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# Essays on Individuals' Information Assessment, Information Disclosure, Participation, and Response Behaviors in Online Health Communities

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# ESSAYS ON INDIVIDUALS' INFORMATION ASSESSMENT, INFORMATION DISCLOSURE, PARTICIPATION, AND RESPONSE BEHAVIORS IN ONLINE HEALTH COMMUNITIES

A Dissertation

by

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ABSTRACT

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Essay 1 investigates how user information characteristics are related to user disclosure mechanisms, how disclosure mechanisms lead to acceptable support response, and the moderating role of anticipated feelings. Results from a moderated support response acceptance model based on the health disclosure decision-making model (DD-MM) reveal that sensitive information increases the density of information disclosure while severe information leads to increase in the efficacy of information disclosure. Further, individuals' disclosure mechanisms increase support response acceptance. The results also show that anticipated feeling has a significant moderating effect on the hypothesized relationships. As a novel theoretical contribution, the study unravels an extended empirically validated DD-MM that can be applied in other related management disciplines. This study also advances the information disclosure literature and provide a framework that helps to explain how users can increase support response acceptance in OHCs.

Essay 2 departs from prior literature that have investigated user online disclosure as a static phenomenon by examining the longitudinal dynamics of user information disclosure and audience support response acceptance.

This study proposes a structural vector autoregression model that assesses the reverse causality in the system of variables based on the DD-MM framework. Findings of the impulse response functions reveal that user information density leads to positive support response acceptance, whereas support response acceptance reduces the information density of a user post over time. Similarly, the results also show that user information efficacy leads to positive support response acceptance, and the latter improves information efficacy in the long run. Theoretically, the findings extend the DD-MM framework by illustrating the recursive relationship between disclosure efficacy and response efficacy. Practically, the results provide insights for managers to promote continuous participation in OHCs.

Essay 3 uses the dimensions of social presence theory to identify first impression cues in users' posts in OHCs. It examines the association of four impression cues, intimacy, immediacy, efficiency, and non-verbal communication with participation using decision trees (DT) technique. The DT induction approach allows for both theory development and testing in two phases. The first phase applies decision tree induction approach to abduct a set of hypotheses using data from inspire.com. Phase 2 empirically tests three new models using data from a different context, patient.info. The findings indicate that, while intimacy moderates the effects of efficiency and nonverbal communication on giving and receiving, respectively, nonverbal communication moderates the effects of intimacy and efficiency on overall participation. The study contributes to the health IT communication literature by proposing and validating theoretical explanations for each user participation type in OHCs: giving, receiving, and general.

## DEDICATION

I dedicate this entire work, first and foremost, to God Almighty who led me to, and guided me through my doctoral studies. Thank you for the strength, wisdom, and guidance that You provided me. Your presence inspired and encouraged me to believe for infinite possibilities. You are my rock.

Second, I dedicate this piece to my wife and our three lovely children. Clarise Ade Manga, my ever-loving wife, you prayed for me, believed in me, encouraged me, and endured me through the frustrating moments. I could never thank you enough! Abijoy, Solien-Pearl, and Zoe-Ann my precious daughters, who never seized to be concerned that I finish my work on time. Joe-Praise, my loving son, thank you for the encouraging smiles you gave me in those tiring moments. You all made me feel supported. I am grateful to my parents, late Pa. Forbang Ade Zacharia and Mama Anobit Ade Julie. You all were such a great support.

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CHAPTER I

# INTRODUCTION

## 1.1. Overview

Individuals crave for various types of supports (emotional, informational, social) to help them manage stressful situations in life, which can be received through different media. Online health communities (OHCs) provide avenues for healthcare stakeholders (patients, professionals, and patients' surrogates) to deliver and receive patient-centered supportive care management (van der Eijk et al., 2013). Through these OHC platforms, individuals increasingly engage in various activities such as, disclosure of information (Zhang et al., 2018), participation in in the community (Gao et al., 2017), and provision of responses to peers (Huang et al., 2019). These activities can be categorized under one concept, supportiveness, an important facet of user interactivity in OHCs.

Recently, investigation of individuals' online support behaviors (i.e., information disclosure, response, and participation) behavior in OHCs is attracting much attention as many people turn to OHCs, a supportive environment that addresses their health needs (e.g., Zhang et al., 2017; Zhang et al., 2018; Liu et al., 2020; Wu & Deng, 2019; Wang et al., 2017). The need for support is one of the reasons driving the interplay between users' information disclosure and response behaviors and information systems.

Such behaviors have attracted considerable attention from scholars and experts in terms of how information systems and technologies shape and impact disclosure and response behaviors, encourage user participation and how user behaviors inform the use and design of technologies and artifacts.

The effects and consequences of user behaviors are crucial to determining individual, collective, and organizational disclosure, and responsive outcomes such as individuals' disclosure efficacy, effective response provision, recursive communication mechanisms between users, and online community participation through giving and receiving.

## 1.2. Motivation and Scope of Study

The emerging world of online health communities will determine the future of healthcare delivery as these platforms provide a medium for patients, caregivers, and healthcare professionals to share sensitive information (personal and health-related) and provide support to one another. These platforms are disrupting the traditional health systems by empowering the patients and healthcare staffs to effectively engage in responsive behaviors such as, patient-care management and quality care delivery through virtual healthcare (van der Eijk et al., 2013). So, it is important to gain an in-depth insight of user support behaviors in these online health platforms. Such behaviors range from information disclosure, information seeking, response provision, participation, knowledge contribution, social support, and community engagement. Patients and platforms management are, thus, benefiting from OHC activities through the support received and continuous participation by users. Individuals' support behaviors through response provision enables patients to handle emotional, social, and health challenges (Huang et al., 2019) while continuous participation by users helps generate huge amounts of patient data that can be used for research in order to improve healthcare management (Jee & Kim, 2013).

While there has been much research on individuals' disclosure, participation, and response behaviors in general sites (e.g., Appari & Johnson, 2010; Bansal & Gefen, 2010; Anderson & Agarwal, 2011; Bélanger & Crossler, 2011; Fichman et al., 2011), none of these studies has specifically explored i) the alignment between the participants' disclosed information and the effectiveness of the response patients receive; ii) how users' assessment of an initial message (first impression present in the message) can affect online content generation (giving) or content consumption (receiving) by participation; and iii) the two-sided relationship between user information disclosure and response behaviors in OHCs, even though the OHCs require effective two-sided communication between disclosers and responders. The increasing prominence of OHCs across the world, suggests that patients, caregivers, clinicians, researchers, academics are highly relying on these platforms for mutual benefits.

However, it is unclear a) to what extent the users consider the supports they receive as beneficial or helpful to the information that is disclosed; b) whether or not there is a two-way interaction between user disclosure and response efficacy behaviors; and c) how users' presence in OHCs demonstrated through their messages affects their participation in generating contents (giving) or consuming contents (receiving) (e.g., Zhou, 2020). Patients' assessment of information and their disclosure abilities in online communities could impact participants' support behaviors in OHCs. To fully understand the current state of user behaviors in OHCs, it is important to gain a more complete picture of patients' disclosure, participation, and response behaviors in online platforms.

### 1.3. Statement of the Problem and Research Questions

Information disclosure literature in OHCs has largely focused on factors that motivate individuals' disclosure abilities including relationships developments and self-expressions (Yang

& Tan, 2011), anonymity of the platforms that enhances user's confidence to disclose information (Kang et al., 2013), patient's privacy protection (Balani & De Choudhury, 2015; Jena, 2015; Kam & Chismar, 2005), and enhancing of individual social capital, informational, emotional supports, and provision of feedback responses (Huang et al., 2019; Chen et al., 2019; Zhang et al., 2018). However, the response provided to the disclosed information sometimes does not necessarily constitute effective feedback unless it is regarded as useful or beneficial to the discloser (Wang et al., 2015).

Furthermore, previous research has mostly modeled OHCs as one-way communication medium by examining the influence of information disclosure on response stakeholders receive, which does not capture the full interactivity among all the stakeholders on the online platforms over time. Finally, in studying user participation in OHCs, prior research has mostly lumped user participation as an aggregate of an individual's overall activity. However, individuals' participation can differ with respect to the knowledge they contribute to others on the platform (giving) or the knowledge they acquire from others on the platform (receiving).

Given the above challenges that arise due to possible limitations in prior research, therefore, I address the following the following research questions. 1. *What participant information disclosure mechanisms elicit effective community response in online health community forums?* 2. *Is there a two-way relationship between users' information disclosure and response behaviors in online health communities?* 3. *How do the dimensions of social presence theory in patients' initial postings interact to influence an individual's giving or receiving participation behavior in an online health community?*

### 1.4. Relevance and Objective of the Study

OHCs facilitate two-way communication between users on the platform and this is crucial because it foster a supportive environment, community engagement, trust, knowledge sharing, and sustained participation. So, to answer the aforementioned questions, this research seeks to establish the alignment between users' information disclosure and response behaviors based on the disclosure decision-making model (DD-MM). DD-MM theorizes the mechanism patients and caregivers make disclosure decisions regarding health condition (Greene, 2009a).

Additionally, this study considers the fact that OHCs constitute a two-way communication medium between disclosers and responders; and it seeks to develop a two-way interactive model that examines users' disclosure and response behaviors in OHCs. This study argues that effective two-way communication leads to user-generated content that is critical to continuous participation by patients and healthcare providers. From an econometric perspective, the study applies the vector autoregression technique to estimate our model and examines the two-way interactions between users' efficacy behaviors.

In OHCs, the knowledge contributed or generated by users on the platforms is acquired or consumed by other peers. Moreover, distinguishing giving participation from receiving participation provide interesting insights at the granular level. Thus, the final goal of this research is to investigate how users' social presence in OHCs expressed in their disclosed messages influence participation in the form of giving or receiving. We follow a decision tree induction approach for the theory development using the social presence theory.

### 1.5. Contributions of the Study

Insights from this study contributes to both theory and practice. To theory, i) by theorizing disclosure efficacy as information density and information breadth, and response efficacy as multidimensional concept comprising information persuasiveness and response persuasiveness, we demonstrate theoretically and empirically that the two higher order/abstract constructs are better represented as first-order constructs with differing relative effects in their relationships; ii) the proposed model theorizes two-way dynamic relationships that foster community engagement and user interactions through the disclosure of information and provision of support to build health resilience. Moreover, the intervening mechanism and outcome of DD-MM have a recursive relationship. This extends the frontiers of DD-MM that had hitherto postulated a unidirectional relationship; iii) reconceptualizing participation into granular components including giving or receiving, the results reveal that first impression in patients' initial communication is important in eliciting user's participation in either giving or receiving.

To practice, i) managers may offer participants tools such as customizable auto-complete text features relevant to the OHCs context to improve the breadth of the sentences in the post.

## 1.6. Definition of Key Concepts

Table 1.1 summarizes the 21 key phrases and variables I use in this thesis. It covers the concepts, definitions, and the source from which the variables are obtained.

Table 1. 1: Concepts and Definition

| Concept | Definition | Source |
|---|---|---|
| Support Behavior | "The degree to which an individual perceives that a response was satisfactory in terms of its appropriateness and relevance in meeting the particular information need." | (Nambisan et al., 2016, p. 90) |
| Information Disclosure | The extent to which individuals are willing and confident to reveal their information in online networks. | (Yang & Tan, 2011) |
| Information Assessment | The degree to which a discloser appraises their information being disclosed. | (Greene, 2015) |
| Information Nature | The degree to which a patient on OHC platform appraises their information being disclosed as discrediting or worthy of disgrace. | |
| Information Sensitivity | The degree to which a patient on OHC platform believes that the information being disclosed is urgent and important to share. | |
| Receiver Assessment | The degree to which the discloser evaluates the response of a specific disclosure target. | (Greene et al., 2012) |
| Anticipated Response | The degree to which a discloser on OHC platform evaluates the expected response before disclosing information. | |
| Disclosure Efficacy | The degree to which disclosers feel confident about revealing their information. | (Greene, 2009a) |
| Information Density | The degree to which the information a patient discloses on an OHC forum is sufficient in depth/scope. | |
| Information Breadth | The degree to which the information a patient discloses on an OHC forum is strong and well written. | |
| Response Efficacy | The degree to which the discloser believes that the recommended response provided will be effective. | (Woon et al., 2005; Johnston & Warkentin, 2010) |
| Information Persuasiveness | The degree to which a patient in an OHC platform assesses the disclosed information or message to be comprehensible and understandable. | |
| Response Persuasiveness | The degree to which a patient on OHC platform assesses that the disclosed information or message can generate feedback that is useful and beneficial. | |
| Participation | "The frequency of communication to the intensity with which an individual engages within a community" | (Johnston et al., 2013) |

Table 1.1, cont.

| | | |
|---|---|---|
| Giving Participation | The degree to which individuals contribute knowledge in online platforms by generating content (e.g., posting messages, replying to posts). | (Chung et al., 2015; Cavusoglu et al., 2016; Zhou, 2020) |
| Receiving Participation | The degree to which individuals acquire online content by consuming content that is generated (e.g., receiving likes, comments, support). | (Chung et al., 2015; Cavusoglu et al., 2016) |
| Social Presence | Social presence is the ability to use communication media to transmit social cues when interacting on a social media platform. | (Xu et al., 2012; Short et al., 1976) |
| Intimacy | Intimacy is defined as the feeling of closeness and belonging that two people may feel with each other. | (Zelizer, 2000) |
| Immediacy | Giving urgency or importance to an exchange. | (Dixson et al., 2017; Cobb, 2009) |
| Efficiency | The degree to which users in an OHC judge the reliability of communicating their messages across to the target. | (Short et al., 1976; Lim et al., 2013) |
| Nonverbal Communication | The extent to which individuals participating in an online forum use cues in their writings to express their feelings and emotions | (Dixson et al., 2017) |

## 1.7. Organization of the Research

The remainder of the study is organized as follows. Chapter 2 reviews previous literature in information disclosure, disclosure decision-making model, participation, social presence theory, and online health communities. Chapter 3 focuses on examining situational factors that influence participants' information disclosure behaviors and the subsequent response to these disclosures. Chapter 4 examines the two-way relationship between individuals' efficacy (disclosure and response) behaviors in online health communities. Chapter 5 discusses how the dimensions of social presence theory interact to influence individuals' participation in giving and receiving. Lastly, chapter 6 summarizes the key findings, contributions, some limitations, and future research directions.

CHAPTER II

LITERATURE REVIEW

## 2.1. Information Disclosure

Information disclosure (also used interchangeably with self-disclosure) has received wide coverage by information systems researchers in the past decades (Zhang, 2015). Recent study suggests that although individuals may disclose information through clickstreams without their awareness, participation in self disclosure requires intentional release of personal information in terms of breadth (amount) and depth (content) (Wakefield, 2013). Furthermore, online information disclosure can be in the form of demographic-type information, psychographic information (e.g., age, location), and through authentication where individuals are required to register before using the service (Wakefield, 2013; Jourard, 1971). Past research has outlined relationship development, social validation, self-expression, anonymity as some motives that affect people's self-disclosure on online social networks (Yang & Tan, 2011). Table 2.1 summarizes the review of past studies that examine the individuals' information disclosure behaviors from a variety of theoretical perspectives and using different methods.

In addition, other motivating factors such as context sensitivity, perceptions of privacy, and the information value of content and feedback also affect people's self-disclosure behaviors (Kam & Chismar, 2005).

In investigating the contributing factors that affect the disclosure of personal information in the online community context, past study found that privacy concerns negatively impacts information disclosure whereas, because of the informational and emotional supports that individuals wish to benefit from online communities, they are willing to disclose their information (Zhang et al., 2018).When it comes to the issue of privacy and information disclosure, research findings are split. While most studies argue for the negative impact of privacy on individuals' willingness to disclose personal health information (Zhang et al., 2018; Yoo et al., 2013; Jena, 2015), some are in support of the fact that some patients tend to disclose more symptoms and undesirable behaviors online because of the benefit of anonymity and the gravity of the conditions (Balani & De Choudhury, 2015; Greist et al., 1973; Smyth, 1998). One possible reason for this disparity could be that the nature of the disease and the characteristics of different community platforms influence can shape individuals' disclosure behaviors.

Additionally, the method used to collect the data for analysis could also affect the findings of previous studies. Therefore, it is necessary to conduct further research to better understand the nature of the information and how the types of communities contribute to individuals' propensity to disclose personal health information. To further address these worries, we draw from the disclosure decision-making model, which constitutes the basis of our conceptual underpinning.

Table 2. 1: Literature Review on Information Disclosure in Leading IS Proceedings/Journals

| **Author/Year/Journal** | **Constructs** | **Theory** | **Method** | **Findings** | **Gaps** | **Context** |
|---|---|---|---|---|---|---|
| (Zhang, 2015) | **DV**: Disclosure **IVs**: log (Asset) for firm size, EBITDA (firm profitability), intangible asset (info. Asymmetry), liability (debt-leverage ratio) | Adoption of new communication media—Social media content and firm stock performance | Cluster analysis with high and low adopters of new media, K-means method for clustering. | A company's voluntary information disclosure on social media is positively related to its adoption level of new media. Engagement of information disclosure on new media increases a company's influence and reach | Only few studies investigate voluntary disclosure on new media including social media, mobile apps, RSS. The effect of technology adoption on a firm's voluntary ID has not been studied. | Organizational or business |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Zimmer et al., 2010) | **DV**: Information Disclosure **IVs**: privacy, trust, intent, benefits, dyadic condition (nondyadic, reasoned, unreasoned). | Social Response Theory and the Principle of Reciprocity | Experiment | Findings show that by implementing a reasoned dyadic condition where the organization provides reasoning on why they are collecting particular information; individuals are more likely to actually disclose more information. Reciprocity can enhance the design of information acquisition systems. | Study treads new grounds by examining the link between intent to and actual disclosure. | Organizational individuals (Non-commercial) |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (De Souza & Dick, 2009) | **DV**: Information disclosure **IVs**: peer pressure, signaling, trust, myopic view of privacy risks, website interface design, relaxed attitudes to privacy | Social networking | Survey for data collection. Regression-to validate a proposed model of the factors influencing information disclosure. Cluster analysis provides an indication of characteristics shared by children who disclose sensitive information. | Results show that children who are taught to value privacy are less likely to disclose sensitive information on-line. Younger children show greater tendency to disclose. | Sharing of personal information in the media has been highlighted as a major concern, especially for younger users. Why children disclose information and their understanding of some privacy issues involved. | Social computing |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Keith et al., 2015) | **DV**: Disclosure **IVs**: mobile computing self-efficacy, perceived risk, perceived benefit, privacy concern, privacy setting, age, gender, ethnicity | Social cognitive theory | Controlled experiment | Results demonstrate the strong direct effect of mobile computing self-efficacy on users' initial trust in location-based app vendors as well as their perceived risk of disclosing information – regardless of the actual trustworthiness of the app vendor | Traditional Indicators (s.a. IT quality, trust, social influence) appear to have a lesser impact on the adoption of mobile commerce via apps because of the nature of mobile-app adoption and subsequent information disclosure. | Smartphones and mobile apps (location-based services). Being skilled in the latest smartphones and apps can cause users to place greater trust in app providers and perceive less risk in the app itself, even when the intentions of the app providers cannot be verified. |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Buckman et al., 2019) | **DV**: willingness-to-accept—value that individuals place on the online disclosure of their private information in the presence of multiple privacy factors (IVs).<br>**IVs**: information context, secondary use, & identifying information, false information, web usage, breach history, gender, age, education. | Privacy valuation literature and privacy calculus. | Randomized experiment | Studying multidimensional information disclosure decisions, which combine important privacy factors, which has not been considered in prior literature. Address the limitations for measuring privacy valuations through experimental economics method. | Results show increased risk introduced by the experimental factors (information context, secondary use, & identifying information), and the increased saliency and awareness do lead to higher privacy valuations on average. | Shopping, students, and industry (AMT). |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Hao & Tan, 2019) | **DV**: Incentive to facilitate information disclosure (S-driven scenario where the supplier dictates whether to facilitate ID and R-driven scenario where retailer dictates to facilitate. **IVs**: product's retail price, wholesale price, degree of informativeness of information, firm's margin, supplier's profit, retailer's profit. | Wholesale pricing model and Agency pricing model | Game-theoretical model | Results show that when a product has medium or high dispersion in its consumers' true valuation distribution and the degree of information disclosure before facilitation is moderate, two parties might have opposing interests as to more information disclosure. | Consumers have different true valuations of a product yet each consumer is uncertain about her own valuation due to lack of full information about the product's characteristics before purchase. Results suggest that information disclosure facilitation has a different interplay with the revenue sharing mechanism in the agency model than with double marginalization in the wholesale model. | Organizational, online retailing. |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Mitra & Ransbotham, 2015) | **DV**: Number of information security attacks. **IVs**: information disclosure (limited or full disclosure)-focal variables. Control variables: complexity of vulnerability (low, medium, & high), impact of vulnerability (confidential, integrity, availability), vulnerability defect types (input validation, design, exception), market, server, signature, patch, alternatives, workload. | Information security and diffusion of innovation | Non-linear least squares estimation and the Cox proportional hazard model. The Cox proportional hazard model estimates the likelihood (hazard rate) that a specific vulnerability is exploited (failure event) at a specific firm on the focal day, given that it has not been exploited at that firm prior to that day. | Findings reveal that full disclosure accelerates the diffusion of attacks, increases the penetration of attacks within the target population, and increases the risk of first attack after the vulnerability is reported. Interestingly, the effect of full disclosure is greater during periods when there are more overall vulnerabilities reported, indicating that attackers may strategically focus on busy periods. | The debate on ID centers on trade-offs inherent in disclosing information that society needs, but that can also be used for nefarious purposes. This study examines the adoption of software vulnerabilities by a population of attackers. We compare attacks based on software vulnerabilities disclosed through full-disclosure and limited-disclosure mechanisms. | Organizational (innovation diffusion—information security context) |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Keith et al., 2012) | **DV**: intent to disclose<br>**IVs**: perceived privacy risk, perceived benefits, existing privacy risk, existing benefits, probability of new risks, impact of new risks, privacy risk awareness, mobile self-efficacy, privacy concerns. | Privacy calculus theory, Prospect theory, & interpersonal choice | 3 x 2 x 2 factorial experimental design | Study finds mobile app consumers strongly consider their previous privacy risk exposure (i.e., "How much of my personal information is already stored and shared unethically?") when making decisions to engage in new forms of privacy risk. Consumers demonstrate "bounded rationality" regarding the immediacy of risks. | Existing research has implied that consumers do not demonstrate perfect rationality regarding their valuation of risks and benefits regarding mobile app information disclosure. This study employs a theoretical lens to explain how and why this "bounded" rationality occurs in information disclosure decisions through mobile apps. | Mobile app context |

Table 2.1, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| (Anderson & Agarwal, 2011) | **DV**: Willingness to provide access to personal health information. **IVs**: Emotion (health status emotion), Cognitive factors (Electronic health info. privacy concerns, Trust in electronic medium), Risk scenario variables (type of information—general health, mental health, genetic, intended purpose—patient care, marketing, research, requesting stakeholder—doctor/hospital, gov't, pharmaceutical). | Privacy boundary theory, Privacy calculus, Communication privacy management theory, Risk-as-feelings, and Emotion literature | Quasi-experimental survey methodology | Results suggest that contextual factors related to requesting stakeholder and the purpose for the requested info. Influence individuals' concerns and trust on willingness to disclose. Also, individuals with negative emotions involving their current health status are more willing to disclose personal health information. | Privacy literature sheds limited light on the determinants of information disclosure to particular vendors (recipients), or of particular types of information. No single study has combined the influence of multiple factors that can influence risk when disclosing personal information. | Digital healthcare setting |

Despite the work already done to address information disclosure behaviors in online communities, extant research is uncertain about the influence of different types of diseases and communities on individuals' disclosure behaviors and there is a call to address this (Zhou, 2018). Additionally, among the different theoretical perspectives used to understand information disclosure behaviors, no study has applied the disclosure decision-making model in in online health communities. This study, therefore, seeks to broaden our understanding of the extent to which people disclose information and how it aligns with the response from the disclosure decision-making model (DD-MM) perspective (Greene, 2009a).

