to make a decision (Chauhan and Sagar, 2021). A previous study by Cao et al. (2020) has already confirmed that information overload leads to resistance to accept eHS. As we grapple with the way that artificial intelligence (AI), information overload, and rejection behavior interact, AI's development and its incorporation into eHS adds an exciting element to this phenomenon (Tagde et al., 2021).

Moreover, previous studies by Deng et al. (2014) and Cao et al. (2020) delved into socio-demographic variables' role in specific populations' intention not to use eHS. For example, Deng et al. (2014) identified technology anxiety as a significant barrier for elderly users, while reluctance to change emerged as a major deterrent to middle-aged patients. Similarly, Cao et al. (2020) found that information overload and system feature overload in mobile health applications contributed to senior patients' resistance by increasing fatigue and technological distress. As previous studies have revealed, other significant factors that influence the intention not to use eHS's include administrative constraints (Ackerman et al., 2012), institutional pressures, communication problems (Bezboruah et al., 2014), infrastructure accessibility, data security measures, and e-health's integration into current healthcare systems (Kujala et al., 2020; Hossain et al., 2019; Adenuga et al., 2020; Sampa et al., 2020). eHS's implementation is more likely to be successful in an environment that promotes innovation and embraces new technology. Conversely, internal opposition within organizations can pose a significant obstacle. e-health technologies' rapid evolution presents both a blessing and a challenge (Wang et al., 2022). While such innovations as AI promise to revolutionize healthcare, they can also introduce complexities and uncertainties (Tagde et al., 2021). In addition, social factors, including subjective norms', influence cannot be underestimated (AlBar and Hoque, 2019).

Tanwar et al. (2020) highlighted a significant gap in the existing literature on eHS, in that they noted a predominant focus on healthcare providers' adoption rather than on understanding the high prevalence of rejection from the patients' perspective. Studies that concentrated particularly on factors associated with eHS rejection are scarce (Talwar et al., 2023). A recent literature review on eHS consumers' resistance highlighted the limited research on its rejection (Talwar et al., 2023). Most studies on eHS's non-acceptance have focused on Asian nations such as China and Pakistan or developed nations like the United States, the United Kingdom, Australia, Germany, and Canada (Talwar et al., 2023). This underscores the need for more diverse geographical samples, including those from developing countries such as Nigeria. A prior study by Talwar et al. (2020) found that the factors that influence consumers' acceptance and rejection are distinct. Consequently, relying on technology adoption theories, such as the technology acceptance model (TAM), the unified theory of acceptance and use of technology, and the theory of planned behavior (TPB) to study consumers' rejection suggests a substantial limitation in theoretical backgrounds (Talwar et al., 2023). More research that focuses solely on consumers' non-acceptance of eHS is needed to inform practice better.

This study seeks to address the research gaps and contribute to the existing literature by exploring the antecedents that contribute to rejection behavior and proposing solutions for related issues. The investigation pursued three main goals. First, it sought to be the first study that integrates the Stimulus-Organism-Response (SOR) framework with the TPB in the context of eHS's rejection, which offers a novel theoretical contribution that other studies have not addressed. Second, it attempted to clarify the variables that influence people's intentions not to use eHS and their contemporary development of negative attitudes toward these services. Lastly, it explored the complex interactions between PBC, subjective norms (SN), communication and choice overload, perceived risk (PR), and lower levels of health literacy to understand the way that these factors affect rejection behavior collectively.

Collectively, these multifaceted goals contribute to an improved understanding of e-health acceptance dynamics by offering valuable insights into developing healthcare policies and strategies in our increasingly digitized society. The remainder of the article is structured as follows. The theoretical foundation and research hypotheses are described in the following section, followed by the methodology and the final model results. The conclusion includes discussions of the study's findings, implications, limitations, and prospects for further studies.

Theoretical foundation and research hypotheses

Theoretical foundation. This research explored external stimuli's influence on individuals' reactions by incorporating the SOR model into our framework. According to this paradigm, when individuals (Organisms) encounter external stimuli (S), their emotional and cognitive responses lead to specific actions or responses (R) (Mehrabian and Russell, 1974). The SOR model served as one of the theoretical foundations for this study, and it is the model used most extensively in the environmental psychology literature and consumer intention studies (Zhu et al., 2016). The SOR model describes primarily the way that external environmental cues affect people's cognitive and emotional states and, consequently, their behavioral reactions (Mehrabian and Russell, 1974). Some of the stimuli identified in this study include communication and choice overload, PR, and health literacy.

As a well-established research framework, the SOR model, which is employed widely to investigate behavior (Liu et al., 2019), was considered an acceptable paradigm for our study. Researchers accept it widely and use it to study behavior in various contexts, including retail purchasing behavior (Chang et al., 2011), social media engagement (Islam and Rahman, 2017), online hotel booking behavior (Pandita et al., 2021), mobile auctions (Chen and Yao, 2018), business relations (Kudla and Klaas-Wissing, 2012), and healthcare (Suess and Mody, 2018). Further, Vergura et al. (2020) used the SOR theory to study customers' attitudes and purchase intentions.

The TPB model served as the theoretical foundation for this study. Introduced by Ajzen (1991) this model has been used extensively to forecast and investigate users' conduct and intentions. According to the TPB, three critical variables—attitude, SN, and PBC—influence a person's intention to engage in a specific behavior (Ajzen, 1991). In the context of this research, we considered the intention not to use eHS. A person's intention to perform the behavior should be stronger if their attitude and SN are more favorable, and their PBC is greater. People's attitude reflects the way that they feel about the behavior's desirability, which could be either negative or positive (Ajzen, 1991), specifically a "negative attitude toward eHS" in the context of this research. In addition, if PBC reflects actual control accurately, it can substitute for absolute control and help predict the behavior (Ajzen, 1991). While TPB has been proven to be a valuable tool in elucidating behavior, it is not without its constraints and limitations (Caso et al., 2022). A previous study by AlBar and Hoque (2019) combined the TAM and TPB models to assess the behavioral intention to adopt e-health, while instead, we adapted and modified these elements to assess people's intention not to do so.

In summary, a fresh approach is needed to unravel the intricate web of e-health rejection behavior. Recent literature by Talwar et al. (2023) on eHS resistance argued that there is a limited theoretical approach, in which only the unified theory of acceptance and use of technology, TAM, and TPB are employed most commonly in the context of eHS rejection. Previous studies, such as those of Qi and Ploeger (2021) and Liu et al. (2023), have integrated the SOR and TPB models to study human behavior in different contexts. However, before this study, SOR theory and the TPB's integration had never been used to study rejection behavior's antecedents in the context of eHS. This innovative framework combines the well-known TPB, which clarifies behavior's social and individual causes, with the SOR model, which stresses the way that external stimuli affect people's reactions. Although the TPB predicts individual goals effectively, it goes only so far in showing the way that environmental factors affect these intentions. By emphasizing external stimuli, the SOR model can shed light on the external elements that influence people's intentions and behaviors. Through this connection, we can forecast both the INTU and external circumstances' influence on these intentions.

Hypothesis development. A total of 9 constructs make up the model proposed for this study, all of which stem from either the TPB or the SOR model. As intention is a well-known and accepted measure to predict actual behavior, we used "intention not to use" to measure the actual behavior, which is "rejection behavior." The hypothesis is presented structurally in Fig. 1.

SOR constructs. Cho et al. (2011) described communication overload as a scenario in which a network's communication requirements surpass an individual's capacity to communicate effectively within that network. This phenomenon can result in interruptions in the individual's schedule (McFarlane and Latorella, 2002). Further, communication overload can disrupt an individual's regular routine and make it challenging to maintain concentration (Cao and Sun, 2018). Studies have shown that frequent interruptions associated with communication overload can have an adverse effect an individual's ability to concentrate and complete tasks effectively (McFarlane, 1998; O'Conaill and Frohlich, 1995). Other studies by Bawden and Robinson (2020), Larson et al. (2020), Whelan et al. (2020), Islam et al. (2021), and van Zoonen et al. (2022) have investigated communication overload in different contexts. Therefore, we propose the following hypotheses:

H1a: Communication overload has a significant positive effect on negative attitudes.

H1b: Communication overload has a direct positive effect on the intention not to use.