### 2.2. Disclosure Decision-Making Model

An individual's decision to disclosure information has been explained using the DD-MM theoretical framework (Choi et al., 2016; Greene, 2009). The DD-MM framework is a mechanism to study the process by which patients make disclosure decisions. Originally, the DD-MM outlines three components in the decision process: information assessment—a discloser's assessment of their health condition or the information under consideration for disclosure, receiver assessment—a discloser's evaluation of the expected response of disclosure target, and disclosure efficacy—a discloser's perceived effectiveness of information sharing or the confidence to disclose (Greene, 2009a).

For the information assessment component, importance is given to how a person appraises the information to be disclosed, whether the nature of the health information is stigmatized or non-stigmatized diseases (Choi et al., 2016). Regarding the receiver assessment, a close and supportive receiver is necessary to reduce the unease from the expected adverse response (Derlega et al., 2002). Consequently, individuals will assess a receiver of the information based on their closeness and the anticipated response from the receiver. Studies have shown that relational quality positively impacts information disclosure (Afifi & Steuber, 2009). Individuals are willing to reveal sensitive information with peers they are closed to. People think about what others will say in response to their disclosed information before revealing their information. Individuals are unlikely to disclose their information to targets from whom they anticipate negative judgements (Afifi et al., 2005).

Lastly, the third component in the DD-MM framework is disclosure efficacy. Disclosure efficacy refers to the degree to which disclosers feel confident (or belief in their ability) to reveal their personal health information (Greene, 2009a). In OHCs, individuals demonstrate their ability to disclose information or the efficacy of their disclosure through the depth of the disclosed message in terms of the amount of information revealed—information density and the strength of the disclosed message covering a range or diversity of information—information breadth (Nguyen et al., 2012). The concept of efficacy originated from the work of (Bandura, 1977), who suggested that an individual's belief in their abilities and efforts will lead to achieving a desired outcome. However, the effects may vary depending on the social, situational, or temporal circumstances. Based on this premise, Greene (2009) posits that individuals evaluate their ability or confidence when disclosing personal information. The DD-MM suggests that the degree to which individuals feel confident to disclose information is influenced by their evaluation of the nature of information being disclosed. Figure 2.1 presents the DD-MM framework.

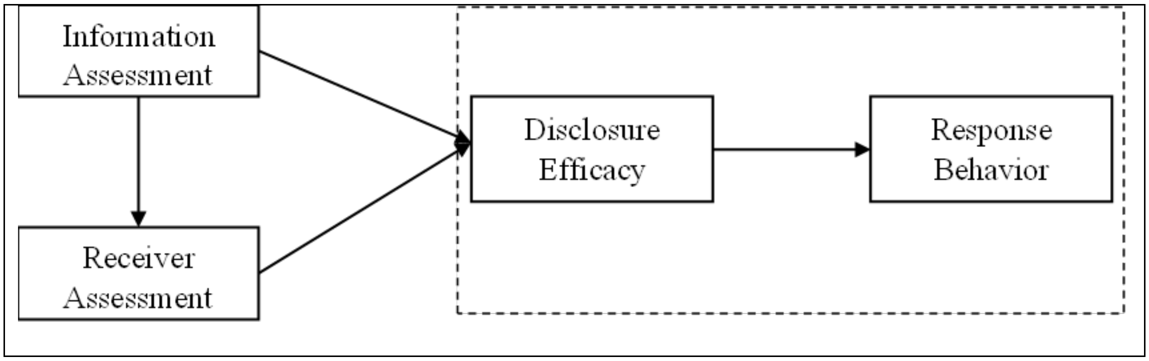

Figure 2. 1: DD-MM Framework and Extension

Although the DD-MM originally focused on individuals' decision to disclosed information based on the evaluation of the three components in the decision process as discussed above, this framework suffers some limitations. First, the DD-MM, however, does not propose the relationship between individuals' information assessment and response behaviors. I argue that there is a link between information assessment and response through the social presence theory. It should be noted that prior to the information disclosure, some components take place, which is the first impression that is being created by patients when they come to the platform. Individuals form first impressions in online social networks through their ability to influence the reactions of their peers through what they post on the platforms. The consequences to first impressions and social presence can define the level of participation in online platforms (Manga et al., 2020). Social presence is the ability for individuals to use communication media to transmit social cues when interacting on a social media platform (Short et al., 1976; Xu et al., 2012). Studies have suggested that individuals' presence in online social settings can bolster their participation or response activities (e.g., Cottrell et al., 1968; Latané et al., 1979). Prior research have also shown that users' social presence reflects the degree of salience of other users. Thus, social presence will affect the degree of interaction taking place, and hence, is required to enhance online community participation (Kreijns et al., 2004).

Second, the DD-MM has been extended to include the likelihood of disclosure, which increases with increased disclosure efficacy (Greene et al., 2012). However, this extension only focuses on individuals' likelihood to disclose information. It does not take into account the supportive outcomes that patients receive when they disclose their information. It is relevant to establish the connection between patients' disclosure efficacy and the response because patients disclose information with the expectation that they will get reactions that support their emotional, social, or informational quests. Otherwise, there is no point revealing personal information in online discussions. Research has expanded the DD-MM by examining the effects of disclosure on outcomes such as supportiveness (Torke et al., 2012). Such supportive outcomes in the online health community context, represent the response to a patient's disclosed message, which could be beneficial or unsatisfactory to the discloser. Thus, in this thesis, I focus on investigating the effectiveness of the response and conceptualize it as response efficacy, which is a part of user support behaviors—the main concept under investigation.

In Figure 2.2, I propose an integrated model that considers the effects of individuals' assessment behaviors on both disclosure and support behaviors and how disclosure efficacy and response efficacy influence each other in a two-way relationship over time. The dotted line for the relationship between the information assessment component and participation in online health communities is supported with the social presence theory. While the solid line proposed relationships are based on the disclosure decision-making model.

### 2.3. Support Behaviors

Online health communities play an integral part in the management of certain health conditions as patients can interact with themselves and with other health professionals. Patients come to online health communities expecting certain levels of support from the communities and other users. The main concept of interest in this dissertation is users' support behaviors. Support behaviors (supportiveness) is defined as "the extent to which an individual is able to participate in the community and is able to provide informational support, emotional support, social support," (Van Zalk et al., 2011, p. 1206).

In the online health community context, not many of their physicians are involved in the healthcare process. Patients depend on the support from others on the platform to manage their health conditions. This support is very important because the lack of developing supportiveness could then lead to a risk for social isolation and lower relationship quality (Van Zalk et al., 2011). Both social isolation and low relationship quality are potential risk factors for developing stress and depressive symptoms (Selfhout et al., 2009). Additionally, lower levels of support behaviors may lead to less general self-esteem (Kimber et al., 2008). Promoting users' support behavior depends on the assessment of the information they reveal and, on their competence, or ability to disclose such information.

There is a growing interest in extant research towards support behaviors through the values users create in the online communities (e.g., Chen et al., 2019; Huang et al., 2019; Liu et al., 2020; Stewart Loane et al., 2015; Zhao et al., 2015). Values are created when users participate and interact in online discussions, share information or knowledge about certain diseases, provide responses to others' inquiries, when give feedback or react to posts, and advocate or help others manage their health conditions (Liu et al., 2020). These activities involve the relationship between patients and supporters, foster relationship formation, and motivate users to actively engage in healthy conversations that improve the lives of others; as well as helping to sustain the online community (Stewart Loane et al., 2015).

Table 2.2 presents a review of representative research that have studied individuals' support behaviors through value co-creation in online communities. These studies have focused on participation, citizenship, and response behaviors such as, knowledge sharing, knowledge contribution, support receipt, support provisioning, community engagement, feedback behavior, etc. The emphasis of examining participation and response behaviors in the context of OHCs suggests that value is created when online community users engage in support behaviors that not only consider their personal needs, but also the needs of their peers on the platform (Liu et al., 2020; Stewart Loane et al., 2015; Zhao et al., 2015).

Table 2. 2: Review of Support Behaviors

| Support Behaviors | Context | Source |
|---|---|---|
| Participation (knowledge contribution) | Online communities | (Ma & Agarwal, 2007) |
| Participation behavior (knowledge sharing) | Weblog | (Yu et al., 2010) |
| Participation behavior (knowledge sharing) | Online question and answer sites | (Jin et al., 2013) |
| Participation behavior (general and specific knowledge sharing) | Online health communities | (Yang et al., 2016) |
| Participation behavior (knowledge sharing intention) | Online health communities | (Zhang et al., 2017) |
| Participation behavior (knowledge contribution), citizenship behavior (online community citizenship behavior) | Online communities and forums | (Chou et al., 2016) |
| Participation behavior (knowledge contribution), citizenship behavior (positive word of mouth) | Online discussion communities | (Ray et al., 2014) |
| Citizenship behavior (virtual community citizenship behavior) | Online communities | (Chiu et al., 2019) |
| Value co-creation behaviors (information sharing, responsible behavior, feedback behavior, advocacy behavior) | Online health communities | (Liu et al., 2020) |
| Value co-creation (social support) | Online health communities | (Stewart Loane et al., 2015) |
| Support and companionship (engagement in companionship activities, and informational and emotional support) | Healthcare virtual support communities | (Huang et al. 2019) |

Table 2.2, cont.

| | | |
|---|---|---|
| Value co-creation (knowledge contribution and membership continuance intentions) | Online health communities | (Zhao et al., 2015) |
| Informational and emotional support (support receipt and support provisioning) | Online health community | (Chen et al. 2019) |

Based on the above discussion, it therefore implies that support behavior in online health communities can be considered as a multifaceted concept of user interactivity including reciprocity in discussion (participation) and speed, frequency, and effectiveness of response (response efficacy) (Nambisan et al., 2016). I discuss these two concepts—participation and response efficacy—in the sections that follow.

### 2.4. Participation in Online Health Communities

In the context of online communities, a main focus for most research is participation. The context of my dissertation is online health communities, and the online community sustainability is based upon users' continuous participation. This implies that participation constitutes the second component of the main concept under investigation—support behavior—under investigation. When patients visit online platforms, they participate by posting messages, which can influence the response they receive. Individuals' participation can be motivated by their initial impressions or feelings expressed in the postings. Information disclosed via participation in an online health community can offer individuals with personal benefits (Nambisan, 2011), such as relationship and friendship formation through social networks, supportive responses, and information and knowledge acquisition. Participation has been defined as the intensity with which an individual engages within a community or the frequency of a user's communication on the platform (Johnston et al., 2013; Nambisan & Baron, 2009). Previous literature has suggested that collaboration or participation in online health communities is inspired by individuals performing task-based behaviors and communication, such as posting and replying to messages (Dahlander & O'Mahony, 2011; Faraj et al., 2015a).

Participation in online health communities has been examined using various theoretical lenses. For instance, social capital theory provide insights into how individuals participate by forming bonds and relationships in the communities (Faraj et al., 2015a). Furthermore, social identity theory provides a contextual understanding of the significance of identifying with the values and goals of the online community for effective participation. This is so because, part of an individual's behavior can be derived from the groups they belong to (Liu & Chan, 2011).

Additionally, word-of-mouth and stickiness promote participation in online community platforms (Gao et al., 2017). Information systems success model posits that information and system qualities are important drivers of IS success. Flow theory suggests that users who are in flow totally participate in platform activities by spending more time without noticing (Gao et al. 2017; Csikszentmihalyi, 1988). Moreover, extant research has used motivational theory and social presence theory to study participation in online communities. Users participate in online communities to seek information, entertain themselves, and socially interact with others (Deci, 1986; Shen & Khalifa, 2008).

Some prior literature assumes that a member's presence on the platform is appropriately recognized, and individuals can begin to make connections. Nonetheless, on the grounds that OHCs are ad hoc in nature, members should be invited before participation. The extent to which the member will be welcome to the platform relies upon how they introduce themselves. Subsequently, patients need to make their first postings to express feelings that will result in individuals showing enthusiasm in their participation. Hence, the current study focuses on this important aspect of patients' participation in OHCs, which is influenced by first impression cues present in the message. Such cues include bonding or intimacy, urgency or immediacy, efficiency, and non-verbal communication cues (Chung et al., 2015).

## 2.5. Response Efficacy

Response efficacy in extant literature refers to the extent to which an individual believes that the proposed response given will be effective (Johnston & Warkentin, 2010; Woon et al., 2005). An effective response needs to be informative, comprehensive, and helpful. Prior study has shown that informativeness and responsiveness are two important outcomes of individuals' disclosure processing decisions (Blankespoor et al., 2020). Thus, this current research builds on the prior literature on DD-MM framework and its extension to examine the how individuals' information disclosure behaviors in online health communities associate with the effectiveness of the response they receive. Individuals disclose information when they participate in online community discussions. Hence, in the next section, we review literature on users' participation in online health communities. Figure 2.2 shows the integrated model for this dissertation.

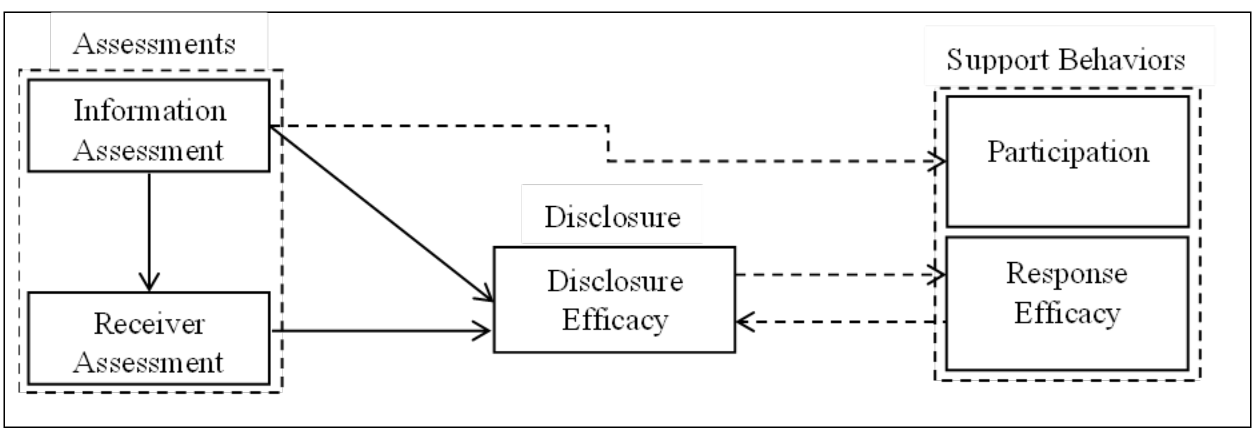


Figure 2. 2: Integrated Research Model

The theoretical model shown in Figure 2.2 operates at an abstract, conceptual level. In the separate studies that follow, I illustrate how the model framework relates to conceptual variables that can be empirically operationalized, tested, and evaluated. From the abstract research framework, I answer different research questions and derive separate models, based on the disclosure decision-making model and social presence theory using online health communities as the research context.

# CHAPTER III

# ACHIEVING SUPPORT RESPONSE ACCEPTANCE IN ONLINE HEALTH COMMUNITIES: AN EXTENDED DISCLOSURE DECISION-MAKING MODEL

Online health community (OHC) users seek acceptable support to enhance their health conditions and well-being. There exist extensive body of research on antecedents of information disclosure in OHCs. The understanding of whether and how disclosed information leads to acceptable support response is critical for the sustainability of OHCs. However, how users' information disclosure mechanisms elicit acceptable support responses that are acceptable is yet to be fully explored in the literature. This study investigates how user information disclosure, and the community anticipated response enhances support response acceptance. We develop a *moderated support response acceptance model* based on the health disclosure decision-making model. Our results, based on data from *inspire.com*, reveal that individuals tend to be concise in their disclosure behaviors when the information is considered intimate.

Further, users are more likely to disclose information broadly if they deem the information to be sensitive, and subsequently attract high support response acceptance. Our results also highlight how users' anticipation of a response significantly influence the relationships among information characteristics, disclosure behaviors, and support response acceptance.

As a novel theoretical contribution, the study unravels an expanded health disclosure decision-making model that can be used to study other information systems phenomenon. The study's findings shed light on how individuals' information assessment and disclosure behaviors can enhance or reduce support response acceptance. Additionally, by investigating how disclosure mechanisms align with acceptable support provision, we advance the information disclosure literature and provide a framework that helps to explain why users stay or exit online platforms. For practice, our results offer pragmatic insights to both OHC platform managers and participants to improve users' skills in crafting information to achieve acceptable support response from the audience.

## 3.1. Introduction

Patients or their caregivers dealing with stigmatized diseases such as HIV/AIDs or non-stigmatized diseases such diabetes need support to improve their health, and cope with the trauma, elevated feelings such as anxiety, depression, loss of control, or distress (e.g., Huang et al. 2019, Anderson and Agarwal 2011, Braithwaite et al. 1999). One major source of technology afforded support for individuals to cope with the health care issues is Online Health Communities (OHC) given the limited flexibility of face-to-face exchange (e.g., Chen et al. 2020, Braithwaite et al. 1999, Teubner and Flath 2019, Huang et al. 2019, Chen et al. 2019, Nambisan 2011). Online health communities have increasingly become salient through wider participants reach and spontaneity of interactions (e.g., Posey et al. 2010, Fan et al. 2014, Wang et al. 2020, Cao et al. 2018, Goh et al. 2016, Huang et al. 2019, Chen et al. 2019).

While prior literature highlights the factors that drive the disclosure of information (e.g., Zhang et al. 2018, Kartal and Li 2020), the under explored novel question is how users form expectation of OHC community members and subsequent association with disclosure behaviors.

Furthermore, insights from prior research assumes user's disclosures behaviors are invariant of medical condition types (e.g., Bansal and Gefen 2010, Anderson and Agarwal 2011, Fichman et al. 2011). However, disclosure of very sensitive conditions like HIV (e.g., Chaudoir and Fisher 2010, Quinn and Earnshaw 2013, Choi et al. 2016, Catona et al. 2016, Meisenbach 2010) is different given the stigmatization that users incur. Thus, users' openness to support response acceptance, defined as recognition of support response as following useful, helpful, and beneficial (Lee et al. 2019), would be duly influenced by the nature of health condition necessitating their joining of the OHC (Boerman, 2020). In response to a call for more research into effective response behaviors amidst diverse disease sensitivity communities (Zhou 2018), this study departs from prior research to understand mechanism for enhancing support response acceptance. The central proposition of this study is that audience anticipated response, defined as users' expectations of the reaction of others in response to their behaviors, is a double edge sword shaping user's disclosure behavior, audience reactions and overall OHC outcome. Hence, the current study's objective is to understand the extent to which an individual's disclosure of information in OHCs leads to positive evaluations of responses. Specifically, RQ1) *How do the information characteristics embedded in users' online health community posts influence individuals to engage in health information disclosure actions?* RQ2) How *does an individual's information disclosure decision elicit effective response (or acceptable support provision) in online health communities?*

The current study advances an extended decision-making model (DD-MM) and develops a moderated audience support acceptance explanatory model. The empirical results provide evidence that user information intimacy (how confidential the information is) is associated with anticipated response (an assessment about the potential response). User information sensitivity (information that could cause potential harm or benefits if shared), impacts both information density (amount of informational content), and information efficacy (the succinctness of the shared information), while anticipated response is a significant explanatory variable of information efficacy. Findings also revealed that information density and information efficacy both significantly influence information efficacy and support response acceptance.

Overall, the findings contribute to the health information technology (a system that supports exchange of health information between users, providers, and platform management) literature and underscore the basis under which participants are motivated to disclose information in OHCs and establish how disclosure behaviors can lead to effective feedback generation and support response acceptance. First, we demonstrate the boundaries of the DD-MM framework through its applicability in the OHC context. Second, we conceptualize both disclosure efficacy and response efficacy as multidimensional concepts, which provide granular insights into how the different subconstructs differentially influence disclosure and response efficacy outcomes. Specifically, disclosure efficacy is categorized into two dimensions – information density and information efficacy. Evidence from our results show that each of these dimensions leads to a novel outcome (response efficacy – support response acceptance), extending the DD-MM framework into the OHC context.

By conceptualizing both disclosure efficacy and response efficacy as multidimensional constructs, this study supports the notion that complex phenomena can be broken down into smaller units, which offer granular understanding of such phenomena otherwise not present in unidimensional analysis (Hong et al., 2014). Lastly, this study unveiled different information sharing behaviors based on the stigmatization labeling of the diseases. Practically, the findings provide insights for managers to offer tools relevant to motivate participants improve their information density and information efficacy skills to receive effective feedback responses from *their peers.*

## 3.2. Theoretical Background

### 3.2.1. Disclosure Decision-Making Model (DD-MM) Framework

The disclosure decision-making model (DD-MM), a health communication framework, affords theorization of mechanism by which participants make important disclosure decisions regarding their health or that of a family member. Prior research in health communication has suggested that the DD-MM provides a lens for understanding participant information disclosure strategy in regular face-to-face health communication settings (Greene, 2009a). We leverage the efficacy of the DD-MM to explore the association between participants' disclosed information and the effectiveness of the response they receive in an online health support setting. The disclosure decision-making model posits that participants decide to reveal information based on the information assessment, the target audience characteristics, and disclosure efficacy (Greene 2009).

Originally, the disclosure decision-making model for self-disclosure outlines three components in the decision process: information assessment--a discloser's assessment of their health condition or the information under consideration for disclosure, receiver assessment--a discloser's evaluation of the expected response of  disclosure target, and disclosure efficacy--a discloser's perceived effectiveness of information sharing (Greene, 2009a). Informativeness and responsiveness have been shown to constitute important outcomes of individuals' disclosure processing decisions (Blankespoor et al., 2020).The DD-MM has been extended to include the effect of disclosure on outcomes such as supportiveness (Torke et al., 2012). In the context of

OHCs, one supportive outcome is the responses to participants' disclosed messages (see Lee et al. 2019).

Furthermore, the literature on health communication examined the relationships among disclosure efficacy, likelihood of future disclosure and the depth of disclosure, and found that a participant's ability to share information affects their willingness to reveal information in the near future (Greene et al. 2012). Consequently, it is expected that a participant's ability to provide effective feedback (response efficacy) depends on the evaluation of the disclosure efficacy of the discloser. Based on the DD-MM framework, we argue that an individual's response efficacy increases with increased disclosure efficacy.

Response efficacy is defined as the degree to which an individual believes that the recommended response will be effective (Y.-C. Wang et al., 2015). Response efficacy has been found to involve consideration of the effectiveness of the response to a disclosed message (e.g., Lewis et al. 2010). A good response needs to be informative, comprehensive, and helpful. However, to the best of our knowledge, research is yet to investigate how an individual's efficacy in disclosing his/her information will stimulate feedback responses that are helpful and beneficial to the discloser. In doing so, the current research should make significant novel contribution to theory in information systems.

Generally, information disclosure, is defined as the extent to which individuals are willing and confident to reveal their information (L. Yang & Tan, 2012). Online health communities continuously provide the right setting to understand outcomes of information disclosure mechanism due to increase affinity for social connection and ease of information disclosure (Choi et al. 2016). These outcomes include psychological benefits, social support, perceived empathy from others, disease and self-management, behavioral, knowledge gain from medical professionals (e.g., Stewart Loane et al. 2015).

The DD-MM has been applied in different contexts. For example, one study showed that among high school footballers, the severity of the symptoms influences self-efficacy to disclose concussions (Cranmer & LaBelle, 2018). DD-MM has also been used to model how people decide to disclose nonvisible health conditions on mental health among students in the offline context (Greene et al. 2012). Another study has suggested that perceived stigma associated with the disease negatively affects disclosure efficacy (Choi et al. 2016). Since individuals with characteristics of stigmatized health conditions have the tendency to exclude themselves from various kinds of face-to-face social interactions (Kurzban & Leary, 2001), OHCs provide discussion opportunities for people in this class of disease. Although some studies have attempted to study the DD-MM framework to include planning and scheduling (e.g., Choi et al. 2016), this current study adds to the body of knowledge in health information technology by investigating the effectiveness of the response to disclose information in the context of OHCs. Thus, the DD-MM provides avenue for understanding the effects of health conditions and various disclosure mechanisms on message effectiveness or persuasiveness (Lewis et al., 2010).

Whereas there exists an extensive body of knowledge addressing information disclosure behaviors in OHCs (e.g., Zhou 2018, Zhang et al. 2018, Oprescu et al. 2013, Kordzadeh and Warren 2017, Kim et al. 2018, Bateman et al. 2011, Liu et al. 2020), scholars are yet to a) conceptualize the abstract level concept of individuals' information disclosure and response behaviors into simpler heterogeneous constructs that elicit easier and wider understanding of the causes and effects of such behaviors and b) investigate how the responses to information disclosure are linked and whether the disclosers consider the responses as beneficial or not. In addition to the above limitations in prior research, there are pending dangers of not understanding an individual's disclosure decisions/behaviors and expectations in online settings. For example, an individual may be revealing a vast amount of information thinking that it is persuasive enough to elicit the support or response they need.

However, the responder may interpret it as jargons, leading to response that may not be adequate to satisfy the discloser's needs. There is a call to address the uncertainty about the influence of different types of diseases and communities on individuals' disclosure behaviors (Zhou 2018). We believe that individuals with different types of diseases and levels of information sensitivity may disclose their personal health information differently (that is, the type of health situation may determine depth and breadth of the disclosure).

For example, a participant with HIV condition may differ in the way he or she shares/discloses their information from another participant with diabetes or migraine headaches. That is, a participant's propensity to disclose personal health information may be contingent on the nature of the information being disclosed. Third, OHCs exhibit some distinctive characteristics from other virtual communities ranging from information sharing, support provision, and disclosure and response behaviors (Chen et al. 2019).

## 3.3. Research Model and Hypotheses Development

Figure 3.1 illustrates our conceptual model based on DD-MM, which distinguishes between information factors that lead to the disclosure decision and disclosure outcomes. The model theorizes the mediating role of disclosure efficacy and the moderating role of anticipated response in OHC setting.

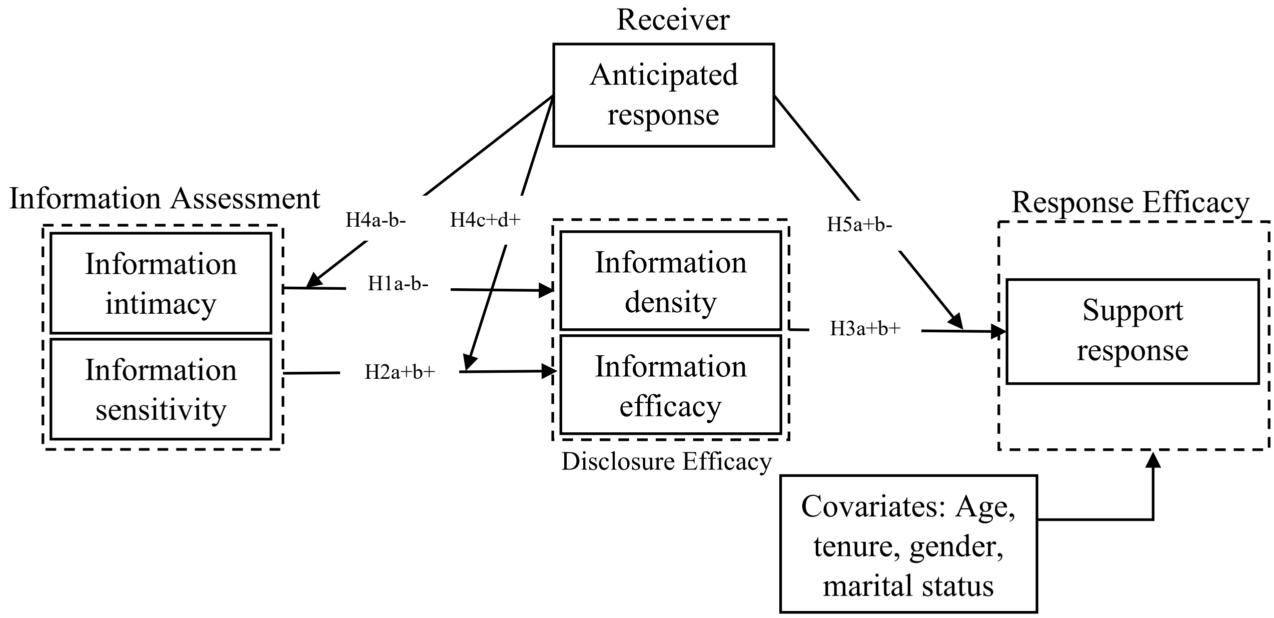


Figure 3. 1: Research Model

### 3.3.1. Information Assessment and Disclosure Efficacy

Disclosure efficacy measures the effectiveness of an individual's willingness to reveal private information (Greene, 2009a). The concept of efficacy, originated from the work of Bandura (1977), refers to a person's belief in his or her ability to achieve a desired outcome. The high-level conceptualization of efficacy could have varied effects depending on the social, situational, or temporal circumstances. Based on this premise, prior research proposes that efficacy is assessed by determining the quantity and quality of information; quantity is determined by the frequency of expressions and quality is assessed by the occurrence of statements (see Mills 1983). The DD-MM suggests that an individual's ability to disclose information (disclosure efficacy) is influenced by their assessment of the information under consideration. In this study, disclosure efficacy, in the context of OHCs, is conceptualized in two dimensions: *information density* – the quantity or extent of a person's disclosure and *information efficacy* – an individual's ability to disclose well-written (or succinct) information.

Information assessment is a person's appraisal of the information being disclosed (Greene, 2015). Two main characteristics of assessed information that influence individuals' ability to share their personal health information are the intimacy or nature and sensitivity of the information. Thus, information assessment is conceptualized as consisting of two dimensions: information intimacy and information sensitivity. Here, importance is given to how a person appraises the information being disclosed (see Choi et al. 2016).

### 3.3.2. Information Intimacy

Information intimacy is the assessment of a person's information to be disclosed as secretive and confidential (Choi et al. 2016). Information intimacy is a more generalized information assessment than stigma and a participant on OHC platform may appraise their information being disclosed as worthy of disgrace (Greene, 2015). Thus, information intimacy can be categorized as stigmatized (e.g., HIV/AIDS and cancer) or non- stigmatized (e.g., diabetes). Stigma is "an attribute that is deeply discrediting that could tarnish reputation, reduce life chances, and even exact social death" (T. L. Anderson, 2014, p. 257) and stigmatized individuals are often characterized by perceptions of negative thoughts about self. These negative thoughts could prompt attitudes of psychological aggression and reflection and increase feelings of risk about disclosure (Johnson, 2008).

Although the sharing of intimate information could increase trust and liking by others, consistent with the DD-MM framework, disclosing such information may expose the disclosers to vulnerability, shame, and ridicule by others (see Choi et al. 2016). Specifically, when considering disclosing intimate information, the discloser may be concerned not only about how they will share the information, but also about how others will react to it.

Furthermore, studies have shown that stigma poses a serious problem in people seeking help or disclosing information (see Corrigan 2004). Individuals with perceptions of stigmatized diseases e.g., HIV and AIDS (see Derlega et al. 2002) develop increased feelings of risks about information disclosure and restrict what and/or how much information to reveal (Choi et al. 2016). Disclosing stigma affects one's identity that is hidden from others, and requires the individual to regulate access to the information before disclosure (Ragins, 2008). According to the DD-MM, individuals will spend cognitive efforts in considering the effectiveness of their disclosure in OHCs if their assessment of the information is characterized as stigmatized (Greene, 2009a). Hence, information that is intimate will be sparsely shared and thus, we expect the information intimacy to have a negative relationship with information density. Additionally, feelings of stigma will cause individuals to restrict their information and disclose poorly articulated messages which results in disclosure of ineffective information.

H1a: *A participant's health information intimacy characterized as stigmatized is negatively related to his/her information density expressed in the message within the OHC.*

H1b: *A participant's health information intimacy characterized as stigmatized is negatively related to his/her information efficacy expressed in the message within the OHC.*

### 3.3.3. Information Sensitivity

Information sensitivity is the assessment of a person's information possibly as harmful or beneficial if shared (Bansal & Gefen, 2010b). For example, terminal illnesses or information could raise a patient's fear of being discriminated or attract sympathetic support (Greene, 2015). In the face-to-face context, some individuals may choose not to reveal many details about a certain disease to the public due to its sensitivity. However, since we are dealing with online platforms as the context, the presumption may not be entirely valid as participants tend to enjoy a certain degree of ease dealing within a community of people of like-mind and interests. Research has shown that information sensitivity is a cognitive process in which a person evaluates health information from the perspective of its possible positive outcomes (Bansal & Gefen, 2010b).

Moreover, since most users visit the online platform in search of a solution to their health, emotional, or social needs, sensitivity may not be an issue given that the benefits of receiving the necessary support and help outweigh the cost of disclosing sensitive information that will be sufficient to elicit the desired response. In the OHC platform, for example, some participants are so secretive to the extent of putting statements like: "my interests are private" or "I have not shared any additional information about myself." While individuals have the right to what they should disclose, respondents may not know how to help and the purpose of the user joining the platform may not be realized, hence, participants may not be satisfied or may leave the platform. Thus, we argue that higher levels of sensitivity of the health information should facilitate participants' willingness to provide sufficient and adequate information about oneself to benefit from the services and support that these online community platforms provide.

Additionally, one main reason why participants decide to go online is that most online platforms give users the opening and leeway to engage with people who come with very sensitive health conditions or who may bare similar diseases (see Huang et al. 2019). Therefore, participants are free and confident enough to talk about their conditions and since the information is sensitive, they seek very conducive outlets through online platforms compared to traditional platforms. Hence, participants are willing to disclose more information on OHCs.

H2a: *A participant's information sensitivity expressed in the message is positively related to his/her information density expressed in the message within the OHC.*

H2b: *A participant's information sensitivity expressed in the message is positively related to his/her information efficacy expressed in the message within the OHC.*

### 3.3.4 Disclosure Efficacy and Response Efficacy

The current study suggests that the alignment between the participant's disclosure expectations and the effectiveness of the response is key to their willingness to share information. Discloser's level of openness is associated with the kind of response they expect. Response efficacy is the degree to which the discloser believes that the recommended response provided will be effective (Y.-C. Wang et al., 2015). In the OHC context, evaluations of responses to users is presented in "helpfulness" which has been conceptualized as *support response acceptance* in prior research (S.-Y. Lee et al., 2019). Thus, response efficacy is operationalized as support response acceptance. Exposure to disclosed information may elicit feelings of sympathy from the audience. We expect that individuals who are willing, able, and are engaging in their disclosure of information will be more likely to receive a good response from the audience. With this conceptualization of response efficacy, we underscore the importance of studying how engaging in online disclosure behaviors is vital in eliciting support responses that are not only general but also considered beneficial to the discloser. In doing so, we advance the information disclosure literature by explaining how disclosure mechanisms align with effective support provision and present a framework explaining why users enter or leave online platforms.

Study has shown that emotional and informational support can foster the knowledge and attitudes of participants in OHCs (Chen et al. 2019). This study, therefore, proposes that the extent of disclosure--in terms of the breadth and depth of the information and the information being strong and well written will determine the amount of support response that is considered useful and beneficial. Evidence from prior research shows that the structure of words via what is written can identify who a person is (Boyd & Pennebaker, 2015) and this is likely to attract favorable reactions from others. Participants on OHC platforms who see their situation as very critical tend to develop more courage (K. V. Lee, 2006) and confidence in providing details about their illnesses in search of emotional, informational, or other forms of support (Chen et al. 2020, Lee et al. 2019). The sufficiency of disclosed information will attract responses that are beneficial. In fact, peers can derive value from the content that is disclosed by other participants; and this can influence and inspire others to reveal their own health conditions. Thus, information that is sufficiently disclosed will generate support responses that are acceptable, helpful, and beneficial.

H3a: *A participant's information density expressed in the message is positively related to the support response acceptance within the OHC.*

Information efficacy captures the art of being succinct or concise when expressing one's feelings for accurate interpretation. Succinctness is the art of writing that benefits easy readability, better clarity and good understanding. Sentences that are succinct comprise few or effective information in a sentence (e.g., Xiao et al. 2022). We argue that unlike traditional settings where disclosure can provide instant feedback or present non-verbal cues that allows for additional inference, information efficacy in terms of fewer words per sentence in OHC can lead to effective interpretation and subsequent higher number of acceptable support responses. Fewer words prevent the introduction of multiple concepts or concerns in a sentence; thus, improving reading and reduces the potential of having grammatical errors that interferes with understanding user post to provide appropriate support. Fewer words per sentence demonstrates a well-written post. This means a post with lower convoluted ideas, lower information overload, and higher information efficacy, has increased chances of receiving higher support response acceptance. So,

H3b: *A participant's information efficacy expressed in the message is positively related to the support response acceptance within the OHC.*

### 3.3.5 Moderating Role of Receiver Assessment

#### 3.3.5.1. Information assessment, receiver assessment, and disclosure efficacy.

Receiver assessment is the degree to which the discloser evaluates response of a specific target disclosure (Greene et al. 2012). It is conceptualized as anticipated response defined as the discloser's assessment about the possible response of the receiver once information is shared (Magsamen-Conrad, 2014). For example, "I would share my secret to this family member if I knew he or she would react positively to it." Participants evaluate how others will respond to disclosed information and decide the extent of disclosure (Petronio, 2002). We argue that the more anticipated response the less the negative effects of information intimacy on information density and information efficacy. When users assess their information as intimate, it reduces their ability to disclose extensively and forcefully to others. In addition, when decrease in anticipated unfavorable responses, decreases the relationship between information intimacy and disclosure efficacy. Research suggests that individuals are reluctant to disclose extensive information to targets from whom they anticipate negative judgements (T. D. Afifi et al., 2005). That is, when undesirable responses are expected, participants tend to lower their morale and optimism to share extensively and forcefully. Thus,

H4a: *Anticipated response negatively moderates the relationship between information intimacy and information density within the OHC.*

H4b: *Anticipated response negatively moderates the relationship between information intimacy and information efficacy within the OHC.*

On the other hand, we propose that anticipated response can positively moderate the positive effect of information sensitivity on information density and information efficacy. Sensitivity of the information conceptualizes a user's assessment of the information as beneficial (as opposed to being harmful) to them. When the information is considered beneficial to be disclosed, users anticipating affirmative responses are more eager to present extensive and well written information to engage other community members to provide them with the needed support. Thus, more anticipation will increase individuals' ability and enthusiasm to disclose dense and well written information. Hence,

H4c: *Anticipated response positively moderates the relationship between information sensitivity and information density within the OHC.*

H4d: *Anticipated response positively moderates the relationship between information sensitivity and information efficacy within the OHC.*

**3.3.5.2. Disclosure efficacy, receiver assessment, and response efficacy**. Anticipated response can also moderate the effect of disclosure efficacy (information density and information efficacy) on support response acceptance. Research suggests that messages that are sufficiently disclosed tend to attract and increase support that is beneficial and acceptable to the user (Chen et al. 2020, Lee et al. 2019). Users' anticipation of supportive responses will further reinforce their disclosure ability to engage the audience to provide helpful and beneficial support. Thus, anticipation is an important variable that affects how users with higher disclosure abilities provide more useful support in OHCs. Consequently, we expect that the effect of disclosing dense or extensive information on support response acceptance is contingent on the level of anticipated response. Thus,

H5a: *Anticipated response positively moderates the relationship between information density and support response acceptance within the OHC.*

Conversely, lower levels of anticipated response will further weaken the effect of information efficacy on support response acceptance for users with low disclosure ability (specifically, low information efficacy). That is,

H5b: *Anticipated response negatively moderates the relationship between information efficacy and support response acceptance within the OHC.*

## 3.4. Research Methodology

### 3.4.1. Empirical Context and Research Protocols

The proposed model is validated using data from *Inspire.com*, a leading health network platform for connecting patients or their caregivers for medical progress and medical research (Inspire, 2021). This site is a public website which builds and manages online support communities while connecting them to life science companies for the purpose of research. Some of the popular communities on the platform fall into the category of stigmatized diseases and non-stigmatized diseases. When users register onto the community, they share personal information and information about their health conditions. Based on the initial information disclosed, other participants provide responses that are considered helpful through the show of helpfulness features. The information and the content generated by users once they are disclosed become public and accessible to everyone (Huang et al. 2019). Informed consent from participants was not required since the authors did not have any direct contact with any of the participants (Flicker et al., 2004). We obtained IRB approval and the platform's permission to conduct the study.

### 3.4.2. Sampling and Data Collection

Data for the analysis were original discussion posts by OHC members and support responses to these posts. Initially, using a web crawler program, about 759 user data records were collected from stigmatized disease community - HIV/AIDS (Sartorius, 2007) and non-stigmatized disease community – diabetes (Rao et al., 2009). Recent studies are increasingly using the web crawling tool to mine data available on internet communities for public access (e.g., Chen et al. 2019, Huang et al. 2019).

Data was sourced from HIV/AIDS, cancer, and diabetes support communities on *inspire.com* online health platform. Members on this platform demonstrate some degree of activeness in posting messages and disclosing information about their health conditions while also benefitting from the support others provide. Hence, to minimize selection bias issue in this study, authors followed the random sampling technique in selecting the sample from the population. Following this technique, the dataset was coded by first removing all posts that focused on advertising instead of health-related information. Second, authors deleted posts that had unrelated information pertaining to the specific support communities of interest. Lastly, authors rejected user posts that were considered influential, that is, posts by users who were themselves community leaders on the platform. This resulted to 223 user posts discarded.

Moreover, authors did not have any direct interaction with the participants used in the study; hence, selection bias was not an issue in this current study. The distribution of the final sample of 536 user discussion posts from the two disease types are stigmatized (84.5%) and non-stigmatized (14.5%). These percentages represent all the participants' initial discussion posts drawn either from the HIV/AIDS communities (for stigmatized disease type) or from the diabetes community (for non-stigmatized disease type) on the platform. Contextual variables captured include information about users (date joined, age, gender, and marital status), and post information (initial post, date of post, and number of useful support votes).

Sentiment analysis output was obtained from the scores of the linguistic inquiry and word count (LIWC) text analysis program (Pennebaker et al., 2015). Information efficacy for example, was derived by extracting the number of words per sentence (making the post well-written or succinct) from the LIWC results output. Users' ages range from 16 to 73. The summary and descriptive statistics show the sample data needed transformation on the key variables (Table 1). Variable transformation is discussed below.

### 3.4.3. Variables and Measures

We identify the factors extracted from the OHC that predict the dimensions of disclosure efficacy and response efficacy while establishing a link between the theoretical/operational constructs and the extracted features. Based on the context of the study, we grouped the theoretical constructs under different operational constructs as shown in Table 2. All theoretical constructs were adapted from prior literature and operationalized to fit the study context using analytic methods based on recent studies (see Lee et al. 2019, Chen et al. 2020). Except for information intimacy variable that was measured as a binary, all other key variables were normalized using natural log transformation. The main *dependent variable* (DV) under investigation is response efficacy conceptualized as *support response acceptance (lnsuppacce).*

*Support response acceptance* is operationalized as aggregate of the number of supports, thanks, and useful votes to a post. The intervening mechanisms *information density (lninfodens)* and *information efficacy (lninfoeffi)* were measured as follows: *Information density* is the number of words in a post while *information efficacy* is the number of words in a sentence, with fewer words per sentence indicating higher information efficacy.