Choice overload occurs when there is an imbalance between what is required of someone and the tools that they have at their disposal to manage excessive possibilities (Zeike et al., 2019; Pfaff, 2013). Choice overload is a phenomenon in which too many options can lead to difficulties in making decisions, dissatisfaction with the option chosen, and even the inability to make decisions (Zhao, 2022). In the context of this study, excessive choices in eHS reduce the motivation to use eHS. The "choice overload" hypothesis suggests that although providing extensive choices may sometimes be desirable initially, it can reduce motivation ultimately (Zhao, 2022). This concept has been studied in the field of psychology, adaptation, and consumer behavior (Rahman and Bansal, 2023). This idea, also known as over-choice, relates to the experience of cognitive overload attributable to many alternative choices (Bingham, 1972). Since this term was coined, multiple studies (Greenwood and Ramjaun, 2020), Settle and Golden, 1974; Keller and Staelin, 1987; Iyengar and Lepper, 2000; Misuraca and Teuscher, 2013) have confirmed that having too many options can lead to a negative outcome.

According to Noguchi and Hills (2016) and Pilli and Mazzon (2016), choice overload's adverse effects include post-decision regret and perpetual decision postponement. In the context of this study, we propose that given all of the problems associated with choice overload, it is possible that it would cause people to

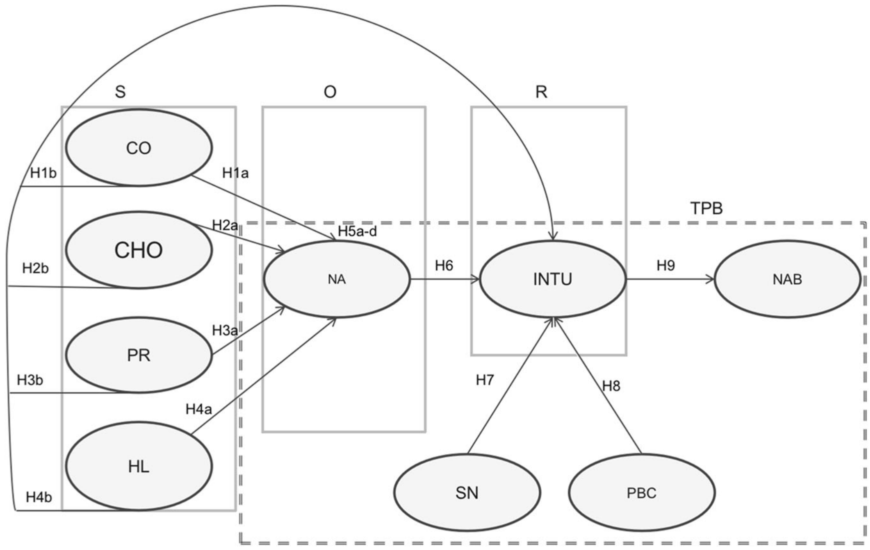

Fig. 1 Research framework and hypotheses. CO communication overload, CHO choice overload, PR perceived risk, HL health literacy, NA negative attitude, SN subjective norms, PBC perceived behavioral control, INTU intention not to use, NAB non-adoption behavior.

have a negative attitude toward eHS. Therefore, we put forward the following hypotheses:

H2a: Choice overload has a significant positive effect on negative attitudes.

H2b: Choice overload has a direct positive influence on the intention to reject.

PR is the subjective assessment of potential adverse outcomes or uncertainties associated with a decision or action (Wu et al., 2020). According to a previous study, PR is a distal factor that affects individuals' intention to perform a behavior by influencing their attitudes and beliefs (Schmiege et al., 2009). Caso et al. (2022) suggested that PR affects attitudes. In the context of this research, we propose the following hypotheses:

H3a: Perceived risk has a positive effect on negative attitude.

H3b: Perceived risk has a direct negative effect on the intention to reject.

Health literacy is the capacity that individuals develop through daily activities and social interactions over time, to obtain, comprehend, assess, retain, and apply health and healthcare-related information in ways that promote and maintain their well-being and that of their community (Organization, World Health, 2022). Introduced in the 1970s by Simonds (1974), health literacy pertains primarily to an individual's ability to navigate the intricate requirements necessary to promote and maintain health within contemporary society.

Low levels of health literacy lead to misunderstandings, confusion, and skepticism about e-health, which could result in refusing to use the technology. This could, in turn, affect a person's intention to use eHS. Therefore, health literacy can be considered a stimulus in this research's SOR framework, as it is an external influence that can affect a person's attitude toward, and intention to accept e-health. We consider the following hypotheses:

H4a: Lower levels of health literacy will have a positive effect on negative attitudes.

H4b: Lower levels of health literacy will have a positive effect on the intention to reject.

Constructs from TPB. Davis (1989) defined attitude as the personal assessment of behavior based upon a particular criterion, such as positive/negative, harmful/beneficial, or pleasant/unpleasant. Ajzen (1991) described attitude as the extent to which an individual has a favorable or unfavorable disposition toward an object, specifically a "negative attitude toward eHS" in the context of this study. The prediction of attitude toward a behavior is based upon the evaluation of the target toward which the behavior is directed (Caso et al., 2022). Studies have demonstrated repeatedly that someone who has a positive attitude toward a certain technology will be quite likely to accept it (Tao et al., 2018; Zhang et al., 2019; Marangunić and Granić, 2015). Therefore, we posit that a person who has a negative attitude toward eHS will not engage in using it. Thus, we propose the following hypotheses:

H5a: A negative attitude mediates the relation between communication overload and the intention to reject.

H5b: A negative attitude mediates the relation between choice overload and intention not to use.

H5c: Negative attitude mediates the relation between perceived risk and intention not to use.

H5d: Negative attitude mediates the relation between health literacy and intention not to use.

H6: Negative attitude will have a positive effect on the intention not to use.

SN refers to an individual's perception of social pressure or influence from their social environment (such as friends, family, or colleagues) to engage in or refrain from a particular behavior (Ajzen, 1991). It is a concept within the TPB that suggests that people's behavior is influenced by their beliefs about whether people they value will approve or disapprove of that behavior. SN can be either descriptive (what an individual perceives that others are doing) or injunctive (what an individual perceives that others think they should do). Caso et al. (2022) used SN as a variable in the TPB model. Therefore, we propose the following hypothesis:

H7: A negative subjective norm toward eHS will increase the intention not to use.

PBC is the perceived ease or difficulty of performing a behavior. It refers to an individual's perception of the extent to which they have the necessary resources, skills, and opportunities to engage in the behavior (Ajzen, 1991). It also includes individuals' belief in their ability to control factors that may affect the behavior. In TPB, PBC is considered a determinant of behavior, and it is believed that individuals are more likely to engage in a behavior if they perceive that they have control over it. Thus, the following hypothesis is proposed:

Table 1 Demographics.

Variable		Number (*N*)	Proportion
Gender	Male	283	52.1%
	Female	260	47.9%
Age (years)	18–24	117	21.5%
	25–34	224	41.3%
	35–44	126	23.2%
	45–54	49	9.0%
	55 and above	27	5.0%
Highest level of education attained	PhD	31	5.7%
	Master's	93	17.1%
	Bachelor's	218	40.1%
	Diploma	93	17.1%
	Secondary Level	96	17.7%
	Primary Level	7	1.3%
	Other	5	0.9%

H8: PBC is related negatively to the intention to reject.

The term "intention" describes a person's readiness and willingness to engage in a specific behavior in the not-too-distant future (Ajzen, 1991). It denotes their determination to engage in such conduct, or in our study, specifically the "intention not to use", which in this study is defined as the lack of willingness or desire to use eHS (de Veer et al., 2015). A crucial component of TPB is intention because it is a reliable indicator of whether a person will engage in the targeted action (Ajzen, 1991; Tao et al., 2018; Cho, 2016). Therefore, in this study, we propose the following hypothesis:

H9: Intention not to use affects rejection behavior positively.

Figure 1 shows the research framework.

Methods

Participants. First, we collected demographic data to profile the participants. The target population comprised those who had never used any eHS before although they are available to them. The gender distribution was nearly balanced, with 283 males (52.1%) and 260 females (47.9%). Age categories ranged from 18 to 55 and above, with the largest proportion in the 25–34 age group (41.3%). Education levels varied widely; 40.1% held bachelor's degrees, 17.1% had diplomas, 17.1% had obtained master's degrees, and 5.7% had obtained Ph.D. degrees. Other educational backgrounds comprised 0.9% of the population. The participants came from different career backgrounds randomly. The descriptive demographics are represented in Table 1. Convenience sampling and a web-based questionnaire survey, an effective tool for gathering data, were employed in this investigation (Regmi et al., 2016). A total of 543 individuals participated in the study.

Instruments. The first section of the questionnaire included a description of eHS and outlined the research's purpose. The participants were given prior notice and asked to consent to fill out the questionnaire. The demographic data were collected in this initial section. The participants could proceed to the second section of the questionnaire only if they had never used eHS before.