The independent variable is *information assessment* and moderating variable is *receiver assessment*. Information assessment includes two dimensions namely information intimacy and information sensitivity. Information intimacy *(infointi)* is conceptualized as stigmatization—classified as a binary variable either stigmatized (1) or non-stigmatized (0) diseases; and *information sensitivity (lninfosens)* is measured as anxiety sentiments in a message. Receiver assessment is conceptualized as *anticipated response (lnantiresp)* measured as the urgency cue or emotional tone sentiment in a message with higher emotional tone numbers indicating that the discloser is more positive and upbeat in their anticipation; lower numbers reveal sadness and less anticipation. Figure 3.2 shows a typical example of information disclosure and support response in OHCs. It also shows the measures extracted from the post (WC is word count).

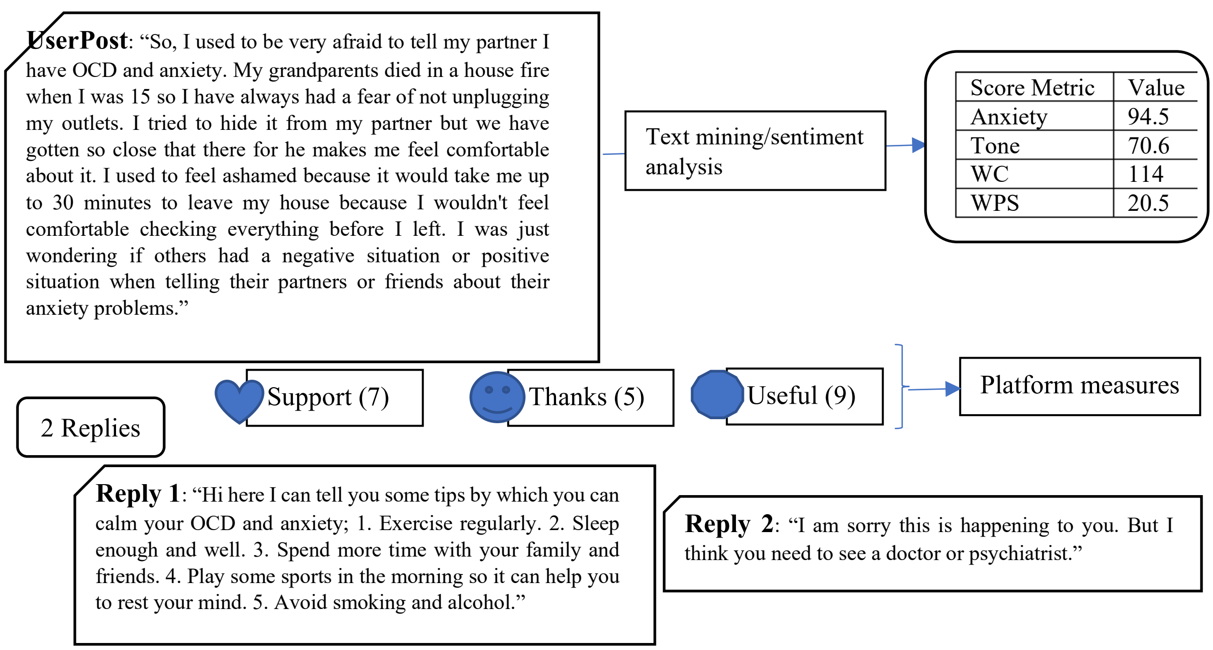


Figure 3. 2: A Typical Disclosure and Support Response Exchange Scenario and Measurement

The descriptive statistics is presented in Table 3.1.

Table 3. 1: Summary and Descriptive Statistics of Variables

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| gender | 0.287 | 0.453 | 0 | 1 |
| age | 43.659 | 27.559 | 0 | 86 |
| marital status | .304 | 0.460 | 0 | 1 |
| lntenure | 7.251 | 0.849 | 4.554 | 8.738 |
| infointi | 0.845 | 0.362 | 0 | 1 |
| lninfosens | 1.184 | 0.377 | 1 | 3.539 |
| lnantiresp | 4.345 | 1.227 | 1 | 5.605 |
| lninfodens | 5.434 | 1.025 | 1 | 8.143 |
| lninfoeffi | 5.066 | 0.736 | 1 | 7.215 |
| lnsuppacce | 3.433 | 1.531 | 1 | 8.797 |

*Note*: N = 536

Other variables used as controls include actual age (*age* – measured as user's actual age in years), gender (*gender* – 1 for male and 0 for female), marital status (*maristat* – 1 if user is married and 0 otherwise), and *tenure* (the length of time a participant has been on the platform – measured as today's date minus the date user joined the platform). Table 3.2 presents the constructs, definitions, and measurements.

Table 3. 2: Constructs, Definitions, and Measurements

| Theoretical Constructs | Theoretical Definition | Contextual Definition | Measurement | Analytic Method |
|---|---|---|---|---|
| Information Assessment (Greene, 2015) | How an individual appraises or evaluates the information to be disclosed on an OHC. | *Information intimacy* – the extent to which a user on an OHC platform appraises their disclosure information as secretive and confidential. | Binary variable: 1 for stigmatized (discrediting) or 0 for non-stigmatized (non-discrediting). | Coded base on disease types |
| | | *Information sensitivity* – the extent to which a user on OHC platform expresses concerns about the information being disclosed. | *Anxiety* in the disclosed message | Text mining/ Sentiment analysis |

Table 3.2, cont.

| | | | | |
|---|---|---|---|---|
| Receiver Assessment (Greene et al. 2012) | An individual's expectation or estimation of the response from a specific receiver or the disclosure target. | *Anticipated response* (urgency cues) – the user's assessment about the potential response from the audience on an OHC platform audience once information is shared. | *Emotional tone* in the disclosed message | Text mining/ Sentiment analysis |
| Disclosure Efficacy (Greene, 2009a) | An individual's evaluation of his/her ability and confident to revealing their information. | *Information density* – the depth or length of information a user discloses on an OHC platform that is sufficient to elicit a response. | Number of words in a post | Text mining/ Sentiment analysis |
| | | *Information efficacy* – the extent to which the information a user discloses on an OHC platform is well-written. | Number of words per sentence | Text mining/ Sentiment analysis |
| Response Efficacy (Y.-C. Wang et al., 2015) | An individual's evaluation of a response to disclosed information as effective. | *Support response acceptance* – the amount of support response feedback that a user in an OHC platform receives or considers as acceptable, useful, and beneficial. | Numbers of useful/helpful support votes | Directly observed on the platform |

### 3.4.4. Data Analysis and Empirical Model Specification

To adjust for any skewness in the data distribution, the natural logarithmic transformation was applied to some of the variables (information sensitivity, information density, information efficacy, anticipated response, and support response acceptance). Table 3 shows the correlations between the main variables and the variance inflation factor (VIF). Estimation problems such as instability and large variances among coefficient estimates can arise when independent variables are highly correlated (e.g., 80% or higher) resulting in collinearity among explanatory variables (Kennedy, 1998). From our analysis, the highest correlation between the independent variables is 0.350 (between information density and information efficacy), which is well below the 80%

benchmark (K. V. Lee, 2006). As shown in Table 3.3, the correlation values did not signal any multicollinearity issues.

Table 3. 3: Correlations Among Variables and Variance Inflation Factors (VIF)

| | infointi | lninfosens | lnantiresp | lninfodens | lninfoeffi | lnsuppacce | VIF |
|---|---|---|---|---|---|---|---|
| infointi | 1.000 | | | | | | 1.22 |
| lninfosens | -0.064<br>0.1408 | 1.000 | | | | | 1.09 |
| lnantiresp | 0.279*<br>0.0000 | -0.225*<br>0.0000 | 1.000 | | | | 1.24 |
| lninfodens | -0.008<br>0.8480 | 0.125*<br>0.0038 | 0.057<br>0.1910 | 1.000 | | | 1.31 |
| lninfoeffi | -<br>0.128*<br>0.0030 | 0.057<br>0.1900 | -0.082<br>0.0571 | 0.350*<br>0.0000 | 1.000 | | 1.35 |
| lnsuppacce | 0.071<br>0.0989 | 0.048<br>0.2667 | 0.107*<br>0.0130 | 0.129*<br>0.0029 | 0.077<br>0.0767 | 1.000 | 1.29 |

*Notes*: * Correlations significant at $p < 0.05$

We constructed two main models Model 1a & b and Model 2 to test different hypothesized and one additional model (Model 3) to test the non-hypothesized relationships. Model 1a and Model 1b are used for testing H1, H2, and H4 and Model 2 for testing H3 and H5. The models share some dependencies as the outcomes of model 1 (information density and information efficacy), which represent disclosure efficacy are also explanatory variables of support response acceptance.

### 3.4.5. Empirical Models

Models for Testing Hypotheses H1, H2, and H4

To test H1, H2, and H4

$$Model\ 1(a){:}\ lninfodens_i = \beta_0 + \beta_1 * infointi_i + \beta_2 * inInfosens_i + \beta_3 * lnantiresp_i + \beta_4 * lnantiresp_i * infointi_i + \beta_5 * lnantiresp_i * inInfosens_i + \varepsilon_i^{\beta} \ldots\ldots\ldots\ldots(1)$$

$$Model\ 1(b){:}\ lninfoeffi_i = \propto_0 + \propto_1 * infointi_i + \propto_2\ lninfosens_i + \propto_3 * lnantiresp_i * infointi_i + \propto_4 * lnantiresp_i * inInfosens_i + \varepsilon_i^{\alpha} \ldots\ldots\ldots\ldots(2)$$

To test H3 and H5

$Model\ 2: lnsuppacce_i = \theta_0 + \theta_1 * lninfodens_i + \theta_2 * lninfoeffi_i + \theta_3 * lninfodens_i * lnantiresp_i + \theta_4 * lninfoeffi_i * lnantiresp_i + Ci + \varepsilon_i^{\theta}$ ..............................................................(3)

To test the indirect effect of assessment on response, we substitute models 1a and 1b into model 2. $The\ resultant\ reduced\ form\ equation\ is$

$lnsuppacce_i = \mu_0 + \mu_1 * infointi_i + \mu_2 * lninfosens_i + \varepsilon_i^{\mu}$ ................................(4)

To test additional non-hypothesized relationships

$Model\ 3: lnantiresp_i = \mu_0 + \mu_1 * infointi_i + \mu_2 * inInfosens_i + \varepsilon_i^{\mu}$ .......................(5)

where *lninfodens*$_i$ denotes the natural log of information density, *infointi*$_i$ denotes information intimacy, *lninfosens*$_i$ denotes the natural log of information sensitivity, *lnantiresp*$_i$ denotes the natural log of anticipated response, *lninfoeffi*$_i$ denotes the natural log of information efficacity, *lnsuppacce*$_i$ denotes the natural log of support response acceptance, $\varepsilon_i$*'s,* are the error terms, $C_i$ represents all control variables, and $\propto_i$, $\beta_i$, $\theta_i$, and $\mu_i$ are the parameters for estimation.

For the statistical analysis, a two-stage least squares (2SLS) regression technique was used to test the model. Since disclosure efficacy acts both as an outcome variable in the first stage and an explanatory variable in the second stage, the 2SLS method was chosen because it is appropriate technique for analyzing models that contain dependent variables whose error terms correlate with the independent variables. We use the predicted or fitted values from the first stage to estimate the values for the second stage since estimating each model separately biases the coefficients and the standard errors (Angrist & Imbens, 1995).

Usually, the 2SLS method is used when we suspect endogeneity issues, a problem that occurs if the regressors in the model correlate with the error terms (Semykina & Wooldridge, 2010). We note that there could be omitted variables that confound the relationship between disclosure efficacy and response efficacy. For instance, the variable anticipated response is difficult to measure empirically; however, it may affect the dimension(s) of disclosure efficacy and response efficacy.

We address this issue through a two-stage instrumental variable regression analysis by performing the Hausman test to assess the existence of endogeneity (Semykina & Wooldridge, 2010). This is a robust model that uses the standard errors in the regression model to control for heteroskedasticity (e.g., Stock and Watson 2008). An ordinary least squares (OLS) fixed effect model was used to estimate the first-stage regression and the *ivregress* command in STATA software was used to compute the 2SLS models. The results are discussed below.

### 3.5. Results/Findings

In Table 3.4, we present the results of the first-stage ordinary least squares (OLS) regression wit robust standard errors, two-stage least squares (2SLS) regression parameter estimates, and the corresponding standard errors are shown in parentheses. The 2SLS method is used to fit models that include instrumental variables; 2SLS comprises four types of variable(s): dependent, exogenous, endogenous, and instrument. In lieu of simple OLS, 2SLS technique is used to provide unbiased estimates when the dependent variable's error terms are correlated with the independent variables (see postestimation for details).

The $R^2$ for information efficacy and support response acceptance are suppressed because they have no statistical meaning in the context of 2SLS. For the first stage fixed effect models, the results show that the proposed model explains 13.6%, 2.8%, and 16.7% of the variance in information density, information efficacy with the controls, and anticipated response including controls, respectively.

### 3.5.1. Hypothesis Test

The results show support for most of the hypothesized relationships. Information intimacy is significant and negatively related to information efficacy (H1b: $\beta = -0.231$, $p < 0.011$); while information sensitivity is significant and positively related to information density (H2a: $\beta = 0.393$, $p < 0.001$). Additionally, information density and information efficacy are positively related to support response acceptance (H3a: $\beta = 1.136$, $p < 0.000$ and H3b: $\beta = 319.12$, $p < 0.032$ supported), respectively. Anticipated response negatively moderates the relationship between information intimacy and information efficacy (H4b: $\beta = -0.049$, $p < 0.007$ supported) and positively moderates the relationship between information sensitivity and information density (H4c: $\beta = 0.066$, $p < 0.000$ supported). Furthermore, anticipated response positively moderates the relationship between information density and support response acceptance (i.e., H5a: $\beta = 0.069$, $p < 0.000$ was supported) and negatively moderates the relationship between information efficacy and support response acceptance (i.e., H5b: $\beta = -0.052$, $p < 0.002$ was supported).

On the contrary, information intimacy did not show any significant association with information density (H1a unsupported) and information sensitivity had no significant relationship with information efficacy (H2b unsupported). Interestingly, anticipated response does not moderate the relationship between information intimacy and information density (H4a was unsupported) and the relationship between information sensitivity and information efficacy (H4d was unsupported).

Table 3. 4: First-Stage Ordinary Least Squares (OLS) Regression and Two-Stage Least Squares (2SLS) Regression Estimations with Standardized Beta Coefficients and Error Terms

| | First-stage OLS regression estimates | 2SLS regression estimates (indirect paths) |
|---|---|---|

Table 3.4, cont.

| Variables | Model 1a<br>lninfodens | Model 1b<br>lninfoeffi | Model A<br>lnantiresp | Model 2<br>Lnsuppacce |
|---|---|---|---|---|
| infointi | -0.074 | -0.231** | 0.783*** | -0.149 |
| | (0.126) | (0.091) | (0.143) | (0.562) |
| lninfosens | 0.393*** | 0.078 | -0.658*** | -0.009 |
| | (0.120) | (0.086) | (0.130) | (0.419) |
| lnantiresp | 0.080** | | | -0.79 |
| | (0.038) | | | (0.129) |
| lnantiresp*infointi | -0.035 | -0.049*** | | |
| | (0.025) | (0.018) | | |
| lnantiresp*lninfosens | 0.066*** | 0.002 | | |
| | (0.014) | (0.007) | | |
| lninfodens | | | | 1.136*** |
| | | | | (0.551) |
| lninfoeffi | | | | 319.12*** |
| | | | | (148.65) |
| lnantiresp*lninfodens | | | | 0.069*** |
| | | | | (0.014) |
| lnantiresp*lninfoeffi | | | | -0.052*** |
| | | | | (0.017) |
| gender | 0.043 | 0.029 | 0.390*** | |
| | (0.102) | (0.077) | (0.117) | |
| age | -0.001 | -0.001 | -0.003 | |
| | (0.003) | (0.003) | (0.004) | |
| maristat | 0.293*** | 0.064 | 0.085 | |
| | (0.106) | (0.080) | (0.124) | |
| lntenure | 0.245*** | -0.035 | 0.221*** | |
| | (0.055) | (0.042) | (0.064) | |
| Constant | 3.807*** | 5.424*** | 2.914*** | 15.90 |
| | (0.473) | (0.315) | (0.469) | (1.50) |
| Observations | 536 | 536 | 536 | 536 |
| R-squared | 0.136 | 0.028 | 0.167 | - |
| Adj. R-squared | 0.118 | 0.012 | 0.155 | - |
| F-value | 7.523*** | 1.710* | 13.241*** | 3.057 (RMSE) |

*Notes*: Parameter estimates; standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

### 3.5.2. 2SLS Postestimations: Hausman Test for Endogeneity and Overidentification

The endogenous regressors (information density and information efficacy) in our model were tested. The null hypothesis of the Durbin and Wu–Hausman tests is that the variable under consideration can be treated as exogenous. The test statistics are highly significant at the 5% level ($p < 0.0000$), so we reject the null hypothesis of exogeneity; we must continue to treat information density and information efficacy as endogenous. This means that we reject the null hypothesis that there is no correlation between the regressors and the error terms of the dependent variable. Hence, we can conclude that the instrumental variables (information density and information efficacy) are endogenous.

The test for overidentification result shows that both Sargan and the Basmann test statistics ($p = 0.3632$, $p = 0.3684$, respectively) are non-significant at the 5% test level, which means that our instruments are valid and that our structural model is specified correctly. Thus, we cannot reject the null hypothesis that our instruments are valid at the 5% significance level.

### 3.5.3. Additional Analysis

For robustness checks, we tested additional un-hypothesized relationships among information intimacy, information sensitivity, and anticipated response and found that information intimacy is positively related to anticipated response ($\beta = 0.783$, $p < 0.000$), while information sensitivity is negatively and significantly related to anticipated response ($\beta = -0.658$, $p < 0.000$ were supported).

In the disclosure decision making process, the discloser analyzes the anticipated reaction from their specific targets (Greene et al. 2012). Disclosers with disease characterized as stigma may anticipate empathy and sympathy from targets (see Zhang et al. 2017) in a face-to-face conversation. However, in OHCs, participants consider referent others in that community to be having similar health conditions. So, having the same health condition and belonging to the same support community reduces the feelings of risk of disclosure as the nature of the disease or the sensitivity of the information serve as urgency cues for the response that disclosers anticipate

(Yan et al., 2016). Hence, individuals who share the disease type have the tendency of communicating intimate information among themselves, thus, leading to higher expectations of support or anticipated response.

On the other hand, we foresee that assessing information that is sensitive will lower the anticipation of a response. Studies have shown that increased information sensitivity will decrease one's ability to reveal information (Chen et al. 2019). Consistent with previous studies and regardless of the gravity of the condition, participants exercise caution in their disclosure decisions when it concerns sensitive information, being discrete  for fear that they may be used against their will (e.g., Chen et al. 2019). This in turn will discourage them, lowering their morale, and hence, lowering their anticipation of a response (see Chatterjee et al. 2009). Consequently, the more sensitive information is assessed to be, the more conserve and difficult it is to pass it across to others and hence, the less expectation an individual will have for a response. Furthermore, anticipated response was found to be significant and positively associated with information density ($\beta = 0.080$, $p < 0.036$). The summary of the results of both supported and not supported hypotheses are presented in Tables 3.5 and 3.6, respectively.

Table 3. 5: Summary of Estimated Results

| Hypothesis | Independent variable | Dependent variable | t-stats | p-value | Sig. | Results |
|---|---|---|---|---|---|---|
| H1a- | infointi | lninfodens | -0.582 | 0.561 | No | Unsupported |
| H1b- | infointi | lninfoeffi | -2.549 | 0.011** | Yes | Supported |
| H2a+ | lninfosens | lninfodens | 3.289 | 0.001*** | Yes | Supported |
| H2b+ | lninfosens | lninfoeffi | -0.912 | 0.362 | No | Unsupported |
| H3a+ | lninfodens | lnsuppacce | 3.893 | 0.000*** | Yes | Supported |
| H3b+ | lninfoeffi | lnsuppacce | 2.150 | 0.032*** | Yes | Supported |
| H4a- | lnantiresp*infoinfi | lninfodens | -1.388 | 0.166 | No | Unsupported |

| | | | | | | |
|---|---|---|---|---|---|---|
| H4b- | lnantiresp*infoinfi | lninfoeffi | -2.695 | 0.007*** | Yes | Supported |

Table 3.5, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| H4c+ | lnantiresp*lninfosens | lninfodens | 4.884 | 0.000*** | Yes | Supported |
| H4d+ | lnantiresp*lninfosens | lninfoeffi | 0.222 | 0.824 | No | Unsupported |
| H5a+ | lnantiresp*lninfodens | lnsuppacce | 4.967 | 0.000*** | Yes | Supported |
| H5b- | lnantiresp*lninfoeffi | lnsuppacce | -3.155 | 0.002*** | Yes | Supported |
| Additional Results (non-hypothesized relationships) | | | | | | |
| | Infointi | lnantiresp | 6.536 | 0.000*** | Yes | Supported |
| | lninfosens | lnantiresp | -5.101 | 0.000*** | Yes | Supported |
| | lnantiresp | lninfodens | 2.107 | 0.036*** | Yes | Supported |

*Notes*: *** p < 0.01, ** p < 0.05, * p < 0.10; Unstd – unstandardized; Std. – standardized; Sig. – significant.