The second part of the questionnaire included items for various constructs. The five items used to measure communication overload were adapted from Cho et al. (2011), Tripathy et al. (2016), and Fan et al. (2021). Choice overload was measured with three items adapted from Nagar and Gandotra (2016). Perceived risk was measured with three items adapted from Rittichainuwat and Chakraborty (2009). Health literacy was measured with five items adapted from Sørensen et al. (2013). Negative attitude was measured with three items adapted from Caso et al. (2022). SN was measured with four items adapted from Caso et al. (2022) as well. PBC was measured with items adapted from AlBar and Hoque (2019) and Caso et al. (2022). Intention not to use was measured with three items adapted from Caso et al. (2022) and Askelson et al. (2010). Rejection behavior, which is the actual behavior of interest, was measured using three items adapted from Ong et al. (2023). All of the measurement instruments are listed in Table 2.

Pilot testing is an important step to ensure the instruments and the research methods' feasibility. The questionnaire was distributed to 95 individuals through WhatsApp and Twitter (known currently as X). The study received 79 responses, which represented an 83% response rate to the survey. After collecting data from the pilot survey, five independent reviewers were invited to assess the questionnaire to ensure the study instrument's clarity and validity in the context of Nigeria. The pilot test also provided insights into the time that the participants took to complete the survey and feedback on any unexpected problems or challenges that they might face.

Data analysis. Data analysis was conducted using both SPSS v. 27 and Smart-PLS v. 4.0. We used the two-step methodology that Becker et al. (2012) provided, which involves the evaluation of measures and the development of a structural model.

Results

Common bias method. SPSS was used to conduct the Kaiser-Meyer-Olkin and Bartlett spherical tests. The value of the Kaiser-Meyer-Olkin test for our study was 0.86, which exceeds the minimum cutoff of >0.50. Bartlett's test was significant at $p < 0.00$. These variables are deemed suitable for factor analysis, as they indicate structural validity. We used Harman's single-factor test to ensure that our data were common method bias-free. A single-factor explained 24.49% of the total variance, well below the 50% acceptable threshold (Podsakoff et al., 2003). The variance inflation factors, which were below 3, indicate common method bias-free data (Hair et al., 2017), and all inner variance inflation factors values in our data were <3, with outer variance inflation factors values below 5, except for NA2 and NA3 and INTU1 and INTU2, which were below 10. The permissible threshold for variance inflation factor values is below 5 (Hair et al., 2011) and a previous study by Mekonnen et al. (2021) used variance inflation factor values below 10. In addition, the correlation-matrix tests for common method bias indicate its presence if the correlation among constructs is >0.9 (Tehseen et al., 2020). None of our constructs showed a correlation above the threshold.

Measurement model. Smart PLS v. 4 was used to run the measurement model analysis and the PLS-SEM is presented graphically in Fig. 2. Item reliability was evaluated by examining the outer loadings of items associated with a particular dimension, following the 0.7 threshold that Hair et al. (2011) recommended. In addition, Cronbach's α values that ranged from 0.90 to 0.95 and exceeded 0.7, as per Nunnally's guidelines, were achieved in this study and thus ensured internal consistency reliability. Consistent with Bagozzi and Yi (1988), the composite reliability values in this study surpassed the threshold of 0.7.

Fornell and Larcker (1981) recommended that the average variance extracted (AVE) values should be ≥0.5 to demonstrate convergent validity. In our study, all AVE values were above the acceptable mark, indicating a satisfactory level of convergent validity. The values for the measurement model can be seen in Table 2. Finally, with respect to discriminant validity, Fornell and

Table 2 Measurement model.

Construct	Measurement items	Loading	Cronbach's α	Composite reliability	Average variance extracted	Variance inflation factor	Skewness
CO	CO1: I receive many junk emails concerning health services.	0.86	0.94	0.97	0.79	3.23	−0.34
	CO2: I often feel overloaded with information concerning related services.	0.92				4.85	−0.25
	CO3: I receive more information than I can process about e-health.	0.92				4.34	−0.173
	CO4: I generally get too many notifications of push messages, news feeds.	0.88				3.549	−0.39
	CO5: I frequently send a greater number of messages than I initially intended to.	0.86				2.29	−0.05
CHO	CHO1: When considering eHS, there are too many options to choose from.	0.92	0.90	0.91	0.84	2.79	−0.23
	CHO2: When considering health-related services online, I need help choosing what would be most suitable for me.	0.91				2.87	−0.32
	CHO3: I feel overwhelmed by the variety of health-related choices available through eHS online.	0.93				3.08	−0.32
PR	PR1: Engaging in eHS can lead to errors and damage to one's health.	0.94	0.93	0.93	0.88	3.77	−0.002
	PR2: It is uncertain whether eHS would be as effective as I think.	0.95				4.61	−0.13
	PR3: It is probable that eHS would not be worth their cost (e.g., subscriptions to use health apps).	0.93				3.31	−0.08
HL	HL1: It is challenging to determine the reliability of health risk information in the media.	0.88	0.93	0.98	0.82	3.49	−0.46
	HL2: It is difficult to determine which everyday behaviors are connected to my overall health.	0.90				3.58	−0.41
	HL3: It is challenging to find information on how to handle health problems such as stress or depression effectively.	0.93				3.39	−0.26
	HL4: Determining how to protect yourself from illness based upon information in the media is not easy.	0.90				3.42	−0.46
NA	NA1: It is not necessary to use eHS.	0.94	0.95	0.95	0.91	4.19	0.02
	NA2: Using eHS is not a good idea.	0.97				7.24	0.14
	NA3: I do not consider eHS a beneficial choice to access healthcare services.	0.96				6.22	0.10
SN	SN1: My doctors think I should not use eHS.	0.89	0.92	0.96	0.80	2.48	0.14
	SN2: Most people think that adopting eHS is not good.	0.92				3.93	−0.12

Table 2 (continued)

Construct	Measurement items	Loading	Cronbach's α	Composite reliability	Average variance extracted	Variance inflation factor	Skewness
	SN3: My family believes that traditional healthcare services (i.e., face to face with a healthcare provider) are preferable to adopting eHS.	0.85				2.67	−0.35
	SN4: Most people think that eHS are not necessary.	0.92				3.84	−0.19
PBC	PBC1: Using eHS is easy.	0.81	0.95	1.00	0.81	3.20	−0.45
	PBC2: Using eHS is possible.	0.93				4.14	−0.84
	PBC3: Using eHS is up to me.	0.92				4.85	−0.79
	PBC4: Using eHS is under my control.	0.90				4.74	−0.63
	PBC5: I am confident in my ability to effectively use eHS.	0.94				4.65	−0.69
INTU	INTU1: I predict that I will not use eHS in the near future.	0.96	0.95	0.96	0.91	6.56	−0.01
	INTU2: I have no plans to use eHS in the near future.	0.97				7.26	−0.02
	INTU3: I am not inclined to try out or explore e-health platforms.	0.94				4.00	−0.12
NAB	NAB1: Using eHS is not in my bucket list when it comes to healthcare.	0.93	0.93	0.96	0.88	3.78	−0.92
	NAB2: I am assured that I do not need to use eHS even if they are available to me.	0.95				3.70	−0.67
	NAB3: I consistently opt for traditional healthcare methods instead of using eHS.	0.93				3.75	−0.88

CO communication overload, *CHO* choice overload, *PR* perceived risk, *HL* health literacy, *NA* negative attitude, *SN* subjective norms, *PBC* perceived behavioral control, *INTU* intention not to use eHS, *NAB* non-adoption behavior.

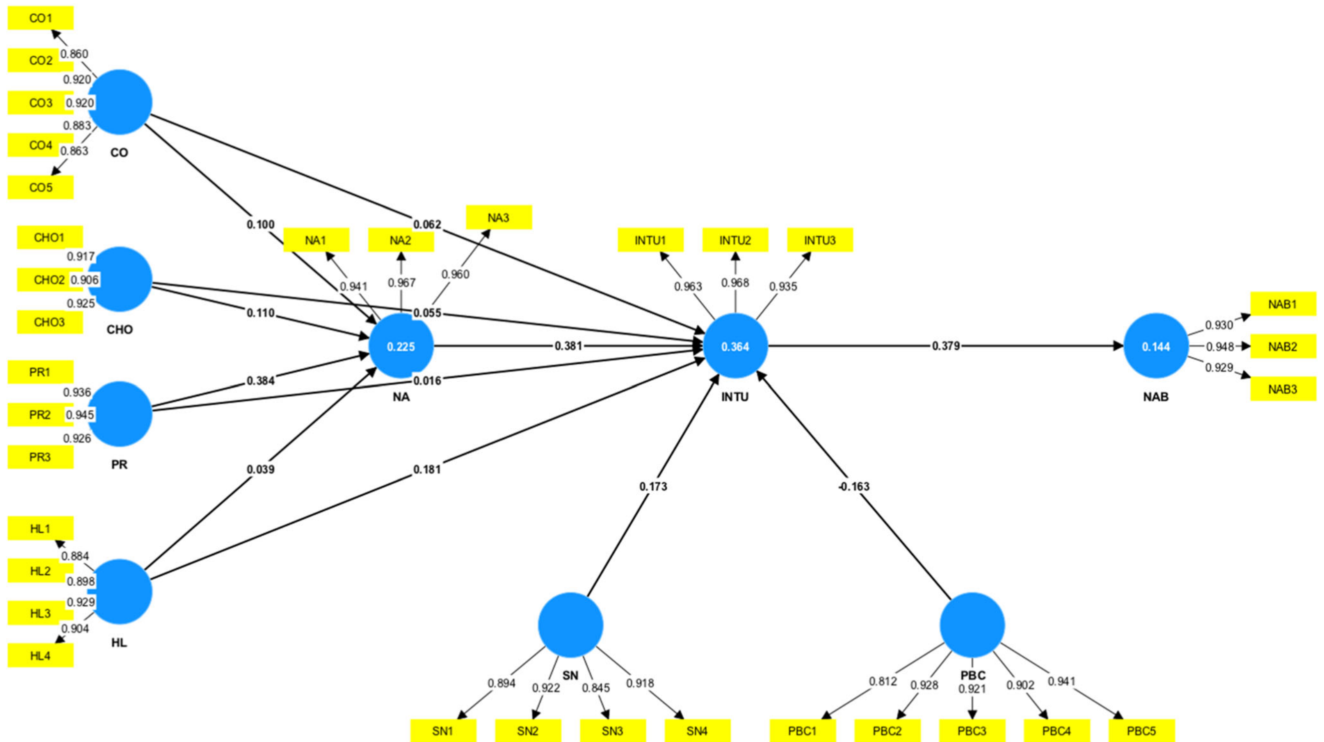

Fig. 2 Structural equation modeling using Smart PLS 4. CO communication overload, CHO choice overload, PR perceived risk, HL health literacy, NA negative attitude, SN subjective norms, PBC perceived behavioral control, INTU intention not to use, NAB non-adoption behavior.

Table 3 Discriminant validity.

Construct	CHO	CO	HL	INTU	NA	NAB	PBC	PR	SN
(a) The Fornell-Larcker criterion: latent variable correlation and the square root of AVE									
CHO	**0.92**								
CO	0.31	**0.89**							
HL	0.27	0.26	**0.90**						
INTU	0.24	0.23	0.32	**0.96**					
NA	0.24	0.22	0.19	0.50	**0.96**				
NAB	0.19	0.23	0.28	0.40	0.32	**0.94**			
PBC	0.11	0.11	0.03	−0.13	0.03	0.13	**0.90**		
PR	0.24	0.20	0.24	0.32	0.44	0.25	−0.004	**0.94**	
SN	0.21	0.20	0.24	0.36	0.31	0.34	0.03	0.38	**0.90**
(b) Heterotrait-Monotrait (HTMT) ratio									
CHO	-								
CO	0.33	-							
HL	0.29	0.27	-						
INTU	0.26	0.23	0.33	-					
NA	0.26	0.22	0.19	0.52	-				
NAB	0.20	0.24	0.298	0.396	0.337	-			
PBC	0.138	0.123	0.07	0.10	0.09	0.15	-		
PR	0.26	0.22	0.26	0.34	0.47	0.26	0.05	-	
SN	0.23	0.21	0.26	0.37	0.31	0.36	0.06	0.41	-

N/B: The figures in bold are the square roots of AVE; the rest denote correlations.
CO communication overload, *CHO* choice overload, *PR* perceived risk, *HL* health literacy, *NA* negative attitude, *SN* subjective norms, *PBC* perceived behavioral control, *INTU* intention not to use eHS, *NAB* non-adoption behavior.

Larcker (1981) asserted that the square root of the AVE for each construct should exceed the correlation of that construct with other constructs in the model. The heterotrait-monotrait ratio provides two options as an additional strategy to assess discriminant validity. As Henseler et al. (2015) described, one method compares the heterotrait-monotrait value to predetermined thresholds such as 0.85 or 0.9. The value must be lower than these cutoffs to confirm discriminant validity in this instance. As recommended in previous studies (Henseler et al., 2015; Franke and Sarstedt 2019; Roemer et al., 2021) researchers may also use an inferential statistic to test the null hypothesis that the heterotrait-monotrait value is 1. Thus, the constructs' discriminant validity was satisfactory. The results for discriminant validity are presented in Table 3.

Table 4 Structural model representation.

Direct effects

Hypotheses	Relation	Path coefficient	*t*-value	*p*-value	Outcome	Inner VIF
H1a	CO→NA	0.10	2.39	0.02	Supported	1.16
H1b	CO→INTU	0.06	1.48	0.14	Not supported	1.19
H2a	CHO→NA	0.12	2.44	0.02	Supported	1.19
H2b	CHO→INTU	0.06	1.31	0.19	Not Supported	1.21
H3a	PR→NA	0.38	9.07	0.00	Supported	1.11
H3b	PR→INTU	0.02	0.37	0.71	Not Supported	1.39
H4a	HL→NA	0.04	0.93	0.35	Not supported	1.15
H4b	HL→INTU	0.18	4.54	0.00	Supported	1.17
H6	NA→INTU	0.38	9.29	0.00	Supported	1.32
H7	SN→INTU	0.17	4.265	0.000	Supported	1.245
H8	PBC→INTU	−0.163	4.20	0.00	Supported	1.02
H9	INTU→NAB	0.38	10.25	0.00	Supported	1.00

Indirect effects

Hypotheses	Relation	Path Coefficient	*t*-value	*p*-value	Outcome
H5a	CO→NA→INTU	0.04	2.36	0.02	Supported
H5b	CHO→NA→INTU	0.04	2.35	0.02	Supported
H5c	PR→NA→INTU	0.15	6.33	0.00	Supported
H5d	HL→NA→INTU	0.01	0.91	0.36	Not Supported

CO communication overload, *CHO* choice overload, *PR* perceived risk, *HL* health literacy, *NA* negative attitude, *SN* subjective norms, *PBC* perceived behavioral control, *INTU* intention not to use eHS, *NAB* non-adoption behavior.

Structural model

Direct effects. The results of our analysis conducted using Smart PLS provided significant support for several hypotheses in our study. Hypotheses H1a (CO→NA), H2a (CHO→NA), H3a (PR→NA), H4b (HL→INTU), H6 (NA→INTU), H7 (SN→INTU), and H9 (INTU→NAB) were all supported, indicating positive or highly significant positive links between the respective variables. On the other hand, Hypotheses H1b (CO→INTU), H2b (CHO→INTU), H3b (PR→INTU), and H4a (HL→NA) were not supported, as no significant associations were found in these cases. Hypothesis H8 (PBC→INTU) was also supported and showed a highly significant negative relation between PBC and INTU. These findings provide valuable insights into the factors that influenced eHS acceptance in our study.

Mediating effects. We examined multiple variables' combined effects on the intention not to use further. We obtained confirmation for hypotheses H5a and H5b, which indicated that communication and choice overload were associated positively with a negative attitude toward eHS which, in turn, influenced the intention not to use, indicating that a negative attitude plays a mediating role between these variables and the intention not to use. It was confirmed that H5c, which examines PR, has a strong positive relation with negative attitude and intention not to use. H5d, which focused on lower levels of health literacy, demonstrated no significant association between negative attitude and intention not to use. The result showed that the direct path from communication overload to intention not to use was non-significant (path coefficient = 0.06, $p = 0.14$), as was the direct path from choice overload to intention not to use (path coefficient=0.06, $p = 0.19$). Further, the direct path from PR to intention not to use was confirmed to be non-significant (path coefficient = 0.02, $p = 0.71$). When negative attitude mediated the relation between communication and choice overload, and PR, respectively, with the intention not to use, we observed significant positive results. We found a significant effect when negative attitude mediated the relation between communication overload and intention not to use (path coefficient = 0.38, $p = 0.02$). The same could be said of the path of choice overload, negative attitude, and intention not to use (path coefficient = 0.04, $p = 0.02$). Negative attitude's mediating effect between PR and intention not to use was substantial as well (path coefficient = 0.15, $p = 0.00$). Further, the direct path from health literacy to intention not to use was significant (path coefficient = 0.18, $p = 0.00$). However, the negative attitude's mediating effect between health literacy and intention not to use was non-significant (path coefficient = 0.02, $p = 0.35$). Matthews et al. (2018) asserted that if the indirect influence is substantial but the direct effect is not significant, mediation is complete; however, if both the direct and indirect effects are substantial, mediation is partial. H5a-H5C were substantial and supported fully. The data for the direct and indirect paths are represented in Table 4.