Table 3. 6: Summary of Hypothesized Results

| ID | Hypothesis | Supported? |
|---|---|---|
| H1a- | *A participant's health information intimacy characterized as stigmatized is negatively related to his/her information density expressed in the message within the OHC.* | No |
| H1b- | *A participant's health information intimacy characterized as stigmatized is negatively related to his/her information efficacy expressed in the message within the OHC.* | Yes |
| H2a+ | *A participant's information sensitivity is positively related to his/her information density expressed in the message within the OHC.* | Yes |
| H2b+ | *A participant's information sensitivity is positively related to his/her information efficacy expressed in the message within the OHC.* | No |
| H3a+ | *A participant's information density expressed in the message is positively related to the support response acceptance within the OHC.* | Yes |
| H3b- | *A participant's information efficacy expressed in the message is positively related to the support response acceptance within the OHC.* | Yes |
| H4a- | *Anticipated response negatively moderates the relationship between information intimacy and information density within the OHC.* | No |
| H4b- | *Anticipated response negatively moderates the relationship between information intimacy and information efficacy within the OHC.* | Yes |
| H4c+ | *Anticipated response positively moderates the relationship between information sensitivity and information density within the OHC.* | Yes |
| H4d+ | *Anticipated response positively moderates the relationship between information sensitivity and information efficacy within the OHC.* | No |
| H5a+ | *Anticipated response positively moderates the relationship between information density and support response acceptance within the OHC.* | Yes |

| | | |
|---|---|---|
| H5b- | *Anticipated response negatively moderates the relationship between information efficacy and support response acceptance within the OHC.* | Yes |

Table 3.6, cont.

| Additional Results (non-hypothesized relationships) | | |
|---|---|---|
| | *A participant's health information intimacy characterized as stigmatized is positively related to the anticipated response expressed in the message within the OHC.* | Yes |
| | *A participant's health information sensitivity is negatively related to the anticipated response expressed in the message within the OHC.* | Yes |
| | *A participant's higher anticipated response expressed in the message is positively related to his/her information density within the OHC.* | Yes |

The results depicted in the hypotheses are shown in Figure 3.3 – the structural model results with path coefficients, R-squares, and p-values (in parentheses) showing the ns: non-supported hypotheses; and significant relationships with standardize beta coefficients, significance level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ and non-significant ns relationships.

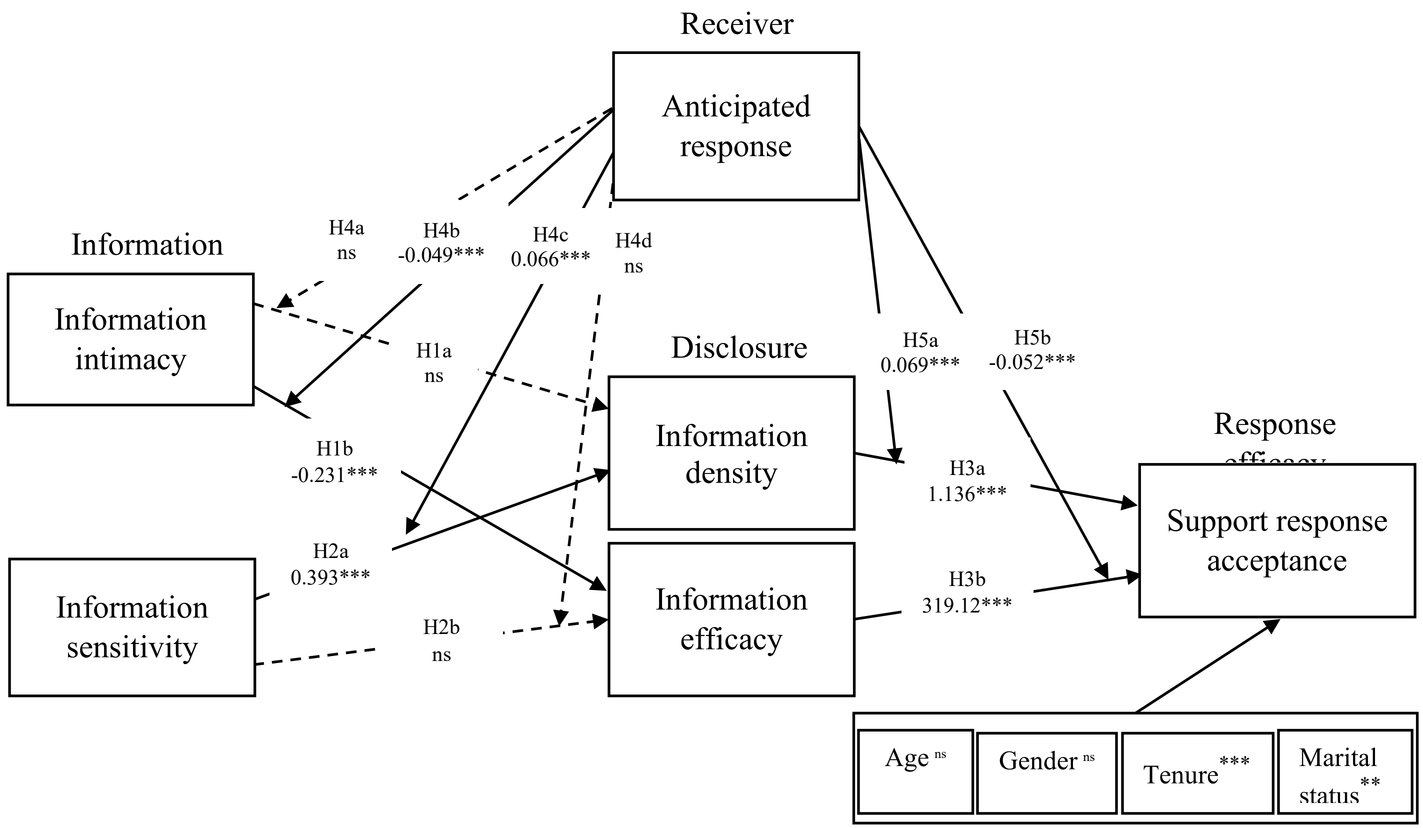


Figure 3. 3: Structural Model Results with Direct and Moderated Path Coefficients, R-squares, and p-values in Parentheses

*Notes*: ns: non-significant; significant relationships with standardize beta coefficients and significance level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; $R^2$ for information and support response acceptance are suppressed because they really have no statistical meaning in the context of 2SLS or instrumental variable.

## 3.6. Discussion

The literature on health information suggests that health communication is still a challenge for some patients (Basu and Dutta 2008, Dutta and Feng 2007, Braithwaite et al. 1999). This study contributes to the health information technology by illustrating the delicate balance between the participant's information and their perception of their audience due to the lack of the ability to process cues in the post. To deepen the understanding of information sharing in OHCs, this current study explicates a two-stage model based on disclosure decision-making model that explains participants' information disclosure decision process.

The information disclosure process begins in the first stage with participants' self-reflection on their circumstances to gauge the need for information disclosure. The findings from this study provide empirical evidence that the breadth and depth of self-disclosure can lead to more intimate relationships based on the degree of a communicators' comfort with others. Although expected, the findings provide additional explanation for the tenets of social penetration theory that suggests that information sharing among individuals is a stage process that deepens over time (Carpenter and Greene 2015, Mongeau and Henningsen 2008, Masaviru 2016).

However, contrary to the findings in prior studies (Choi et al. 2016, Greene et al. 2012), the results of this current study demonstrate intricate relationship among information intimacy, stigmatization, and anticipated response. A possible explanation for these interesting findings that depart from prior research is the consideration of the study's online context. In the offline context, participants with disease types categorized as stigmatized will not feel accepted because they anticipate the response of their target to be undesirable. Such users may abstain from joining or discussing their condition in face-to-face groups. However, in the online context, participants anticipate interacting with individuals with similar health condition or in need of support. Thus, when participants with diseases considered shameful realize that they share similar health conditions with peers of the same community, their feelings of the risk of disclosure are reduced. Hence, they are motivated to disclose as sharing their information serves as cues for the response participants expect. This is an extension of the literature on health information technology that homophily is critical to online health community participation (Kordzadeh and Warren 2017).

Most health consumers visit OHCs to share their health or personal concerns with like-minded participants with the hope that they will receive unambiguous, relevant, and actionable information from the audience. Disclosing sufficient information in breadth and depth tend to elicit responses that are comprehensible and useful. In particular, the information density (i.e., depth of disclosure) dimension of disclosure efficacy significantly influences support response acceptance. Although this is not new results, it is interesting as stigmatized individuals need to be encouraged to disclose information against the odds as it has overall benefits in receiving acceptable responses from their peers. The communication literature provides support for this assertation as self-disclosure follows onion model with breadth and depth (Taylor et al., 1973). On the other hand, messages that are overload in word count tend to lower support response acceptance. Specifically, findings reveal that information efficacy negatively influences support response acceptance. Messages with high information efficacy could be voluminous or interpreted as having long running sentences. Sentences that are not succinct may include too many concepts that might require the recipient to spend more efforts to decode and understand. Sometimes, long running sentences may have double negatives or opposite concepts that neutralize the intended signal in the message. Thus, messages that are highly verbose make it difficult for the audience to understand a participant's health needs, thereby reducing the acceptance of the support that is provided. Additionally, the cognitive effort required by the recipient to decode the ambiguity in overload messages dissuades the respondent from providing feedback that is helpful and beneficial. Consistent with previous studies, a high breadth message may be convincing to the discloser  (Sagadevan et al., 2015), but could be less appealing to the target. Hence, the response may come back just in few words such as “I agree with you”, or “You are right”, or “Thumbs up”. These types of responses may not be considered as helpful to the disclosing participant.

Furthermore, the results of this study demonstrate the effects of information assessment characteristics on the support response acceptance mediated by disclosure efficacy. Anticipated response provides the boundary conditions by enhancing the relationships among information assessment, disclosure efficacy, support response acceptance. The negative relationship between information intimacy and information efficacy is stronger with lower anticipated response, while the positive relationship between information sensitivity and information density is also reinforced as anticipated response increases. When anticipated response increases, the positive relationship between information density and support response acceptance and the negative relationship between information efficacy and support response acceptance decrease.

In the conceptual model, we proposed that information assessment (information intimacy and information sensitivity) mediated by disclosure efficacy characteristics (information density and information efficacy) are associated with support response acceptance. Although mediation was not the focus of this study, the results of the two-stage least squares analysis suggest that the mediated influence of information intimacy through information efficacy and the mediated influence of information sensitivity through information density are supported. However, the mediated influence of information intimacy through information density and the mediated influence of information sensitivity through information efficacy are not supported. The results show that information intimacy and information efficacy both determine support response acceptance. The results also suggest that information sensitivity and information density both are associated with support response acceptance.

### 3.6.1. Implications for Theory

This study makes five specific contributions to the literature on health information technology and to DD-MM theory. First, the study expands the literature on the often neglected user groups particularly in health communication (e.g., Liang et al. 2017) by demonstrating the significance of stigmatization in online health disclosure behavior. Designation of a disease highlights the effect of ailment type but also communications by affected individuals. Although, stigmatization is a growing concern for doctors, health professionals and patients, its effect on victims' information disclosure has not received particular attention. The study provides initial evidence of stigmatization effect and lays the ground for further exploration of explanatory power.

Second, the study empirically validates an expansion of the dimensions of disclosure efficacy and response efficacy of DD-MM. Considering the relative effect of each dimension provides richer insights into disclosure and response behaviors. By identifying and measuring two dimensions of disclosure efficacy and response efficacy, the study strengthens the nomological network of DD-MM and enhances its explanatory power. In accordance with prior literature on conceptualizing multidimensional constructs (e.g., Wright et al. 2012, McKnight et al. 2002), the conceptualization of disclosure efficacy and response efficacy is used in this study to relay complex ideas by examining the differing factors that compose individuals' disclosure and response behaviors in OHCs. By theorizing disclosure efficacy as information density and information efficacy, and response efficacy as multidimensional concept comprising information efficacy and support response acceptance, we demonstrate theoretically and empirically that the two higher order/abstract constructs are better represented as first-order constructs with differing effects in their relationships.

Third, the different outcome effect of information density and information efficacy provide basis for future research to deploy DD-MM in explanation communication behaviors in other contexts. Such increase utility of DD-MM could help explain the information disclosure paradox in other context.

Fourth, the use of disclosure decision-making model in the online context, OHCs, demonstrate the adaptability of key communication theories from the face-to-face context, albeit with relevant modification. The disclosure decision making model has been used to understand individual information sharing behavior in traditional settings (Greene, 2009a). By using it to explicate an information disclosure model, the study demonstrates the applicability of the DD-MM in the OHC context.

Fifth, this study departs from the current use of DD-MM by examining the intervening effect of anticipated response instead of its direct relationships with the outcome variable. Developing anticipatory feelings when disclosing information is important because it indicates the expected value of experiencing an outcome either by re-enforcing positive events or reducing negative outcomes (see Hardisty and Weber 2020). Thus, the boundary conditions of DD-MM have been clarified.

### 3.6.2. Implications for Practice

For practice, first, the findings regarding dimensions of disclosure efficacy can help OHC managers improve the writing experience of participants. Managers of OHC may offer participants tools such as customizable auto-complete text features relevant to the OHCs context to improve information disclosure efficacy by crafting succinct sentences in the post. Such effort will reinforce the usefulness of the auto-complete features in other technologies. Second, management can design the text fields, with suggested number of words to motivate participants to improve the information density of a post. Such tools offer an opportunity for guiding participants into the depth or extent of messages that result in helpful support responses. Third, our results show that users' information density increases the number of acceptable support responses, and the effect is greater when they anticipate more responses. Platform management can heighten user's anticipation by showing them some of the benefits of belonging to a community during the registration process and present users with testimonials of how individuals with high anticipation increase the number of details they provide in their disclosures.

Fourth, the more intimate a user information is, the less succinct it is written. Thus, to reduce the likelihood of revealing such information, platform management should provide precautionary alert system that warns the user of the implications of providing information that is discrediting and shameful. Fifth, our results show that information sensitivity leads to an increase in information density. When a user senses that the information being disclosed is beneficial not only to him/her but also to others, they will disclose more. Management can provide users with the options of classifying the information being disclosed as beneficial (to encourage extensive disclosure) or harmful (to discourage misuse of information systems).

### 3.6.3. Limitations and Future Research

This study has some limitations that necessitates further investigation. First, this study examined only one online health community platform. Future research could extend this work by considering different online health platforms and non-health platforms to expand on DD-MM theory on individual health communication needs and process. Second, the analysis in this study was carried out using secondary online data. In future research, it could be useful to use primary data from interviews to validate the concepts and outcomes under investigation.

Third, the results of the study do not establish a causal link between the components of DD-MM. Future experimental study would provide additional insights on how to improve online health communication. Fourth, what disease type considered as stigmatized is transient and culturally dependent. Although, prior literature provided support for considering HIV/AIDS as stigmatized health considerations, future research should consider other health considerations in different cultures to provide additional contextualized refinement of the current study's findings.

### 3.7. Conclusion

Although OHCs provide a means for health consumers to seek, share, and disclose vital information, understanding  users' online disclosure decision-making behaviors still require theoretical inquiry (Hodgkin et al., 2018). Based on DD-MM, this study advanced a two-stage model that explains information disclosure process in OHCs. Leveraging the power of text analytics, the study obtained objective data to test a model that explains why people make decisions to disclose their personal health information in online support community settings. The model also examined alignment between the disclosed information and the effectiveness of the response to determine whether the responses they received were such that the disclosers derived the benefits they expected from revealing their information.

We found that participants on OHCs are more likely to receive responses that are usable and beneficial when the density of the information disclosed is high but not verbose (i.e., information efficacy). Additionally, the study demonstrates that participant' decisions to disclose personal health information are influenced in part by the nature of the information/disease. This study highlights the fact that the nature of the disease, classified as stigmatized or non-stigmatized diseases show differing effects on individuals' decision to disclose their personal health information.

Comparative to participants with non-stigmatized conditions, users who face more stigmas will have the courage to disclosure more information and the extent of the disclosure will further impact the effectiveness of the response received. This is so because they feel unwelcomed by the larger society and thus, they show greater needs for support and appreciation for help they receive from their peers in the OHC context. The study findings complement prior research that has extensively investigated the antecedents of information disclosure by examining the contextual factors that support the alignment between what individuals expect from information disclosed and effectiveness of the response they get back.

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CHAPTER IV

# INVESTIGATION OF NON-LINEAR EFFECTS OF FIRST IMPRESSION CUES ON PARTICIPATION IN ONLINE HEALTH COMMUNITIES: EVIDENCE FROM DECISION TREE INDUCTION THEORY DEVELOPMENT AND EMPIRICAL APPROACHES

This study identifies impression cues in the initial posts of users to examine participation in online health community (OHC). The first phase uses decision tree induction approach to abduct a set of hypotheses. In the second phase, we empirically tested the set of hypotheses with user data collected from a different OHC. Findings indicate that, while intimacy moderated the effects of other cues on giving and receiving participation, nonverbal communication moderated the effects of other cues on overall participation. The study contributes to theory by developing and testing three different theoretical explanations for users' giving, receiving, and overall participation behaviours.

## 4.1. Introduction

In the healthcare context, many individuals or their caregivers visit *online health communities* (OHC) for emotional health support or information (e.g., Huang et al., 2019).

As the need for support increases, recent studies suggest that more people participate in online discussions by providing and seeking helpful responses from other peers with whom they share similar health conditions in OHCs (Alasmari & Zhou, 2021; Wang et al., 2020; Zhang et al., 2018). Researchers have used different theories to explain participation in OHCs. For example, research has suggested that leadership characteristics (task-based behaviours and technical communications) are effective influencers of knowledge collaboration in OHCs (Dahlander & O'Mahony, 2011; Faraj et al., 2015b). Additionally, the social capital theory has been used as a basis for understanding how participation in online communities can lead to the formation of bonds and relationships (Faraj et al., 2015b).

Moreover, the passing of information from person to person in online communication that encourages a visitor to stay longer (stickiness) facilitates participation within online communities (Gao et al., 2017). According to flow theory, users who experience flow spend more time on platforms without noticing (Csikszentmihalyi, 1988; Gao et al., 2017). Moreover, prior research that used motivational theory and social presence theory found that users participate in online communities to seek information, entertain themselves, and socially interact with others (Bao & Wang, 2021; Chung et al., 2015).

Although prior studies provide insights into understanding participation in online platforms, it is mostly assumed that the audience will respond to any post irrespective of the content or style of the inviting post. However, since the OHCs are ad hoc and members have to respond to several enticing posts, participants would be selective in their response and maximize their participation time by focusing on messages that create appropriate impressions (Xu et al., 2012). Therefore, to gain empathic participation, users should craft their first postings in a way that enhances their presence and makes a strong impression on the audience. Thus, this study explores users' first impression cues in online discussion posts as a function of different forms of participation in OHCs through the lens of social presence theory (Jahng & Littau, 2016). The current study departs from prior literature to test the interactive effects of social presence cues that shape a user's first impression, particularly in health context.

In online health communities, users participate by interacting and exchanging information with each other. High levels of member engagements and participation in these online communities facilitate knowledge flow and value co-creation (Mozaffar & Panteli, 2021; Priharsari & Abedin, 2021). OHCs characteristics such as ad hoc nature, flexibility, and change over time, may discourage users from establishing long-term relationships if the initial support experience is negative. Cranefield et al. (2015) report that users who lurk or who do not participate online discussion forums constitute a majority of the membership and they need to be encouraged and motivated to participate by making initial impressions through personal characteristics such as self-disclosure (e.g., Sun et al., 2014). First impressions are important in online communication because audience response depends on the interpretation of cues of varied expressions, which are difficult  to decipher in online communication (Cummings & Dennis, 2018; Hadjistavropoulos & Craig, 2002). In online interactions, expression cues, such as immediacy, belongingness, nonverbal signals, or the reliability of the message are difficult to decipher. This expectation holds true for communication in online health communities especially where the informational and emotional supports individuals receive and/or give is vital based on the first impression cues expressed in the message.

Consider, for example, the *immediacy sense of enthusiasm first impression* cues displayed in the following two messages:

*A – "How to deal with Suicidal?: I've been HIV diagnosed since last month and right now my mental health is so bad. My mindset is full of negative thinking. I would like to ask your experience, how could you deal with this problem?"*

*B – "Forgive the Person that Gave You HIV: I found out 2015 that I had HIV & Heart Disease the person I was with he knew but never said a word, said he did not want to lose me. My days are highs and lows. He is a nice guy came into my life was down and out. But I'm angry very angry I feel lost just lost."*

Message A appears to express a higher sense of immediacy than message B. The level of audience response in the form of support that may be given or received for message A will be different from message B due to participants' understanding of key immediacy communication indicators in these initial posts (see Love et al., 2012; Rueger et al., 2020; Smith et al., 2020; van Riessen et al., 2016). The more first impression cues are appreciated, the more members enjoy responding to each other and subsequently, the higher the level of online engagement and peer support (Turel & Serenko, 2012).

Furthermore, while prior research treats participation as a unidimensional construct, an individual's overall activity in online discussion forums (e.g., Faraj et al., 2015; Xu et al., 2016), the current study considers participation both as a single construct and as a multi-dimensional concept. A user's assessment of an initial message can affect content generation (giving response) and content consumption (receiving response) differently (H. Ma et al., 2017; Sillence, 2013). For example, a post that does not forcefully request in-depth feedback from the audience may only receive nonverbal responses such as votes, thumps-up, or thumps-down from responders on the platform. Thus, the current study examines audience participation through giving and receiving information and support responses (Cavusoglu et al., 2016; Chung et al., 2015). The study seeks to specifically answer the following research questions:

- *RQ1: What OHC member communication cues shape their first impression?*
- *RQ2: How does OHC member first impression influence audience response (participation) on the online platform?*

By investigating our research questions, we theoretically establish the interaction effect of social presence construct dimensions on participation in OHCs. The conceptualization of participation as a multi-dimension phenomenon unravels the effect of first impressions in communication, enhancing the online participation literature.

Our first research question (RQ1) aims to understand what OHC member communication cues shape their first impression, and the findings indicate that, while intimacy is the most important predictor of giving and receiving participation, nonverbal communication is the most important predictor for overall participation. Furthermore, our OHC participation model led to the formation of three theoretical explanation for giving, receiving, and overall participation. This novel contribution allows for critical assessment of theoretical underpinnings of online participation behaviours. Thus, managers can focus on the efficacy of current platform design features that promote the establishment of first impressions. Additionally, the boundary conditions obtained from investigating our second research question (RQ2) provide platform administrator insights on platform features that enable participants to share or receive content on the platform. Furthermore, the findings indicate the need for different mechanisms for improving giving and receiving separately to encourage and enhance online participation in health communities.

The following section discusses the literature and theoretical background on participation in online communities and the social presence theory. Next, we examine the methodological approaches taken to answer the research questions. Last, we present the results and discuss the contributions to theory and practice.