Model fit. The R^2 values are considered weak, moderate, or substantial if they are 0.19, 0.33, and 6.0, respectively (Cohen, 2013). According to Falk and Miller (1992), R^2 values up to 0.10 are acceptable. In our study, the R^2 value for rejection behavior was 0.14. This indicated that the combined effect of intention not to use and negative attitude accounted for 14.4% of the variation in rejection behavior; rejection behavior and negative attitude accounted for 36.4% of the variation in intention not to use eHS, and 22.5% of negative attitude variance was explained, all of which surpassed the minimum threshold of 0.10 required for significance. We used cross-validated redundancy (Q^2) to assess the model's performance, where values greater than 0 indicate predictive relevance. A particular endogenous construct has small, moderate, or substantial predictive importance for an exogenous construct when the values are 0.02, 0.15, and 0.35, respectively. In our analysis, rejection behavior and negative attitude showed moderate predictive relevance, while intention not to use eHS exhibited substantial predictive relevance. The values for f^2 are given in Table 5. To evaluate the model's fit, we employed the standardized root mean square. Hu and Bentler's (1998) study suggested that a good fit should have a standardized root mean square below 0.05, although values below 0.10 are also

Table 5 Model fit assessment.

Construct	Effect size				Coefficient of determination (R^2)					Standardized root mean square
	SSO	SSE	Q^2 (= 1-SSE/SSO)		R^2	Adj. R^2				
NAB	1629.00	1432.13	0.12		0.14	0.14				0.04
INTU	1629.00	1099.11	0.33		0.36	0.36				
NA	1629.00	1300.26	0.20		0.23	0.22				
f^2										
	CHO	CO	HL	INTU	NA	NAB	PBC	PR	SN	
CHO	-	-	-	0.004	0.01	-	-	-	-	
CO	-	-	-	0.01	0.01	-	-	-	-	
HL	-	-	-	0.04	0.002	-	-	-	-	
INTU	-	-	-	-	-	0.17	-	-	-	
NA	-	-	-	0.17	-	-	-	-	-	
NAB	-	-	-	-	-	-	-	-	-	
PBC	-	-	-	0.04	-	-	-	-	-	
PR	-	-	-	0.00	0.17	-	-	-	-	
SN	-	-	-	0.04	-	-	-	-	-	

CO communication overload, *CHO* choice overload, *PR* perceived risk, *HL* health literacy, *NA* negative attitude, *SN* subjective norms, *PBC* perceived behavioral control, *INTU* intention not to use eHS, *NAB* non-adoption behavior.

considered permissible. Our model showed a standardized root mean square of 0.04, which suggested a good fit. The results for model fit are summarized in Table 5.

Discussion

To comprehend the factors that influence people's decisions about whether to use eHS, we integrated two influential models: the TPB and the SOR framework. This integration yielded crucial findings that elucidated potential reasons for people's intention not to use eHS and the factors that contribute to their negative attitudes toward eHS.

This research discovered that communication overload increases negative attitudes, which is consistent with Barrett et al. (2023) findings in a previous study. This suggests that patients who experience communication overload may develop a more negative attitude toward eHS. While no direct positive significant effect of communication overload on intention not to use was found in this study, a significant indirect effect was identified through the mediation of negative attitude. Previous studies by Lin et al. (2020) and Pang and Ruan (2023) have also indicated that communication overload has a significant indirect effect on intentions. This implies that communication overload may affect patients' intention not to use eHS through the mediating role of negative attitude. In simpler terms, although the association between communication overload and intention not to use may not be straightforward, communication overload can still affect patients' intention not to use eHS by influencing their negative attitude.

This study confirmed that choice overload contributes directly and significantly to an increase in negative attitudes as well, consistent with the findings of Park and Eves (2023), who emphasized that choice overload leads to adverse outcomes. For instance, Chauhan and Sagar (2021) found that having too many options frequently causes making decisions to be confusing. While no significant direct relation between choice overload and intention not to use was identified, our findings revealed a strong indirect positive effect of choice overload on intention not to use mediated by a negative attitude. This implies that the overwhelming choices in the eHS context may not affect patients' intention not to use eHS directly, but they can influence their intention indirectly through the lens of negative attitude.

In addition, this study confirmed that PR increased negative attitudes, consistent with Caso et al.'s (2022) findings. It also demonstrated that PR increased the intention not to use indirectly through the mediating role of negative attitude. Consistent with Schmiege et al. (2009), who asserted that PR functions as a distal factor that influences an individual's intention by shaping their attitudes and beliefs, this suggests that patients' perceptions of risk lead to negative attitudes and influence their intention not to use indirectly through negative attitude.

Contrary to the expectations presented in H4a, our results indicated that low levels of health literacy had no significant positive effect on negative attitudes. This implies that patients with lower health literacy may not exhibit more negative attitudes inherently, which challenges the assumption that it influences negative attitudes directly. This result is inconsistent with both Chisolm et al. (2011) and Duplaga's (2020) research findings. However, this study did find that lower health literacy had a significant direct relation with intention not to use.

Further, the study revealed that negative attitude affects the intention not to use directly and significantly. A previous study by Bondzie-Micah et al. (2022) also affirmed attitudes' effect on the willingness to use eHS. This implies that patients' negative attitude can affect their engagement with eHS, which highlights the importance of addressing and understanding these attitudes to enhance patients' acceptance and use of eHS.

SN influenced the intention not to use eHS significantly. This indicates that social pressures affect a person's intention to use or not use these services strongly. People are influenced by what those in their social circle think. This finding is consistent with previous literature (AlBar and Hoque, 2019; Hamilton et al., 2021), which affirmed that SN influences people's acceptance of eHS.

In addition, we found that PBC exhibited a solid negative relation with the intention not to use eHS. In simpler terms, when individuals feel more in control of their actions, they are less likely to express an intention not to use eHS. This is an important finding because it suggests that giving people a sense of control over their decisions may motivate them to use eHS. This result is consistent with one from a previous study (AlBar and Hoque, 2019), in which the authors reported that there was no significant association between PBC and behavioral intention to accept eHS, as they also found a significant negative relation between PBC and the intention not to use eHS. This also means that individuals who feel a greater sense of control over their decisions will likely express willingness to use eHS, which is consistent with Bondzie-Micah et al. (2022) and Elkhalifa et al. (2022) findings. This conclusion emphasizes the need to give people a sense of control and confidence in their ability to understand and use eHS. By giving users clear instructions, user-friendly interfaces, and support systems that remove any perceived hurdles, policies and initiatives that promote e-health acceptance should emphasize increasing users' perceived control.

Moving on to the relation between the intention not to use and the actual behavior, which is NAB, we found a strongly positive relation. A previous study by Ong et al. (2023) emphasized the way that intentions can affect actual behavior. Another study by AlBar and Hoque (2019) confirmed that intention affects patients' acceptance of eHS greatly. Similarly, our study demonstrated that the intention not to use affected patients' rejection of eHS. This means that if someone is opposed strongly to using eHS, they are likelier to follow through with rejection behavior.

These results provide valuable insights into the synergies among factors that influence eHS's rejection and offer guidance for policymakers and service providers in developing strategies to enhance eHS acceptance in the context of Nigeria.

Theoretical and practical contributions

Theoretical implications. This study advances our theoretical comprehension of e-health services' rejection significantly by merging two influential models, the TPB and SOR models. This novel integration offers a more comprehensive and nuanced perspective on the crucial factors that influence individuals' intention not to use eHS. By synthesizing these frameworks, we gain a deeper understanding of the complex synergy of psychological and environmental factors in the context of e-health.

Further, this research illuminates eHS rejection's multifaceted nature. First, it challenges conventional assumptions by revealing a non-significant relation between lower levels of health literacy and negative attitudes toward eHS. This finding underscores the issue's complexity and emphasizes that factors that contribute to rejection are not always straightforward. This realization prompts a reevaluation of our approach to addressing e-health rejection.

An important theoretical discovery of this study is the pivotal role that PBC plays. The significant negative relation between PBC and the intention not to use highlights the critical importance of individuals' perceived control over their actions in shaping their intention not to use eHS. This finding extends the TPB framework by underscoring the need to empower individuals with a sense of agency and control in their interactions with e-health platforms.

Practical implications. In addition to its theoretical contributions, this research has practical implications for healthcare practitioners, policymakers, and service providers in Nigeria. Identifying communication and choice overload as contributors to a negative attitude toward eHS offers actionable insights. Nigerian healthcare providers can enhance the user experience by simplifying information and minimizing choices to make e-health platforms more user-friendly and less overwhelming.

Further, recognizing lower levels of health literacy's significance in predicting intention not to use underscores the need for targeted interventions. Health literacy programs can empower individuals, particularly vulnerable populations, with the knowledge and skills to engage with eHS confidently. This practical approach is consistent with improving accessibility and equity in healthcare. The study also emphasizes the importance of enhancing users' sense of control, as evidenced by PBC's role. Practitioners in Nigeria can focus on designing user-centered platforms, providing clear instructions, and establishing robust support mechanisms. By doing so, they can help individuals feel more confident and capable of navigating eHS effectively.

From a policy perspective, this research calls for thoughtful consideration of PBC and communication and choice overload's effects. Policymakers in Nigeria's e-health sector should work to create an environment that fosters individual control and minimizes communication and choice overload simultaneously. Such policies are consistent with the broader goal of increasing eHS acceptance and improving healthcare delivery. These implications may not apply solely to the Nigerian healthcare sector, but also to that of other developing nations, such as Ghana, Cameroon, and Liberia.

Lastly, this study can serve as a catalyst for future research on eHS rejection behavior. It encourages further exploration of the intricate relationship between health literacy and negative attitudes toward eHS acceptance. In addition, it prompts deeper investigations into PBC's dynamics in various e-health contexts. These future studies have the potential to refine strategies to promote e-health services' acceptance and enhance the quality of healthcare delivery in our digital era overall.

In summary, this research enriches our theoretical understanding of e-health services' rejection and offers practical insights into addressing this complex issue. Bridging theory and practice contributes to the overarching mission of improving healthcare accessibility, quality, and equity.

Conclusion

The goal of this study was to reveal the factors that influence people's decisions about whether or not to use eHS in Nigeria by integrating the TPB and SOR frameworks. Our findings showed that communication and choice overload and perceived risk contribute to negative attitudes toward eHS. Contrary to the initial expectation outlined in H4a, which proposed that individuals with lower health literacy would exhibit a negative attitude toward eHS, the findings indicated that, while these individuals showed a greater intention not to use, this inclination did not result necessarily in a negative attitude toward eHS. Social pressures influenced people's intention not to use eHS significantly, thereby highlighting subjective norms' role. On the other hand, perceived behavioral control played a crucial role, in which greater perceived control made people less inclined to refuse to use eHS. These insights have practical implications, as they suggest that simplifying information and offering health literacy programs can enhance acceptance. Policymakers in Nigeria and other developing countries can create user-friendly environments and minimize communication and choice overload to increase eHS's acceptance. This study bridges theory and practice and thus advances our understanding of e-health services' rejection and offers guidance to improve healthcare accessibility and quality in the digital age.

Data availability

The data for this study is freely available at the following link: https://doi.org/10.5281/zenodo.8373862.

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References

Ackerman SL, Tebb K, Stein JC, Frazee BW, Hendey GW, Schmidt LA, Gonzales R (2012) Benefit or burden? A sociotechnical analysis of diagnostic computer kiosks in four California hospital emergency departments. Soc Sci Me 75(12):2378–2385. https://doi.org/10.1016/j.socscimed.2012.09.013

Adenuga KI, Iahad NA, Miskon S (2020) Telemedicine system: service adoption and implementation issues in Nigeria. Indian J Sci Technol 13(12):1321–1327
Ajzen I (1991) The theory of planned behavior. Organ Behav Hum Decis Process 50(2):179–211. https://doi.org/10.1016/0749-5978(91)90020-T
AlBar AM, Hoque MR (2019) Patient acceptance of e-health services in Saudi Arabia: an integrative perspective. Telemed E-Health 25(9):847–852. https://doi.org/10.1089/tmj.2018.0107
Aririguzoh S, Amodu L, Sobowale I, Ekanem T, Omidiora O (2021) Achieving sustainable e-health with information and communication technologies in Nigerian rural communities. Cogent Soc Sci 7(1):1887433. https://doi.org/10.1080/23311886.2021.1887433
Askelson NM, Campo S, Lowe JB, Smith S, Dennis LK, Andsager J (2010) Using the theory of planned behavior to predict mothers' intentions to vaccinate their daughters against HPV. J School Nurs 26(3):194–202
Atinga RA, Abor PA, Suleman SJ, Anaba EA, Kipo B (2020) E-health usage and health workers' motivation and job satisfaction in Ghana. PLoS ONE 15(9):e0239454. https://doi.org/10.1371/journal.pone.0239454
Bagozzi RP, Yi Y (1988) On the evaluation of structural equation models. J Acad Market Sci 16:74–94
Barrett AK, Ford J, Zhu Y (2023) Communication overload in hospitals: exploring organizational safety communication, worker job attitudes, and communication efficacy. Health Commun 38(13):2971–2985. https://doi.org/10.1080/10410236.2022.2129313
Bawden D, Robinson L (2020) Information overload: an overview. In: Oxford Encyclopedia of Political Decision Making. Oxford University Press, Oxford. https://doi.org/10.1093/acrefore/9780190228637.013.1360
Becker S, Bryman A, Ferguson H (2012) Understanding research for social policy and social work: themes, methods and approaches. Policy press
Bezboruah KC, Paulson D, Smith J (2014) Management attitudes and technology adoption in long-term care facilities. J Health Organ Manag 28(3):344–365. https://doi.org/10.1108/JHOM-11-2011-0118
Bingham NE (1972) Toffler, Alvin. Future shock. New York: Bantam Books, Inc., 1971 (540 Pages). Sci Educ 56(3):438–440. https://doi.org/10.1002/sce.3730560328
Blaya JA, Fraser HSF, Holt B (2010) E-health technologies show promise in developing countries. Health Aff 29(2):244–251
Bondzie-Micah V, Qigui S, Arkorful VE, Lugu BK, Bentum-Micah G, Aurelia Naa Ayikaikor Ayi-Bonte (2022) Predicting consumer intention to use electronic health service: an empirical structural equation modeling approach. J Public Aff 22(4):e2677. https://doi.org/10.1002/pa.2677
Cao X, Sun J (2018) Exploring the effect of overload on the discontinuous intention of social media users: an S-O-R perspective. Comput Hum Behav 81(April):10–18. https://doi.org/10.1016/j.chb.2017.11.035
Cao Y, Li J, Qin X, Hu B (2020) Examining the effect of overload on the mhealth application resistance behavior of elderly users: an SOR perspective. Int J Environ Res Public Health 17(18):6658. https://doi.org/10.3390/ijerph17186658
Caso D, Capasso M, Fabbricatore R, Conner M (2022) Understanding the psychosocial determinants of Italian parents' intentions not to vaccinate their children: an extended theory of planned behaviour model. Psychol Health 37(9):1111–1131. https://doi.org/10.1080/08870446.2021.1936522
Chang H-J, Eckman M, Yan R-N (2011) Application of the stimulus-organism-response model to the retail environment: the role of hedonic motivation in impulse buying behavior. Int Rev Retail Distribut Consum Res 21(3):233–249
Chauhan V, Sagar M (2021) Consumer confusion in healthcare decision-making and choice: a qualitative exploration of patient confusion. J Market Theor Pract 29(3):323–342. https://doi.org/10.1080/10696679.2020.1840276
Chen C-C, Yao J-Y (2018) What drives impulse buying behaviors in a mobile auction? The perspective of the stimulus-organism-response model. Telemat Inf 35(5):1249–1262
Chisolm DJ, Hardin DS, McCoy KS, Johnson LD, McAlearney AS, Gardner W (2011) Health literacy and willingness to use online health information by teens with asthma and diabetes. Telemed J E-Health 17(9):676–682. https://doi.org/10.1089/tmj.2011.0037
Cho J, Ramgolam DI, Schaefer KM, Sandlin AN (2011) The rate and delay in overload: an investigation of communication overload and channel synchronicity on identification and job satisfaction. J Appl Commun Res 39(1):38–54
Cho J (2016) The impact of post-adoption beliefs on the continued use of health apps. Int J Med Inf 87(March):75–83. https://doi.org/10.1016/j.ijmedinf.2015.12.016
Cohen J (2013) Statistical power analysis for the behavioral sciences. Academic Press
Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 13(3):319. https://doi.org/10.2307/249008
de Veer AJE, Peeters JM, Brabers AEM, Schellevis FG, Jany JD, Rademakers JM, Anneke LF (2015) Determinants of the intention to use E-health by community dwelling older people. BMC Health Serv Res 15(Mar):103. https://doi.org/10.1186/s12913-015-0765-8
Deng Z, Mo X, Liu S (2014) Comparison of the middle-aged and older users' adoption of mobile health services in China. Int J Med Inf 83(3):210–224. https://doi.org/10.1016/j.ijmedinf.2013.12.002
Duplaga M (2020) The acceptance of key public health interventions by the polish population is related to health literacy, but not ehealth literacy. Int J Environ Res Public Health 17(15):5459. https://doi.org/10.3390/ijerph17155459
Elkhalifa AME, Ahmed BH, EL Mobarak WM (2022) Factors that influence e-health applications from patients' perspective in the Kingdom of Saudi Arabia: an exploratory study. IEEE Access 10:109029–109042. https://doi.org/10.1109/ACCESS.2022.3214203
Falk RF, Miller NB (1992) A primer for soft modeling. University of Akron Press
Fan M, Huang Y, Qalati SA, Shah SMM, Ostic D, Pu Z (2021) Effects of information overload, communication overload, and inequality on digital distrust: a cyber-violence behavior mechanism. Front Psychol 12:643981
Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Market Res 18(1):39–50
Franke G, Sarstedt M (2019) Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. Internet Res 29(3):430–447
Greenwood E, Ramjaun TR (2020) Exploring choice overload in online travel booking. J Promot Commun 8(1):86–104
Hair JF, Ringle CM, Sarstedt M (2011) PLS-SEM: indeed a silver bullet. J Market Theor Pract 19(2):139–152
Hair Jr, JF, Sarstedt M, Ringle CM, Gudergan SP (2017) Advanced issues in partial least squares structural equation modeling. Sage publications
Hamilton K, Keech JJ, Peden AE, Hagger MS (2021) Changing driver behavior during floods: testing a novel e-health intervention using implementation imagery. Safe Sci 136:105141
Henseler J, Ringle CM, Sarstedt M (2015) A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Market Sci 43:115–135
Hossain N, Yokota F, Sultana N, Ahmed A (2019) Factors influencing rural end-users' acceptance of e-health in developing countries: a study on portable health clinic in Bangladesh. Telemed E-Health 25(3):221–229. https://doi.org/10.1089/tmj.2018.0039
Hu L-T, Bentler PM (1998) Fit indices in covariance structure modeling: sensitivity to underparameterized model misspecification. Psychol Method 3(4):424
Islam, Najmul AKM, Whelan E, Brooks S (2021) Does multitasking computer self-efficacy mitigate the impact of social media affordances on overload and fatigue among professionals?. Inf Technol People 34(5):1439–1461
Islam JU, Rahman Z (2017) The impact of online brand community characteristics on customer engagement: an application of stimulus-organism-response paradigm. Telemat Inf 34(4):96–109
Iyengar SS, Lepper MR (2000) When choice is demotivating: can one desire too much of a good thing? J Pers Social Psychol 79(6):995
Keller KL, Staelin R (1987) Effects of quality and quantity of information on decision effectiveness. J Consum Res 14(2):200–213
Kudla NL, Klaas-Wissing T (2012) Sustainability in shipper-logistics service provider relationships: a tentative taxonomy based on agency theory and stimulus-response analysis. J Purch Supply Manag 18(4):218–231
Kujala S, Ammenwerth E, Kolanen H, Ervast M (2020) Applying and extending the FITT framework to identify the challenges and opportunities of successful ehealth services for patient self-management: qualitative interview study. J Med Internet Res 22(8):e17696
Larson LE, Harris AM, Asencio R, Carter DR, DeChurch LA, Kanfer R, SJ Zaccaro SJ (2020) Cross-disciplinary team design, communication overload, and innovation. In: Academy of Management Proceedings, 2020:21054. Academy of Management Briarcliff Manor, NY 10510
Lin J, Lin S, Turel O, Xu F (2020) The buffering effect of flow experience on the relationship between overload and social media users' discontinuance intentions. Telemat Inf 49(Jun):101374. https://doi.org/10.1016/j.tele.2020.101374
Liu Y, Cai L, Ma F, Wang X (2023) Revenge buying after the lockdown: based on the SOR framework and TPB model. J Retail Consum Serv 72:103263
Liu C, Bao Z, Zheng C (2019) Exploring consumers' purchase intention in social commerce: an empirical study based on trust, argument quality, and social presence. Asia Pacific J Market Logist 31(2):378–397
Marangunić N, Granić A (2015) Technology acceptance model: a literature review from 1986 to 2013. Univ Access Inf Soc 14(1):81–95. https://doi.org/10.1007/s10209-014-0348-1
Matthews L, Hair JOE, Matthews R (2018) PLS-SEM: the holy grail for advanced analysis. Market Manag J 28(1):1–87
McFarlane DC, Latorella KA (2002) The scope and importance of human interruption in human-computer interaction design. Hum-Comput Interact 17(1):1–61
McFarlane DC (1998) Interruption of people in human-computer interaction. The George Washington University