## 4.2. Theoretical Background – Social Presence Theory

Social presence explains how people develop relationships at the initial stages (Wei et al., 2017). When an individual interacts on a social media platform, their social presence consists of the social cues they express and convey through communication media, such as Facebook (Short et al., 1976; Xu et al., 2012). Tu and McIsaac (2002) define social presence as the feeling of community that learners experience in online environments. The concept of social presence also refers to noticing and appreciating the interpersonal aspects of interaction (Short et al., 1976).

Social presence is central in several settings, such as the electronic learning (e-learning) context where a student's ability to portray themselves as active members of a community in social and emotional ways promotes subsequent active learning (Jahng & Littau, 2016). Tu (2000) proposes three dimensions of individuals' social presence within distance learning: social context, online communication, and interactivity. In a computer-mediated environment, images and writings heighten the degree of social interaction (Chung et al., 2015; Gefen & Straub, 2003). For example, pictures and posts on Facebook have a higher degree of social presence than blogs, whose contents are mainly writings (Chung et al., 2015; Kaplan & Haenlein, 2010).

The online context requires the exhibition of a high degree of social presence due to textual, verbal, and nonverbal communication features as noted in past studies (Franceschi et al., 2009; Srivastava & Chandra, 2018). First, a high social presence early in the online context drives content generation due to the motivation to read others' responses and reply to messages

(Robert & Dennis, 2005). Second, a sense of closeness in relationships, a sense of enthusiasm when making decisions, and a sense of trust when transmitting messages increase with social presence (Franceschi et al., 2009). Third, higher social presence leads to increase response participation by individuals in discussions and communication on online platforms (Chung et al., 2015). Accordingly, having membership within a community is not sufficient to promote participation or contributions unless it creates a sense of social presence early in the online community (Lu et al., 2016). Kim and Sundar (2014) argue that when individuals perceive others' presence positively, they tend to engage in more social activities in the community. Hence, an individual's social presence reflects degree of salience of each other in the interaction in the context of an online community. Therefore, enhancing social presence is essential for the development of engagement in online platforms (Kreijns et al., 2004).

The literature has suggested a connection between how users present themselves and behave in response to social presence cues (Cui et al., 2013; Koh et al., 2007; Tu & McIsaac, 2002; Zhang et al., 2018). Although the concept of participation has been studied as a single phenomenon, the literature suggests that the practice of participation may consist of information, knowledge, or support contribution (hereafter known as giving) and information, knowledge, or support acquisition (hereafter known as receiving) (see Ma et al., 2017; Sillence, 2013; Zhou, 2020). It is important to consider participation in terms of giving and receiving because when individuals act like givers, they help others without expecting anything in return. They can provide support, share knowledge, or create valuable online content. On the other hand, when individuals act as receivers, they expect others to serve them while carefully protecting their knowledge, expertise, and time (e.g., see Grant, 2013). In addition, givers may be motivated by their ability to build efficient and larger network ties while receivers may be forced to establish stronger relationships in order to access the supports, they need and to benefit from others.

Therefore, we propose that individuals' social presence cues displayed in their initial posts in online health communities will predict whether they will participate more readily through giving or receiving or both. Evidence indicates that different communication methods (verbal, nonverbal, written, listening, and visual) lead to different voluntary participation outcomes (Hann et al., 2013; Valkenburg, 2017). In addition, when social presence is high, community members communicate more effectively (H. Ma et al., 2017; Short et al., 1976; Wasko & Faraj, 2005; X. Yang et al., 2017). As noted earlier, the main components of social presence theory are intimacy, immediacy, efficiency, and nonverbal communication (Short et al., 1976).

### 4.2.1. Intimacy

Intimacy signifies the sense of closeness and belonging those two individuals experience with one another. Several factors affect intimacy in interpersonal interactions, including physical distance (Argyle and Dean, 1965). When individuals interact for the first time, they will usually create intimacy. Although using emotional vocabulary is helpful in the early phases of communication, it does not allow for a prolonged process or the development of a lasting relationship, rather it facilitates the staging of one's story (Bar-Lev, 2008).

Participants in health forums frequently seek out small, homogeneous support networks where individuals interact and develop intimacy (Driskell & Lyon, 2002). So, individuals who effectively communicate by sharing information on the site will find it easier to participate through getting support from others (Hackworth & Kunz, 2011). As a result, users can build closer relationships by posting and replying to each other's messages. Stronger bonds of intimate relationships, therefore, lead to higher levels of participation in online health communities.

#### 4.2.2. Immediacy

Immediacy refers to showing urgency or importance to an exchange (Cobb, 2009; Dixson et al., 2017). When communicating with others, urgency indications convey a sense of value and significance to the relationship (Dixson et al., 2017). We refer to immediacy as how individuals demonstrate the need to act quickly to the messages, they share in an online health community. Members of the community demonstrate their urgency by showing empathy, participating immediately in discussions, and responding promptly to posts. These qualities are evidence of higher commitment in online discussion forums.

Research has shown that community commitment affects the support individuals get in the form of replies (receiving)  and the content people post (giving) in online discussion platforms (Bateman et al., 2011). Consequently, a strong sense of urgency, which reflects immediacy will lead to more participation from others, as they read and respond more urgently.

#### 4.2.3. Efficiency

Efficiency refers to the degree to which users judge the reliability of the message they communicate across to the target (Lim et al., 2013; Short et al., 1976). Individuals use online communities as the communication media through which they interact with their peers. A user judges a medium to be efficient when it performs consistently well. A higher efficiency will increase participation in the discussions (see Driskell & Lyon, 2002). Thus, social media efficiency will increase user participation in giving and receiving.

#### 4.2.4. Non-verbal communication

Non-verbal communication refers to how people use cues and prompts to express their feelings and emotions through their writings in an online forum. (Li et al., 2021) found that physical nonverbal cues, such as body language and vocal intonation, do not exist in the online context, and social presence is thus, low (e.g., Chung et al., 2015). Lack of nonverbal cues may lead to less understandable communication and less engaging participation.

Since users typically visit online platforms for support rather than for connection, they make efforts to provide more nonverbal cues to engage their audience to receive expected responses. Therefore, nonverbal communication cues can increase or decrease participation and interest on online platforms.

### 4.3. Research Methodology

Given that we expect all dimensions of SPT to act as first impression cues that influence participation, but that the SPT does not specify the interaction between its key tenets, we need an appropriate approach for identifying and evaluating relevant causal model. Kositanurit et al. (2011) presented a hybrid process for empirically-based theory development, where the latter parallels the traditional ideal model of scientific inquiry (Chen et al., 2020). Similar to Donalds and Osei-Bryson (2020), in Table 4.1 below, we have divided this hybrid process into two main phases, where Phase 1 was proposed in Osei-Bryson and Ngwenyama (2011) and applied in Andoh-Baidoo et al. (2012) and Donalds and Osei-Bryson (2019), and Phase 2 is equivalent to traditional methodology used in quantitative empirical behavioural science studies. Figure 4.1 provides a graphic representation of the operationalization of this hybrid process for empirically based theory development for this study.

Table 4. 1: Hybrid Process for Empirically Based Theory Development

| Phase | Step | Description |
|---|---|---|
| 1 | 1 | o 1a: Use existing theory to identify variables that are likely to be relevant to the phenomena of interest.<br>o 1b: Based on Substep 1a above, gather data related to the phenomena of interest. |

Table 4.1, cont.

| | | |
|---|---|---|
| | 2 | ○ 2a: Use data mining approach to do automatic generation and preliminary testing of hypotheses.<br>2b: Based on the results of Substep 2a, generate a preliminary model that appears to explain the phenomena of interest.<br>○ 2c: Examine, and if necessary, revise the preliminary model generated in Substep 2b. This revision may be based on the researcher's knowledge of existing theory. |
| 2 | 3 | ○ Design an experiment to test the logical consequences of the hypotheses. Conventional data analysis approaches may be included in the experimental design. |
| | 4 | ○ 4a: Collect observations about the phenomena.<br>○ 4b: Conduct measurement validity.<br>○ 4c: Determine if hypotheses of the current model are supported based on data analysis of the given dataset. |

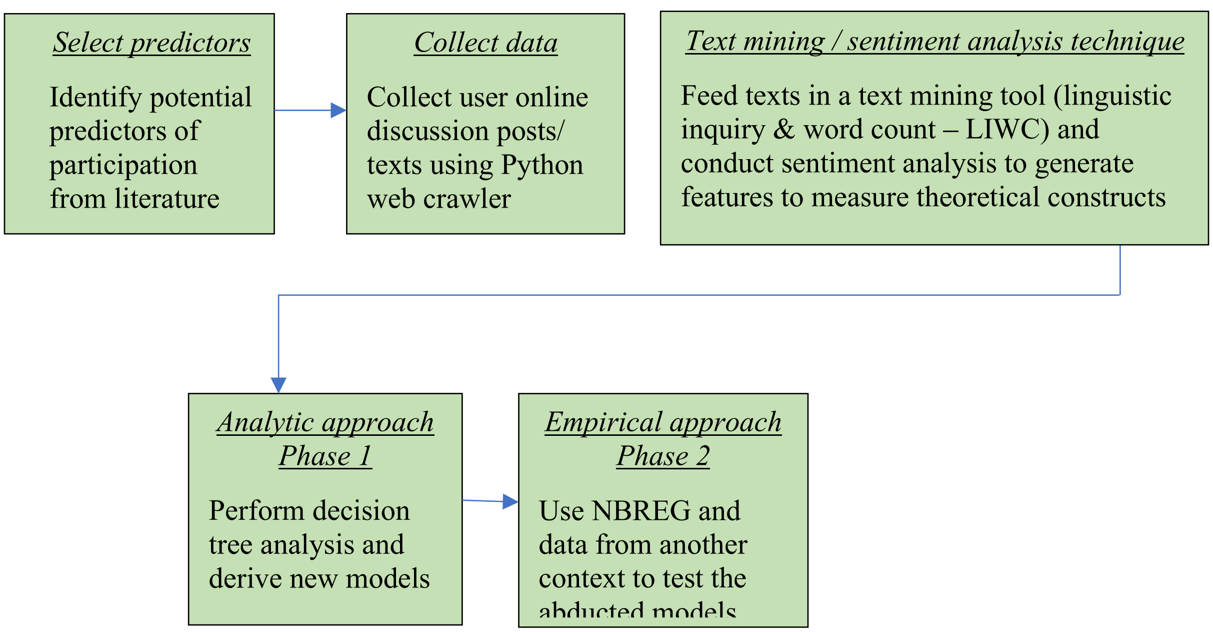



Figure 4. 1: Research Methodology Design

### 4.3.1. Step 2a: Automatic Generation and Preliminary Testing of Hypotheses

Osei-Bryson and Ngwenyama (2011) presented a data mining-based approach for the automatic abduction of hypotheses from data that involved the use of decision tree (DT) induction. Similar to that study and that of (Andoh-Baidoo et al., 2012) used and Donalds and Osei-Bryson (2019) we also use DT induction in this study.

DT induction is used to partition the dataset into subsets based on input variables selected by the relevant splitting method. Each node represents values that resulted from the partitioning of the data set based on the discriminating variable associated with their immediate parent node. In a DT (e.g., see Figure 4.2 below, nodes that have the same non-root parent node (i.e., input variable) are referred to as sibling nodes (e.g., Node 1 & Node 2; Node 3 & Node 4), where each sibling is associated with a mutually exclusive subset of the values of the relevant immediate parent discriminating variable (*Intimacy* for Nodes 1 & 2; *Efficiency* for Nodes 3 & 4), and the relevant value of any higher ancestor node (*Intimacy* for Nodes 3 & 4).

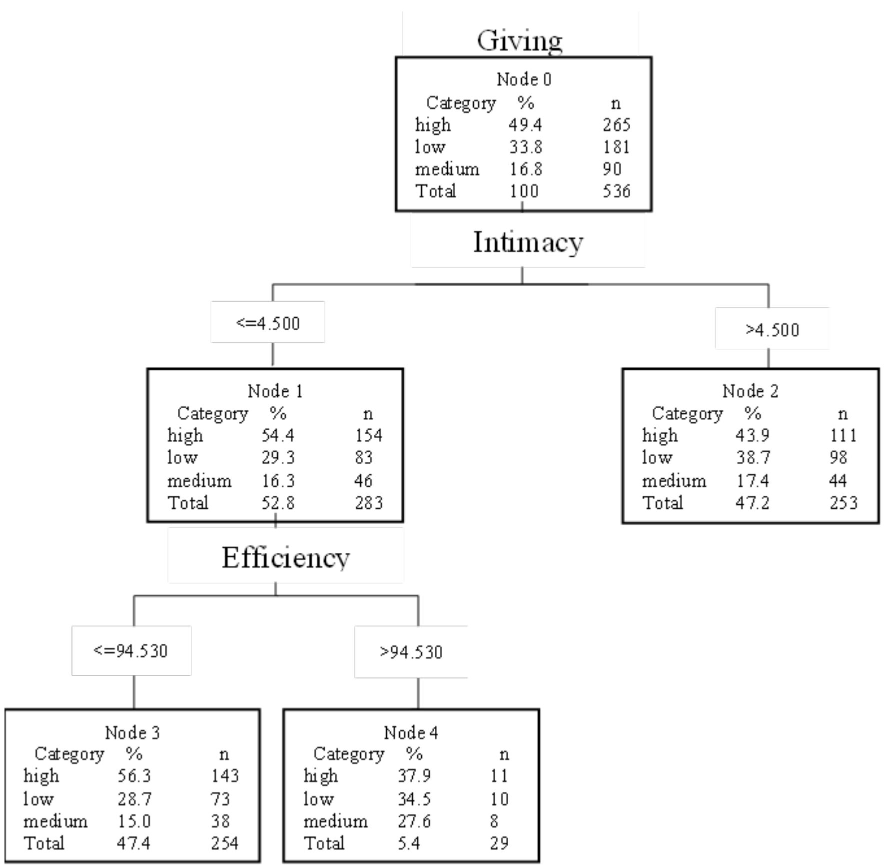



Figure 4. 2: Example Decision Tree with *Giving Participation* as the Target Variable

Osei-Bryson and Ngwenyama (2011) presented two types of hypotheses that could be abducted from the results of DT induction: Sibling Rules Hypothesis and Strong Single Rule Hypothesis.

### 4.3.2. Abducting Sibling Rules Hypothesis

In hypothesis abduction methodology of Osei-Bryson and Ngwenyama (2011), for any set of sibling rules, a corresponding *Sibling Rules Hypothesis* is abducted if for any pair of sibling nodes, the difference between the relevant posterior probabilities (i.e., relative frequencies) for the selected target event (e.g., Giving Participation = *High*) is statistically significant, as this would suggest that the given immediate discriminating variable is a predictor for the target variable. Table 4.2 presents an example abduction of sibling rule hypothesis using the decision tree in Figure 4.2 above.

Table 4. 2: Abduction of Sibling Rule Hypothesis – Example

| Backend condition | Sibling nodes/ frontend conditions | Giving = *High* | | Candidate sibling rules hypothesis | Abduct? |
|---|---|---|---|---|---|
| | | Proportion (N) | | | |
| | **1**: *Intimacy* ≤ 4.5 | 0.544 | 283 | *Intimacy* impacts *Giving Participation* | **Yes** $p = 0.007 < 0.05$ |
| | **2**: *Intimacy* > 4.5 | 0.439 | 253 | | |
| *Intimacy* ≤4.5 | **3**: *Efficiency ≤ 94.53* | 0.563 | 254 | If *Intimacy* ≤4.5, Then *Efficiency* impacts *Giving Participation* | **Yes** $p = 0.030 < 0.05$ |

### 4.3.3. Abducting Strong Single Rule Hypothesis

A *single rule hypothesis* would have the form: If *Condition* applies then the *probability* of *target event* (e.g., Giving Participation is High) is Strong (i.e., $p_0 \geq \tau_0$). In this study, we are only interested in *Single Rule* hypotheses for which the value of $p_0$ satisfies the specified test worthiness threshold (i.e., $\tau_0$). Similar to Osei-Bryson & Ngwenyama (2011), we used $\tau_0 = 0.5$.

### 4.3.4. Step 2b: Automatic Generation of the Preliminary Model

This sub-step involves for each target variable (e.g., *Overall, Giving, Receiving*), the integration of its set of abducted hypotheses, where each hypothesis is a causal link.

## 4.4. Phase 1: Application of the Research Methodology

### 4.4.1. Sub-step 1a: Identify Potential Predictors

Table 4.3 presents the operational definition and measurement of the key variables.

Table 4. 3: Constructs, Definitions, and Measurements

| Variable | Theoretical definition | Operational definition |
|---|---|---|
| Intimacy (INT) | Degree to which users in an OHC feel a sense of closeness and belongingness (Argyle and Dean, 1965) | The number of friends a user has on the platform. |
| Immediacy (IMM) | The tone of a user message that highlight the need for urgent response(Dixson et al. 2017) | Measured by obtaining the *tone* scores in the *patient's initial post* from the sentiment analysis |
| Efficiency (EFF) | User's sincerity in the message on the platform (Xu & Zhang, 2018) | Measured by obtaining the *authentic* scores from sentiment analysis of *patient's initial post* |
| Nonverbal communication (NVComm-NVC) | User's feelings expressed in online message (Bhattacherjee, 2001) | Measured by obtaining the *affect* scores from the sentiment analysis of *patient's initial post* |

Table 4.3, cont.

| | | |
|---|---|---|
| Giving participation (Giving) | Degree to which users participate in OHC discussions by the amount of content they generate (Ma et al., 2017; Sillence, 2013) | The total number of posts a user provides less their initial post to group discussions and replies to others' posts normalized by user length of stay on the platform |
| Receiving participation (Receiving) | Degree to which users participate in OHC discussions by amount of feedback a user's post gets from other users (Ma et al., 2017; Sillence, 2013) | The total number of votes (support, thanks, and useful) a user's post receives from others normalized by user length of stay on the platform |

### 4.4.2. Sub-step 1b: Data Collection

To accomplish the research objective, data was sourced from a popular online health community, *inspire.com*. Previous IS studies have shown the beneficial effects of online communities such as *inspire.com* in addressing key challenges including global health (Tim et al., 2017; Zhang et al., 2019) because online technologies constitute growing pools of users and offer users the opportunities to interact through giving support, receiving support, include networking features, and are real-time research platforms (Solberg, 2014). For example, a support group, "spontaneous coronary artery disease (SCAD)," on the website inspired some researchers to initiate the creation of a registry that studies rare diseases such as SCAD (Tweet et al., 2011).

The inspire.com platform has various communities for different disease types (Inspire, 2020). For this study, data was randomly obtained on patient participation from the HIV/AIDS community. Due to the members' reliance on this online community for support, the support groups and communities have a reputation for being sympathetic and interactive. Users demonstrate supportive behaviours by reacting to or reading other's posts. Participation is key to the survival of online health communities (Solberg, 2014).

The dataset consists of 536 unique user posts in the HIV/AIDS community from August 2017 to November 2020. The data includes user initial postings and observable response information regarding supportive behaviours on the platform (number of replies, "support votes," "thanks votes," and "useful votes"). Additionally, users' demographic information such as age, gender, and the length of time on the platform (tenure) were collected for the analysis.

Scores for the measures were extracted from the sentiment analysis method using the linguistic inquiry and word count (LIWC) program (e.g., Li & Wu 2010; Agarwal et al., 2010). Specifically, LIWC measures the level of emotional strength within the post, which reflects the intensity of the feelings expressed in the post. Some of the features obtained from LIWC include affect score, authentic score, analytic score, and emotional tone score. All the features from LIWC (tone, authentic, and affect) are scored on a 100-point scale from 0 to 100, with higher scores indicating greater strength of a user's impressions or opinions in the post and lower values indicating weaker expressions of opinions or impression formation.

The dependent variable (DV) of the study is participation, which is treated as a two-dimensional variable—giving and receiving participation normalized by the user length of stay on the platform. Giving is the ratio of the total number of posting and responding activities that a user provides to others/groups (posts and replies a user provides) to the user's tenure on the platform. Receiving is the ratio of the total number of support a user gets from others (as support votes, thanks votes, useful votes) to user tenure on the platform. The DVs were transformed from continuous variables into categorical variables of "low," "medium," and "high" participation. Each of the continuous DVs in the dataset was categorized using the percentile approach (e.g., Templeton, 2011). Participation was categorized as low if the value is less than the 25th percentile; medium if the value is between the 25th and 50th percentile; and high if the value is greater than the 50th percentile. Overall participation is operationalized as a measure of an individual's total giving and receiving participations. Table 4.4 presents the descriptive statistics.

Table 4. 4: Descriptive Statistics

| Variables | Minimum | Maximum | Mean | Std. deviation |
|---|---|---|---|---|
| Immediacy | 0.00 | 99.00 | 46.16 | 35.01 |
| Intimacy | 0 | 205 | 23.00 | 45.60 |
| Efficiency | 0.00 | 99.00 | 45.46 | 35.26 |
| Nonverbal Communication | 0.00 | 28.57 | 4.64 | 3.89 |
| Giving | 0.00 | 2.06 | 0.03 | 0.13 |
| Receiving | 0.00 | 2.57 | 0.05 | 0.17 |
| Overall Participation | 0.00 | 4.63 | 0.08 | 0.28 |

*N = 536*

**4.4.3. Sub-step 2a: Automatic Generation & Preliminary Testing of Hypotheses**

The classification and regression tree (CART) algorithms were used to generate the DTs. Decision tree analysis in this study was performed using IBM SPSS Statistics 25 software with CRT methodology. The CRT methodology is recommended when the data mining task contains classifications or predictions of outcomes, and the goal is to generate rules that can be easily explained and translated into a natural query language (Andoh-Baidoo et al., 2012).

Results obtained from our analysis for *Overall Participation, Giving Participation*, and *Receiving Participation*. In each case the values of target variable were discretized into 3 categories: *Low, Medium*, and *High*. Figure 4.3 shows the decision tree for participation.