Mehrabian A, Russell JA (1974) An approach to environmental psychology. an approach to environmental psychology. The MIT Press. Cambridge, MA, USA
Mekonnen ZA, Gelaye KA, Were MC, Tilahun B (2021) Mothers intention and preference to use mobile phone text message reminders for child vaccination in northwest Ethiopia. BMJ Health Care Inf 28(1):e100193. https://doi.org/10.1136/bmjhci-2020-100193
Misuraca R, Teuscher U (2013) Time flies when you maximize—maximizers and satisficers perceive time differently when making decisions. Acta Psychol 143(2):176–180
Nagar K, Gandotra P (2016) Exploring choice overload, internet shopping anxiety, variety seeking and online shopping adoption relationship: evidence from online fashion stores. Glob Bus Rev 17(4):851–869. https://doi.org/10.1177/0972150916645682
Noguchi T, Hills TT (2016) Experience-based decisions favor riskier alternatives in large sets. J Behav Decis Making 29(5):489–498
Norman ID, Aikins MK, Binka FN (2011) Ethics and electronic health information technology: challenges for evidence-based medicine and the physician-patient relationship. Ghana Med J 45(3):115–124
O'Conaill B, Frohlich D (1995) Timespace in the workplace: dealing with interruptions. In: Conference Companion on Human Factors in Computing Systems. pp. 262–263
Ong AKS, Prasetyo YT, Borja A-KFP, Hosillos FA, Perez YFN, Robas KP, Persada SF, Nadlifatin R (2023) Factors affecting revisiting behavior to taal volcano during the post recovery 2020 eruption: an extended theory of planned behavior approach. Int J Disaster Risk Reduct 86(Feb):103552. https://doi.org/10.1016/j.ijdrr.2023.103552
Ossebaard HC, Van Gemert-Pijnen L (2016) eHealth and quality in health care: implementation time. Int J Qual Health Care 28(3):415–419
Pandita S, Mishra HG, Chib S (2021) Psychological impact of Covid-19 crises on students through the lens of stimulus-organism-response (SOR) model. Child Youth Serv Rev 120:105783
Pang H, Ruan Y (2023) Determining influences of information irrelevance, information overload and communication overload on WeChat discontinuance intention: the moderating role of exhaustion. J Retail Consum Serv 72(May):103289. https://doi.org/10.1016/j.jretconser.2023.103289
Park S, Eves A (2023) Choice overload in tourism: moderating roles of hypothetical and social distance. J Travel Res (Sept) 00472875231197379. https://doi.org/10.1177/00472875231197379
Pfaff H (2013) Optionsstress und Zeitdruck. In: Immer schneller, immer mehr. Bundesanstalt Für Arbeitsschutz Und Arbeitsmedizi, Gisa Junghanns, and Martina Morschhäuser, (eds.). Springer Fachmedien Wiesbaden, Wiesbaden. pp. 113–143
Pilli LE, Mazzon JA (2016) Information overload, choice deferral, and moderating role of need for cognition: empirical evidence. Revista de Administração (São Paulo) 51:36–55
Podsakoff PM, MacKenzie SB, Lee J-Y, Podsakoff NP (2003) Common method biases in behavioral research: a critical review of the literature and recommended remedies. J Appl Psychol 88(5):879–903. https://doi.org/10.1037/0021-9010.88.5.879
Pomerleau M (2008) Electronic health record: are you ready for the next step? Nurs Women's Health 12(2):151–156. https://doi.org/10.1111/j.1751-486X.2008.00300.x
Qi X, Ploeger A (2021) An integrated framework to explain consumers' purchase intentions toward green food in the Chinese context. Food Qual Pref 92(Sept):104229. https://doi.org/10.1016/j.foodqual.2021.104229
Rahman KT, Bansal R (2023) Combating choice overload via a growth mindset in the age of social media. In: Strengthening SME Performance Through Social Media Adoption and Usage. IGI Global. pp. 96–105
Regmi PR, Waithaka E, Paudyal A, Simkhada P, van Teijlingen E (2016) Guide to the design and application of online questionnaire surveys. Nepal J Epidemiol 6(4):640–644. https://doi.org/10.3126/nje.v6i4.17258
Rittichainuwat BN, Chakraborty G (2009) Perceived travel risks regarding terrorism and disease: the case of Thailand. Tour Manag 30(3):410–418. https://doi.org/10.1016/j.tourman.2008.08.001
Roemer E, Schuberth F, Henseler J (2021) HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. Ind Manag Data Syst 121(12):2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082
Sampa MB, Hossain MN, Hoque MR, Islam R, Yokota F, Nishikitani M, Fukuda A, Ahmed A (2020) Influence of factors on the adoption and use of ICT-based eHealth technology by urban corporate people. J Serv Sci Manag 13(01):1
Schmiege SJ, Bryan A, Klein WMP (2009) Distinctions between worry and perceived risk in the context of the theory of planned behavior. J Appl Soc Psychol 39(1):95–119
Settle RB, Golden LL (1974) Consumer perceptions: overchoice in the market place. ACR North Am Adv 1(1):29–37
Simonds SK (1974) Health education as social policy. Health Educ Monogr 2(1_suppl):1–10. https://doi.org/10.1177/10901981740020S102
Sørensen K, Van den Broucke S, Pelikan JM, Fullam J, Doyle G, Slonska Z, Kondilis B, Stoffels V, Osborne RH, Brand H (2013) Measuring health literacy in populations: illuminating the design and development process of the European Health Literacy Survey Questionnaire (HLS-EU-Q). BMC Public Health 13(1):10
Suess C, Mody M (2018) The influence of hospitable design and service on patient responses. Serv Ind J 38(1–2):127–147
Tagde P, Tagde S, Bhattacharya T, Tagde P, Chopra H, Akter R, Kaushik D, Rahman MH (2021) Blockchain and artificial intelligence technology in e-health. Environ Sci Poll Res 28(38):52810–52831. https://doi.org/10.1007/s11356-021-16223-0
Talwar S, Talwar M, Kaur P, Dhir A (2020) Consumers' resistance to digital innovations: a systematic review and framework development. Australas Market J (AMJ) 28(4):286–299. https://doi.org/10.1016/j.ausmj.2020.06.014
Talwar S, Dhir A, Islam N, Kaur P, Almusharraf A (2023) Resistance of multiple stakeholders to E-health innovations: integration of fundamental insights and guiding research paths. J Bus Res 166:114135
Tanwar S, Parekh K, Evans R (2020) Blockchain-based electronic healthcare record system for healthcare 4.0 applications. J Inf Secur Appl 50(Feb):102407. https://doi.org/10.1016/j.jisa.2019.102407
Tao D, Yuan J, Shao F, Li D, Zhou Q, Qu X (2018) Factors affecting consumer acceptance of an online health information portal among young internet users. Comput Inf Nurs 36(11):530. https://doi.org/10.1097/CIN.0000000000000467
Tehseen S, Hassan Qureshi Z, Johara F, Ramayah T (2020) Assessing dimensions of entrepreneurial competencies: a type II (reflective-formative) measurement approach using PLS-SEM. 15(2):108–145
Teviu EAA, Aikins M, Abdulai TI, Sackey S, Boni P, Afari E, Wurapa F (2012) Improving medical records filing in a municipal hospital in Ghana. Ghana Medical Journal 46(3):136
Tripathy S, Aich S, Chakraborty A, Lee GM (2016) Information technology is an enabling factor affecting supply Chain performance in Indian SMEs: a structural equation modelling approach. J Model Manag 11(1):269–287. https://doi.org/10.1108/JM2-01-2014-0004
van Zoonen W, Sivunen A, Rice RE (2022) Benefits and drawbacks of communication visibility: from vicarious learning and supplemental work to knowledge reuse and overload. J Knowl Manag 26(11):214–233
Vergura DT, Zerbini C, Luceri B (2020) Consumers' attitude and purchase intention towards organic personal care products. An application of the S-O-R model. Sinergie Italian J Manag 38(1):121–137. https://doi.org/10.7433/s111.2020.08
Walle AD, Demsash AW, Adem JB, Wubante SM, Shibabaw AA, Mamo DN, Kebede SD et al. (2023) Exploring facilitators and barriers of the sustainable acceptance of e-health system solutions in Ethiopia: a systematic review. PLoS ONE 18(8):e0287991. https://doi.org/10.1371/journal.pone.0287991
Wang T, Wang W, Liang J, Nuo M, Wen Q, Wei W, Han H, Lei J (2022) Identifying major impact factors affecting the continuance intention of mHealth: a systematic review and multi-subgroup meta-analysis. NPJ Digit Med 5(1):145
Whelan E, Najmul Islam AKM, Brooks S (2020) Is boredom proneness related to social media overload and fatigue? A stress–strain–outcome approach. Internet Res 30(3):869–887
Wilson J, Heinsch M, Betts D, Booth D, Kay-Lambkin F (2021) Barriers and facilitators to the use of e-health by older adults: a scoping review. BMC Public Health 21(1):1556. https://doi.org/10.1186/s12889-021-11623-w
World Health Assembly, 58. (2005) Fifty-Eighth World Health Assembly, Geneva, 16–25 May 2005: Resolutions and Decisions: Annex. WHA58/2005/REC/1. World Health Organization. https://apps.who.int/iris/handle/10665/20398
World Health Organization (2022) Health literacy development for the prevention and control of noncommunicable diseases: volume 4: case studies from WHO national health literacy demonstration projects. World Health Organization
Wu I-L, Chiu M-L, Chen K-W (2020) Defining the determinants of online impulse buying through a shopping process of integrating perceived risk, expectation-confirmation model, and flow theory issues. Int J Inf Manag 52(Jun):102099. https://doi.org/10.1016/j.ijinfomgt.2020.102099
Yusif S, Hafeez-Baig A, Soar J (2020) An exploratory study of the readiness of public healthcare facilities in developing countries to adopt health information technology (HIT)/e-Health: the case of Ghana. J Healthcare Inf Res 4(2):189–214. https://doi.org/10.1007/s41666-020-00070-8
Zeike S, Choi K-E, Lindert L, Pfaff H (2019) Managers' well-being in the digital era: is it associated with perceived choice overload and pressure from digitalization? An exploratory study. Int J Environ Res Public Health 16(10):1746. https://doi.org/10.3390/ijerph16101746
Zhang T, Tao D, Qu X, Zhang X, Lin R, Zhang W (2019) The roles of initial trust and perceived risk in public's acceptance of automated vehicles. Transp Res Part C Emerg Technol 98(Jan):207–220. https://doi.org/10.1016/j.trc.2018.11.018
Zhao J (2022) Artificial intelligence and corporate decisions: fantasy, reality or destiny. Catholic Univ Law Rev 71(4):663–698