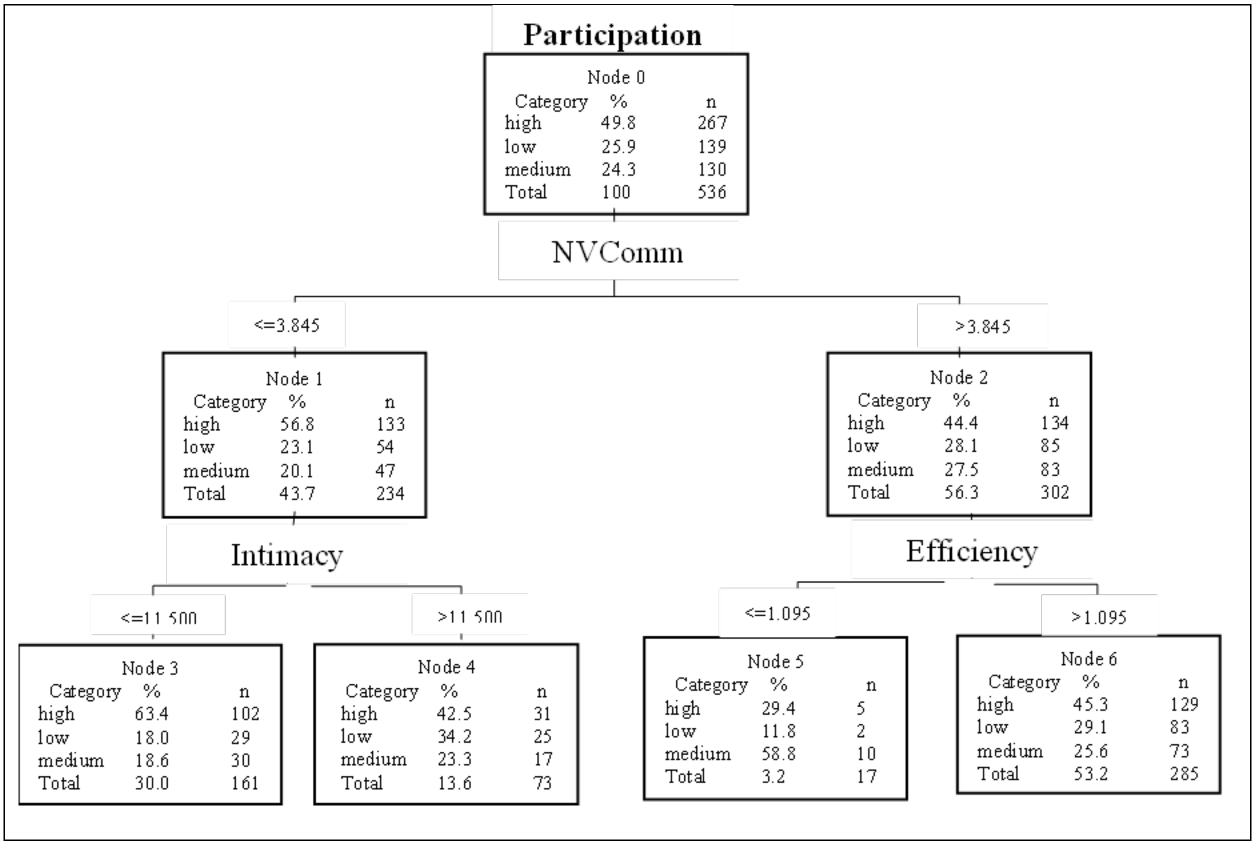


Figure 4. 3: Classification Decision Tree Diagram for Participation (Overall)

### 4.4.4. Abduction of Sibling Rule Hypotheses

A sibling rule hypothesis can have a direction—for example, X positively or negatively predicts Y, or it can be non-directional—for example, X predicts Y (Osei-Bryson & Ngwenyama, 2011). We followed the non-directional approach since the interaction of the dimensions of SPT has not been previously published. Tables 4.5-4.7 show the results of the sibling rules hypotheses that were supported and further abducted based on Target Event *High* (e.g., *Participation is High*). Appendix A1 presents the decision tree for receiving participation.

Table 4. 5: Participation (Overall)

| | **Condition Events** | | | | | |
|---|---|---|---|---|---|---|
| ID | Backend | Frontend | N | RF(f) | Abducted? (Supported?) | Candidate sibling rule hypothesis |

Table 4.5, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 | | NVC <= 3.845 | 234 | 0.568 | YES<br>p = 0.0021 | NVC has a significant impact on Participation |
| 2 | | NVC > 3.845 | 302 | 0.444 | | |
| 3 | NVC <= 3.845 | INT >11.500 | 73 | 0.425 | YES<br>p = 0.0013 | Given NVC > 3.845, then INT has a significant impact on Participation |
| 4 | | INT <= 11.500 | 161 | 0.634 | | |
| 5 | NVC > 3.845 | EFF <= 1.095 | 17 | 0.294 | NO<br>p = 0.0823 | Given NVC <= 3.845, then EFF has no significant impact on Participation |
| 6 | | EFF > 1.095 | 285 | 0.453 | | |

*Notes: RF (f): relative frequency; p: p-value; ID: denotes pairs of sibling nodes in the DTs.*

Table 4. 6: Giving Participation

| | **Condition Events** | | | | | |
|---|---|---|---|---|---|---|
| ID | Backend | Frontend | N | RF(f) | Abducted? (Supported?) | Candidate sibling rule hypothesis |
| 1 | | INT <= 4.500 | 283 | 0.544 | YES<br>p = 0.0073 | INT has a significant impact on Giving Participation |
| 2 | | INT > 4.500 | 253 | 0.439 | | |
| 3 | INT <= 4.500 | EFF <= 94.530 | 254 | 0.563 | YES<br>p = 0.0268 | Given INT <= 4.500, then EFF has a significant impact on Giving Participation |
| 4 | | EFF > 94.530 | 29 | 0.379 | | |

*Notes: RF (f): relative frequency; p: p-value; ID: denotes pairs of sibling nodes in the DTs.*

Table 4. 7: Receiving Participation

| | **Condition Events** | | | | | |
|---|---|---|---|---|---|---|
| ID | Backend | Frontend | N | RF(f) | Abducted? (Supported?) | Candidate sibling rule hypothesis |
| 1 | | INT <= 27.000 | 440 | 0.516 | YES<br>p = 0.0001 | INT has a significant impact on Receiving Participation |
| 2 | | INT > 27.000 | 96 | 0.323 | | |
| 3 | INT <= 27.000 | NVC <= 4.220 | 208 | 0.606 | YES<br>p = 0.0001 | Given INT > 27.000, then NVC has a significant impact on Receiving Participation |
| 4 | | NVC > 4.220 | 232 | 0.435 | | |

*Notes: RF (f): relative frequency; p: p-value; ID: denotes pairs of sibling nodes in the DTs.*

### 4.4.5. Abduction of Strong Single Rule Hypotheses

Table 4.8 presents the strong rules from the DT analyses for all the target variables for participation (overall, giving, and receiving).

Table 4. 8: Strong Rules (Overall Participation, Giving, and Receiving)

| Target variable | Condition event | N | F | Abducted (Supported)? | Candidate Strong Sibling Rule Hypothesis |
|---|---|---|---|---|---|
| Participation | NVC <= 3.845 & INT <=11.500 | 161 | 0.634 | Yes; F > 0.500 | Given NVC <= 3.845, then INT has a significant impact on Participation |
| Participation | NVC <= 3.845 & INT > 11.500 | 73 | 0.425 | No; F < 0.500 | Given NVC <= 3.845, then INT does not have a significant impact on Participation |
| Participation | NVC > 3.845 & EFF <= 1.095 | 17 | 0.294 | No; F < 0.500 | Given NVC > 3.845, then EFF does not have a significant impact on Participation |
| Participation | NVC > 3.845 & EFF > 1.095 | 285 | 0.453 | No; F < 0.500 | |
| Giving | INT <= 4.500 & EFF <= 94.530 | 254 | 0.563 | Yes; F > 0.500 | Given INT <= 4.500, then EFF has a significant impact on Giving |
| Giving | INT <= 4.500 & EFF > 94.530 | 29 | 0.379 | No; F < 0.500 | Given INT <= 4.500, then EFF does not have a significant impact on Giving |
| Receiving | INT <= 27.000 & NVC <= 4.220 | 208 | 0.606 | Yes; F > 0.500 | Given INT <= 27.000, then NVC has a significant impact on Receiving |
| Receiving | INT <= 27.000 & NVC > 4.220 | 232 | 0.435 | No; F < 0.500 | Given INT <= 27.000, then NVC does not have a significant impact on Receiving |

*Notes: NVC: non-verbal communication, EFF – efficiency, INT: intimacy.*

### 4.4.6. Sub-step 2b: Automatic Generation of Models

Consistent with the approach of Osei-Bryson & Ngwenyama, (2011), we construct a separate model for each target variable (e.g., *Overall Participation, Giving Participation, Receiving Participation,*) by integrating the relevant set of hypotheses that were abducted in Sub-

Step 2a. Table 4.9 presents the abducted hypotheses from Phase 1, which are shown in Figures 4.4 and 4.5, respectively for overall participation, and giving and receiving.

Table 4. 9: Abducted Hypotheses from Phase 1

| ID | Hypothesized Relationship |
|---|---|
| $H_{1,P}$ | Non-verbal communication (NVC) is related to participation. |
| $H_{2,P}$ | Intimacy (INT) is related to participation. |
| $H_{1,M}$ | Non-verbal communication (NVC) moderates the relationship between intimacy (INT) and participation. |
| $H_{2,M*}$ | Non-verbal communication (NVC) does not moderate the relationship between efficiency (EFF) and participation. |
| $H_{3,P}$ | Efficiency (EFF) is related to participation. |
| $H_{1,G}$ | Intimacy (INT) is related to giving. |
| $H_{2,G}$ | Efficiency (EFF) is related to giving. |
| $H_{3,M}$ | Intimacy (INT) moderates the relationship between efficiency (EFF) and giving. |
| $H_{1,R}$ | Intimacy (INT) is related to receiving. |
| $H_{2,R}$ | Non-verbal communication (NVC) is related to receiving. |
| $H_{4,M}$ | Intimacy (INT) moderates the relationship between non-verbal communication (NVC) and receiving. |

** We include the non-significant relationship because we are testing the main effect between efficiency and participation.*

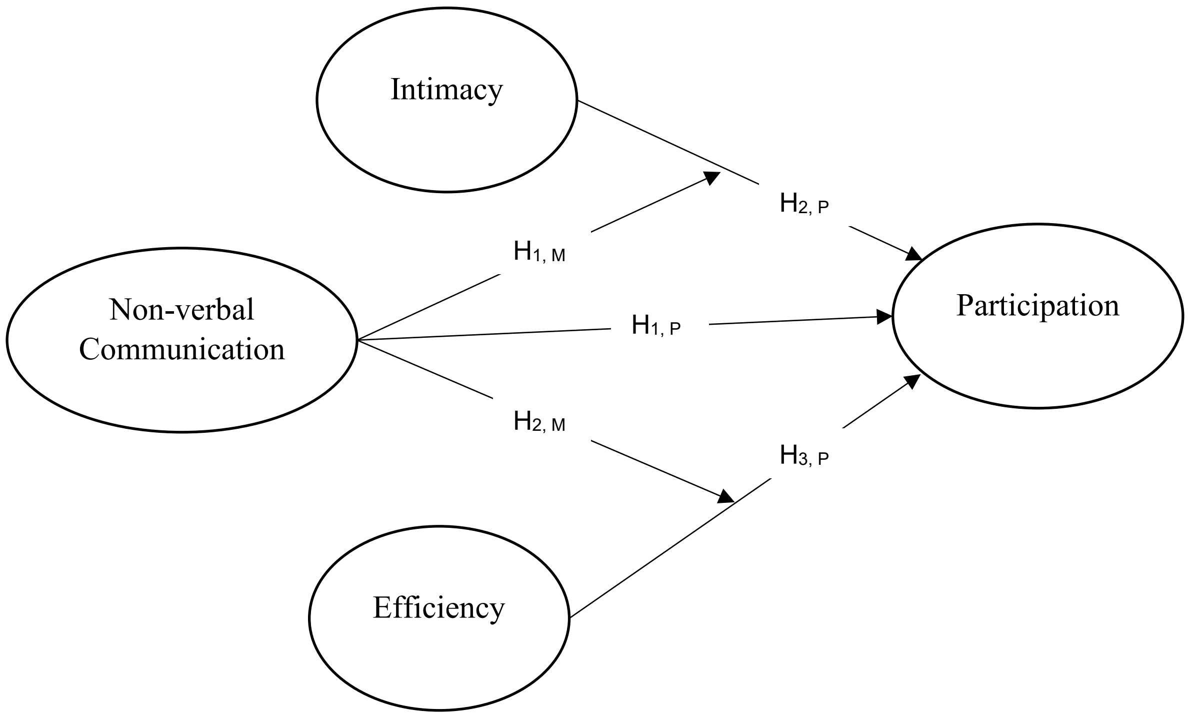



Figure 4. 4: Abducted Research Model for Overall Participation.

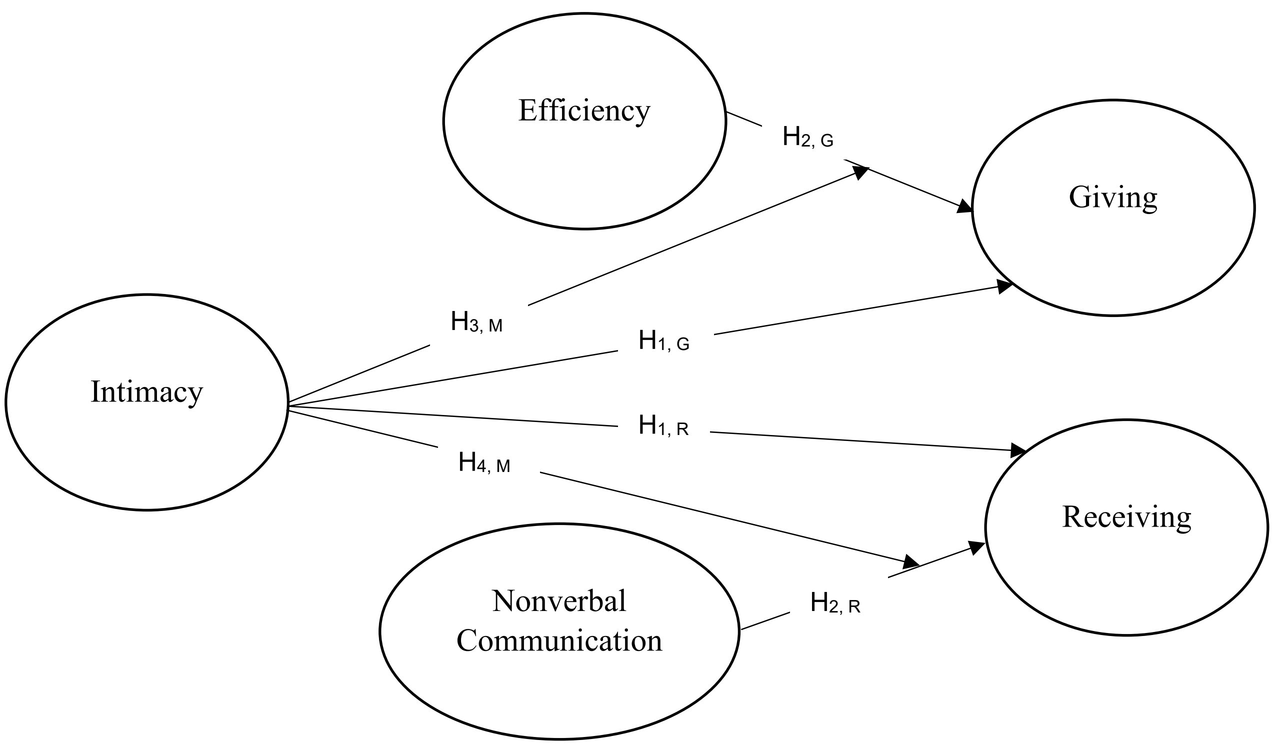



Figure 4. 5: Abducted Research Models for Giving and Receiving.

## 4.5 Phase 2: Empirical Validation

### 4.5.1 Step 3: Design Experiment

In phase 2, the goal is to test the derived models for overall participation, giving and receiving (see Figures 4.4 and 4.5 above) using data collected from a different online health community context. To test the proposed models, data was collected from *patient.info* OHC platform, specifically, the anxiety disorder support community. This community hosts individuals who may be suffering from anxiety disorders and needing social or informational support from other peers on the platform to overcome these challenges. Like Phase 1, the main dependent variables were measured from features directly observed on the patient.info platform while the independent variables were measured using features obtained from analysing the first impression cues in the user online discussion post.

### 4.5.2. Sub-step 4a: Collect New Data

The sample includes 230 user textual posts collected using web crawler. Data was processed to remove duplicates. A final sample of 203 unique posts was retained for the analysis for different users who participated in discussions on anxiety disorder in *patient.info* online health community. Table 4.10 presents the descriptive of the data and the variables used.

Table 4. 10: Descriptive Statistics (N = 203)

| Variables | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| Giving | 0 | 1185 | 24.20 | 93.05 |
| Receiving | 0 | 47 | 1.23 | 4.32 |
| Participation | 0 | 1232 | 25.43 | 96.96 |
| Intimacy | 1 | 509 | 14.21 | 42.33 |
| Immediacy | 1.00 | 99.00 | 7.88 | 14.39 |
| Efficiency | 1.00 | 99.00 | 89.75 | 18.58 |
| Non-verbal communication | 0.00 | 15.89 | 6.75 | 3.04 |

### 4.5.3. Sub-step 4b: Conduct Measurement Validity

The correlations and collinearity statistics are shown in Table 4.11. There appears to be no high pairwise correlations. Hair et al. (1995) suggest a variance inflation factor (VIF) less than 10 is indicative of inconsequential collinearity. The highest VIF was 5.373, below the acceptable level of 10. Thus, the correlations do not pose collinearity problems.

Table 4. 11: Correlation Matrix and Variance Inflation Factors (VIFs)

| Variable | NVComm. | Receiving | Efficiency | Immediacy | Giving | VIF |
|---|---|---|---|---|---|---|
| NVComm. | 1.000 | -.076 | -.078 | .205 | .079 | 1.067 |
| Receiving | -.076 | 1.000 | -.026 | -.042 | -.902 | 5.373 |
| Efficiency | -.078 | -.026 | 1.000 | .210 | .013 | 1.064 |
| Immediacy | .205 | -.042 | .210 | 1.000 | .025 | 1.105 |
| Giving | .079 | -.902 | .013 | .025 | 1.000 | 5.370 |

### 4.5.4. Sub-step 4c: Determine if Hypotheses are Supported by New Data

The purpose of Phase 2 is to test the derived models from the inductive approach in Phase 1. We start by examining the distribution of the outcome variables. The distributions reveal the pattern often found with distributions of counts events. At the initial stage of first impression creation in online social discussions, many users have very few or no followers/friends, provide, and receive less or no support. Few users have many friends, giving, and receiving participation making for a distribution that appears to be far from normal. Since the dependent variables are count variables, we expect the outcomes to follow a Poisson distribution (see equation 1). Thus, Poisson regression is the appropriate technique used to model our data and test our hypotheses.

$P(Y_{ij}=\mu_{ij}) = PD(\mu_{ij}) = (e^{-uij})*(u^{Y})/Y\,!,$ ………………………………………………………….(1)

where $j$=(1, 2, 3, 4) represents the four dependent variables participation, intimacy, giving, and receiving, $Yij$ is the participation for the *ith* post, PD(.) is a Poisson distribution with mean and variance $\mu j$, *εij is the error term, and γij, βij, and αij are the constants to be estimated.*

$\mu_P ij = exp(\gamma 0j + \gamma 1jIntimacyij + \gamma 2jImmediacyij + \gamma 3jEfficiencyij + \gamma 4jNVCommij) + \varepsilon_P ij)$……………………………………………………………………………………………(2)

$\mu_G ij = exp(\beta 0j + \beta 1jIntimacyij + \beta 2jEfficiencyij + \varepsilon_G ij)$…………………………………..(3)

$\mu_R ij = exp(\alpha 0j + \alpha 1jIntimacyij + \alpha 2jNVCommij) + \varepsilon_R ij)$………………………………(4),

*where* $\mu_P ij$, $\mu_G ij$, *and* $\mu_R ij$ are the exponential equations for *overall participation, giving*, and *receiving*.

SPSS Statistic 25 analytical tool was used to perform the analysis. Tables 4.12 and 4.13 present the results for *Overall Participation* (model 1) and *Giving/Receiving Participation* (model 2), respectively. Figure 4.6 and Figure 4.7 show the models for *Overall Participation* and for *Giving and Receiving*, respectively with the beta coefficients (unstandardized) and the significance level. The hypothesized relationships for overall participation and giving/receiving models are summarized in Table 4.14 and Table 4.15, respectively.

Table 4. 12: Model 1 Results (Overall Participation)

| DV: Overall participation | Unstandardized Coefficient (B) | Significance (p-value) | Exp(B) | Lower | Upper |
|---|---|---|---|---|---|
| (Intercept) | 3.978*** | 0.000 | 53.427 | 46.259 | 61.706 |
| Intimacy | 0.007*** | 0.000 | 1.007 | 1.004 | 1.009 |
| Efficiency | -0.013*** | 0.000 | 0.694 | 0.660 | 0.729 |
| Nonverbal Comm. | -0.366*** | 0.000 | 0.987 | 0.985 | 0.989 |
| NVC x INT | 0.000** | 0.016 | 1.000 | 1.000 | 1.001 |
| NVC x EFF | 0.004*** | 0.000 | 1.004 | 1.003 | 1.004 |

*Note: ** $p < 0.05$; *** $p < 0.01$; ns nonsignificant; DV: dependent variable; NVC: non-verbal communication; INT: intimacy; EFF: efficiency.*

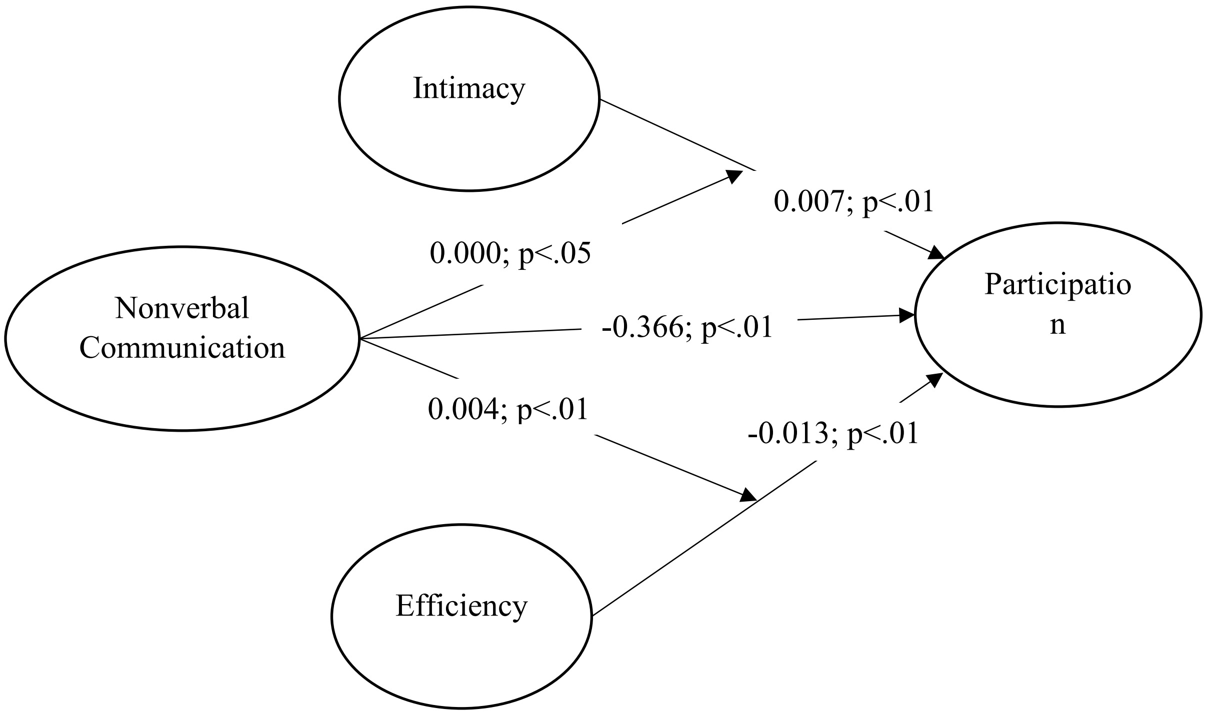



Figure 4. 6: Overall Participation Model with Beta Coefficients and Significance Levels.