Zhu H, Yang Z, CXJ Ou, Liu H, Davison RM (2016) Investigating the Impacts of Recommendation Agents on Impulsive Purchase Behaviour. arXiv Preprint 1–15. https://doi.org/10.48550/arXiv.1606.01349

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Author contributions
MF, BCE, and SAQ made equal and significant contributions to all aspects of the research, including conceptualization, design, data analysis, manuscript preparation, and final approval for submission.

Competing interests
The authors declare no competing interests.

Ethical approval
This study was conducted in strict adherence to the ethical guidelines outlined in the Ethical Principles of Psychologists and Code of Conduct of the American Psychological Association. The research proposal, including its objectives, methods, and participant engagement strategies, was rigorously reviewed and subsequently approved by the Ethics Committee of the Management School at Jiangsu University. Approval was granted on September 2023, with the assigned ethical approval number being JU-ECMS-2023-002. This approval confirms that the study's design, recruitment plan, and data handling procedures were deemed to meet the required ethical standards for research involving human subjects.

Informed consent
Informed consent was rigorously sought and obtained from all participants prior to their involvement in the study. This process was initiated by clearly communicating the study's objectives, procedures, potential risks, and benefits to the participants. Each participant was informed of their right to withdraw from the study at any point without facing any repercussions. Consent was documented in writing, with participants signing consent forms that were then securely stored as per the ethical guidelines. This process ensured that all participants voluntarily agreed to partake in the study with a full understanding of what their involvement would entail. The consent forms and process were reviewed and approved by the Ethics Committee of Management School at Jiangsu University as part of the ethical approval process, ensuring adherence to ethical standards for informed consent.

Additional information
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