Table 4. 13: Model 2 Results (Giving and Receiving)

| DV: Giving | Unstandardized Coefficient (B) | Significance (p-value) | Exp(B) | Lower | Upper |
|---|---|---|---|---|---|
| (Intercept) | 0.690*** | 0.000 | 1.993 | 1.428 | 2.781 |
| Intimacy | 0.072*** | 0.000 | 1.075 | 1.069 | 1.081 |
| Efficiency | 0.021*** | 0.000 | 1.021 | 1.017 | 1.024 |
| INT x EFF | -0.001*** | 0.000 | 0.999 | 0.999 | 0.999 |
| | | | | | |
| DV: Receiving | | | | | |
| (Intercept) | 0.255 n.s. | 0.217 | 1.290 | 0.861 | 1.933 |
| Intimacy | -0.017*** | 0.000 | 0.983 | 0.977 | 0.989 |
| Nonverbal Comm. | -0.087** | 0.004 | 0.916 | 0.863 | 0.973 |
| INT x NVC | 0.004*** | 0.000 | 1.004 | 1.003 | 1.005 |

*Note: ** p < 0.05; *** p < 0.01; ns nonsignificant; DV dependent variable; NVC: non-verbal communication; INT: intimacy; EFF: efficiency.*

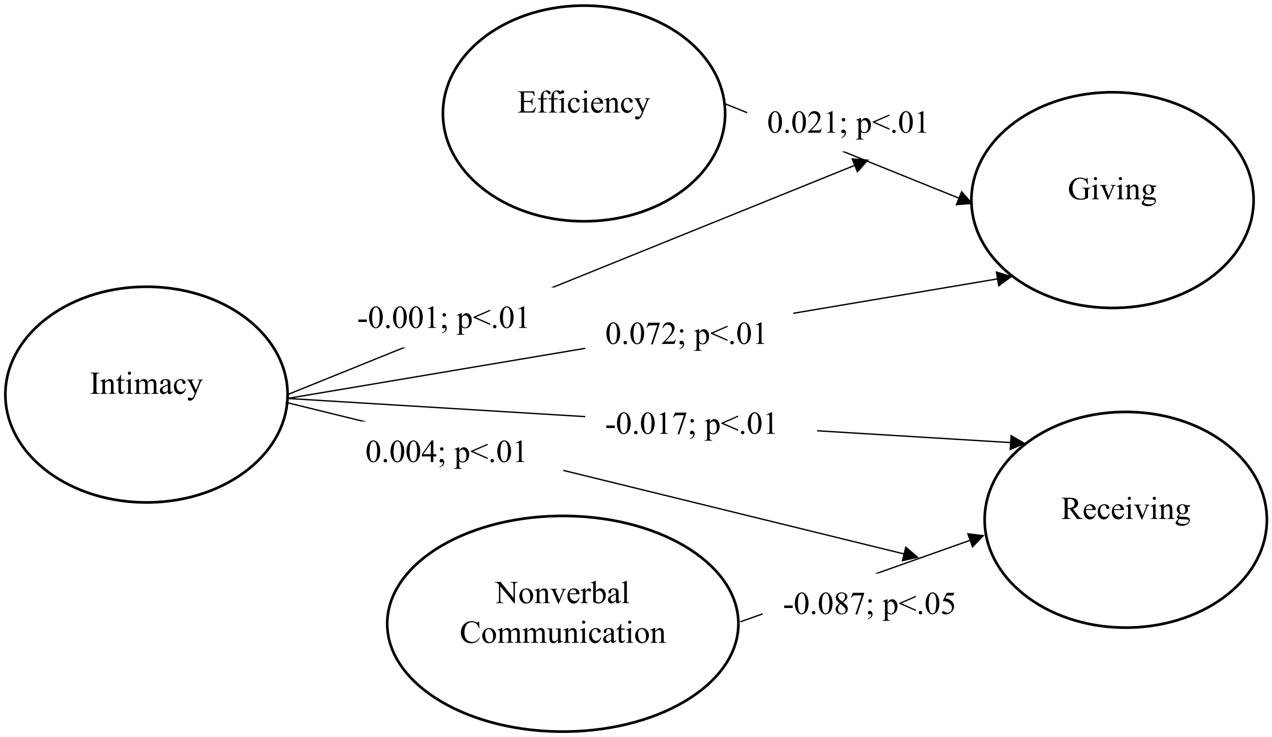



Figure 4. 7: Giving and Receiving Model with Beta Coefficients and Significance Levels

Table 4. 14: Summary of Hypotheses for Overall Participation

| Label | Relationship | Direction | Supported/ Unsupported? |
|---|---|---|---|
| $H_{1,P}$ | *Nonverbal communication has a significant impact on user participation in online health communities.* | Negative | Supported |
| $H_{2,P}$ | *Intimacy has a significant impact on user participation in online health communities.* | Positive | Supported |
| $H_{3,P}$ | *Efficiency has a significant impact on user participation in online health communities.* | Negative | Supported |
| $H_{1,M}$ | *Nonverbal communication moderates the relationship between intimacy and participation.* | Positive | Supported |
| $H_{2,M}$ | *Nonverbal communication moderates the relationship between efficiency and participation.* | Positive | Supported |

*Notes: $H_{i,P}$ denotes the i-th hypothesized relationship for overall participation; where i = 1, …, 3; $H_{1,M}$ and $H_{2,M}$ denote the moderation relationships for intimacy and efficiency, respectively.*

Table 4. 15: Summary of Hypotheses for Giving and Receiving

| Label | Relationship | Direction | Supported/ Unsupported? |
|---|---|---|---|
| $H_{1,G}$ | *Intimacy has a significant impact on user Giving participation in online health communities.* | Positive | Supported |

Table 4.15, cont.

| | | | |
|---|---|---|---|
| $H_{2,G}$ | *Efficiency has a significant impact on user Giving participation in online health communities.* | Positive | Supported |
| $H_{3,M}$ | *Intimacy moderates the relationship between efficiency and giving.* | Negative | Supported |
| $H_{1,R}$ | *Intimacy has a significant impact on user Receiving participation in online health communities.* | Negative | Supported |
| $H_{2,R}$ | *Nonverbal communication has a significant impact on user Receiving participation in online health communities.* | Negative | Supported |
| $H_{4,M}$ | *Intimacy moderates the relationship between nonverbal communication and receiving.* | Positive | Supported |

*Notes: $H_{i,G}$ denotes the i-th hypothesized relationship for giving; $H_{i,R}$ denotes the i-th hypothesized relationship for receiving, where i = 1, …, 2; $H_{3,M}$ and $H_{4,M}$ denote the moderation relationships for efficiency and non-verbal communication, respectively.*

### 4.6. Discussion and Implications

This study inductively identified first impression cues and empirically tested their role in OHC through the understanding of giving, receiving and overall participation. Our results (see Table 13) confirm that the important cues from the DT are effective in explaining OHC member participation in phase 2 except efficiency and participation in the overall participation model. Our results extend the introduction of SPT theory (i.e., impression cues) in a new context.

Additionally, our results illustrate OHC members overall participation is different from their giving or receiving participation behaviours. While intimacy and the interaction of nonverbal communication and efficiency positively influence overall participation, the direct relationship between intimacy and nonverbal communication on overall participation is negative. This implies that whereas a member's network of friends and affect in their initial posting interactively influence their participation, individually those factors do not increase participation. This can be explained by the fact that when member has a large network of friends it could lead to thinning of their effort, the affect in their message arouses responses resulting in increased discussion (i.e., participation). Thus, increase effective deployment of nonverbal communication and efficiency simultaneously get other users to participate. Consistent with prior research about customer participation on social media sites, task and affection cues are relevant activities (Zhang et al., 2015). Online users' giving and receiving behaviours are facilitated by intimacy, that is, the sense of closeness and belonging to a community.

Furthermore, as an individual's friendship network enable mutual benefits in OHCs (Claridge, 2018), the more access a user has to a vast network of resources, the greater the benefits in terms of responses to health needs. Our results show that social support provision (giving) is a function of increase message authenticity (efficiency) and friendship network while social support receipt (receiving) is a function of affect (non-verbal communication) and friendship network in online health communities. These findings extend prior results who found that structural social capital is a significant factor to social support exchange in the online context (Chen et al., 2019). Similarly, there is evidence  that interpersonal relationships and bond formation among peers in virtual communities positively influence participants' willingness to give information to others and to get information from others (Ridings et al., 2002).

Finally, we compare the results from Phase 1 and Phase 2 to ascertain the generalizability of our theoretical model. In Phase 1, we identified and abducted sibling rule hypotheses that were significant. Appendix C summarizes the comparison of the results of the data-driven discoveries—Phase 2 with extant theory and literature—Phase 1 (see Müller et al., 2016). Majority of the results of the hypotheses are similar for Phase 1 and Phase 2 except for participation where the main effect of efficiency is different. The similarities of the results between the two studies confirm the stability of our theoretical model; thus, the models can be generalizable across different contexts. Phase 1 results are based on the difference of proportion test with Z-scores significant at the 5% level while Phase 2 results are based on the generalized linear models (for Poisson distribution) with beta coefficients.

#### 4.6.1. Implications for Research

Our research expands the literature on value extraction from online health platforms (Chamakiotis et al., 2021), by identifying and establishing cues in first impression and their effect on OHCs. We establish that the tenets of social presence theory (SPT) are not linear in their effect on participation in OHC, which is different from prior literature (Srivastava & Chandra, 2018). We, thus extend the boundaries of SPT. Using the exploratory process allowed for the identification and conceptualization of participation not only as a continuum of an individual's overall engagement activities in online communication media but also as the extent of the value they generate (giving) or as the benefits they gain (receiving) when interacting with peers. Our study reveals there are interactions among various components of the SPT from the inductive process in Phase 1 (Vaast & Walsham, 2013). Additionally, in explaining the effects of the components, Phase 2 study confirms the proposed theoretical models. We have developed three different theoretical explanations for participation in online health community platforms (giving, receiving, and overall participation). The antecedents of the three different participations are different, which are marked departure from prior literature (Maier et al., 2015; Fan & Lederman, 2018).

Furthermore, the study unravels that the route through which overall participation is enhanced is different from giving or receiving participation. This is marked departure and extension of the principle of SPT that assumes that low social presence is associated with low levels of emotional and personal expression in messages. In the OHC context, individuals' overall participation is motivated by first impressions cues in the writings to express feelings and emotions, while the giving or receiving individuals' participation is based on the sense of closeness and belonging cues expressed in the initial postings. Furthermore, SPT assumes that better communication will result in more cues in the initial postings and a greater sense of closeness and attachment expressed in the messages. From the findings of this study, this assumption holds for users inclined to giving or receiving participation in contrast to those persuaded to participate in both.

With the granular view of OHC participation, we uncover that the first impression in users' initial communication is instrumental in eliciting the user's participation in either giving or receiving. Specifically, the findings reveal that users' giving behaviours can follow a gradual process of first developing intimacy with the initiator of the post followed by the efficiency of the message. On the other hand, users also demonstrate participation in receiving through the impression created primarily through intimacy, followed by nonverbal communication, and then efficiency.

Additionally, for methodology, the study demonstrates the effectiveness of inductive-deductive explanation approach in IS investigation. The results illustrate through the inductive approach that the dimensions of SPT do not act linearly and are mutually exclusive in exerting their influence. The establishment of the sibling rule sets of classification demonstrates the nonlinear mechanisms and through the predictive approach illustrate which impression cues in an initial post reveal the efficacy of SPT (Kathuria et al., 2020).

#### 4.6.2. Implication for Practice

Practically, online health community users, management, and designers can benefit from our findings in guiding them. First, by understanding which social presence features they should pay attention to, platform managers can make informed decisions about improving participation. Our model for giving and receiving helps platform management understand that individuals will cherish intimacy—bonding formation and closed relationships with other peers on the platform as a prelude to effective participation through giving and receiving (Posey et al., 2010).

Second, users participate more in online conversations by giving support to others and receiving support from peers when they can effectively express their feelings, which is an art of communication competence. As a result, it facilitates individuals' social presence capabilities and improves their social, mental, and emotional well-being. Thus, examining participation in terms of giving or receiving could help platform management know those users who are motivated to participate by giving, thus stimulating receiving, and those who are inclined to participate by receiving, hence stimulating giving in them (Matook et al., 2015). When platform management understand how to differentiate giving motivations from receiving motivations, they can provide personalized and customizable interfaces on the platform that differentiate givers from receivers, which meet their needs. Platform operators can separate giving and receiving activities in design of platform features such that different salient features are activated for two different participation types, i.e., giving and receiving.

Third, developers of online health platforms can encourage participation through the provision and reception of support by incorporating tools that reveal platform statistics of how much help users have received and how their engagements in online activities have benefited others on the platform. The design tools/features can help facilitate participation in giving or receiving as users can know and assess how well they are engaging in the community. For instance, designing games and reward systems in for high givers, receivers, and total participation through badges, points, and leader boards could improve online user engagement, lead to motivations to engage in meaningful collaborations, and enhance user online experience (Liu et al., 2017).

### 4.7. Conclusion and Future Research Direction

This study set out to identify the factors of social presence theory (SPT) in users' initial postings that influence participation in OHCs. This was based on the premise that first impression drives long-term responses. SPT does not discriminate on the efficacy of each variable. The unstated assumption is that intimacy, immediacy, efficiency, and nonverbal communication dimensions of SPT work equally as motivators of participation. That is, SPT assumes that each of the variables has the same effect. This study argued that each dimension of SPT has a different effect on participation through giving and receiving in OHCs. The decision tree results revealed that intimacy and nonverbal communication have better effects on participation than efficiency and immediacy.

This research provides support for theory development by generating single and sibling rule hypotheses from a set of classification trees. The sibling rule hypotheses were developed based on social presence theory and decision induction technique. The proposed rule hypotheses were validated using statistical inference proportions test with literature on participation and theory development in the information systems discipline.

This study has limitations. First, prior research has identified different genres of participants in OHCs (Moser et al., 2013). Future research could provide additional insights by examining if social presence dimensions have different effects among the genres of OHC participants. Second, only the original posts were analysed in this study; replies to the posts were not included. Future research should consider analysing the threads—both the original posts and related replies might reveal more interactive patterns in the online communities. Finally, this current study used data from only one health support community or platform. Data from other online platforms could provide deeper insights and could serve as a robustness check to validate the results of this study.

Despite the limitations, the study provides valuable information to assist platform managers in decision-making for sustaining platform membership and participation. For instance, members with low intimacy, low immediacy, and low efficiency may receive more support than they give. Thus, management can watch out for such behaviours and develop motivational tactics to get these members engaged in giving.

# CHAPTER V

# UNDERSTANDING USER INFORMATION DISCLOSURE CHARACTERISTICS AND SUPPORT RESPONSE ACCEPTANCE BEHAVIOR DYNAMICS IN ONLINE HEALTH COMMUNITIES: AN ECONOMETRIC PERSPECTIVE

User participation in online health communities (OHCs) requires active interactions between disclosers and responders. This dynamic engagement serves as an opportunity for enhancing individual health welfare and for reshaping healthcare delivery. Previous research has extensively discussed the effects of user information disclosure and different types of supports using different theoretical lenses. However, the dynamics that evolve among this connected system of variables over time is yet to be fully examined. The dynamic between user information disclosure characteristics and support response provision is important to researchers, practitioners, and platform management as it can reveal insights for understanding the role of health information systems in fostering a supportive environment, community engagement, bond formation, knowledge sharing, and sustained participation. Given that user disclosure and response activities are highly endogenous, this paper proposes a structural vector autoregression (SVAR) model that addresses the reverse causality in the system of variables of interest.
Based on the health disclosure decision-making model framework and using daily time series data from 2014 to 2022, we decompose disclosure efficacy into information density and

information efficacy and examine their effects on support response acceptance and vice versa. Findings of the impulse response functions reveal that user information density can lead to positive support response acceptance, whereas support response acceptance may reduce the information density of a user post. Similarly, the results also show that user information efficacy can lead to positive support response acceptance, and the latter can improve information efficacy in the long run. The findings suggest several theoretical and practical implications to the broader context of user activities in online communities and to OHC platform management.

## 5.1. Introduction

Online health communities (OHCs) provide avenues for healthcare stakeholders to deliver and receive patient-centered supportive care management (Liu et al., 2022, van der Eijk et al., 2013). For instance, OHCs facilitate physicians' participation in online healthcare delivery through interaction with patients in regard to health concerns (e.g., Wang et al., 2020). Patients on their part can benefit from online health platforms by receiving informational, emotional, and companionship supports in dealing with different health challenges (see Chen et al., 2019; Huang et al., 2019).

Despite the possible impact of online health platforms that connects information seekers--disclosers to support providers--responders  (Chen et al., 2020), research is yet to explore users' information disclosure and response behaviors dynamics in OHCs. Considering that users constitute the majority of people who visit online platform and in view of the fact that many of these users share their personal health information in search for answers or support to their health needs (S.-Y. Lee et al., 2019), it is intuitive that their disclosure behavior activities likely affect the support response they receive and vice versa. For example, users' who demonstrate effective information disclosure characteristics in their posts can attract acceptable support responses. On the contrary, users may become dormant or inactive if the support from responders do not commensurate with their disclosure expectations revealed in their online posts (Sun et al., 2014). This means that through efficacious disclosure mechanisms, users can increase the level of support from the audience, and they can also take advantage of the support they receive to improve their disclosure abilities in subsequent conversations.

Given the dynamic nature of OHCs, we postulate that active user participation depends on the degree of effective two-way interaction between discloser and responder. Thus, in this current study, we are interested in examining the dynamics of individuals' information disclosure characteristics and support response behaviors in online health platforms. Specifically, we seek to answer the following questions: *How do the characteristics of individuals' online information disclosure behaviors affect support response acceptance and vice versa?* To address our research question, we leverage the health disclosure-decision making model (DD-MM) as the theoretical lens and utilize a time series data set for the analysis. The DD-MM framework posits that an individual’s ability to disclose information depends on his/her assessment of the information and their expectation of the response.

The sample contains daily user observations (posts) obtained from a popular online health community from March 2014 to February 2022. Modeling a system of equations and relationships between user information disclosure and support response dynamics introduces endogeneity problems and this limits the use of traditional econometric techniques as these tools may produce biased estimates (e.g., Luo et al., 2013). Endogeneity occurs when the explanatory variable is correlated with the error term in the causal model (i.e., problems of autocorrelation and reverse causality). Thus, a structural vector autoregression presents a more suitable technique used to develop our model. SVAR models are useful tools to analyze the dynamics of a causal system by subjecting it to an unexpected shock and imposing additional contemporaneous restrictions into the standard reduced form vector autoregression model. Our SVAR model captures three main variables in the causal system: users' disclosure efficacy conceptualized into *information density* (amount of informational content) and *information efficacy* (the succinctness of the shared information), and response efficacy conceptualized as *support response acceptance* (support considered as acceptable, useful, or beneficial).

The empirical analysis reveals some interesting dynamics among the variables in the system of structural equations. First, we find that an increase in information density and information efficacy can lead to more acceptable support responses implying that users' disclosure efficacy behaviors can improve the level of support response they receive from the audience. On the contrary, the findings show that an increase in the number of support response acceptance can reduce the information density of a user post over time, but it can improve the information efficacy of a user post in subsequent time periods. The results indicate that when a user post receives acceptable support responses, the user tend to reduce the quantity of information disclosed and increase the succinctness and quality of their post in the future.

The findings have the following contributions to the broad context of health information systems healthcare literature and specifically to disclosure decision-making model (DD-MM) literature. First, the dynamic engagement among users in OHC platforms demonstrate the importance of using health platforms in healthcare delivery. We show that user information disclosure and support response behaviors can be modeled dynamically to provide interesting insights otherwise not possible when using traditional econometric techniques such as OLS models. Second, our results prove that dimensions of information disclosure efficacy elicit more acceptable response over time, which is an indication that disclosure efficacy can be treated as multi-construct concept, which is an extension of the DD-MM framework, thus, providing opportunities for future research using these subconstruct by studying their effects on other disclosure outcomes (Chaudoir & Fisher, 2010). Third, while information density and information efficacy have increasing effects on support response acceptance, the effects of support response acceptance on the two variables are different. This is an indication that modeling users' online disclosure and response behaviors dynamically can produce varying effects. These results can be generalizable and applicable to other research contexts. Practically, the results show that effective online disclosure engages responders to contribute value and knowledge on the platform while good support responses enhance positive feelings and emotions in the disclosers. Next, our model suggest that users can boost their efficacy behaviors on the OHC platform so that their disclosure and support response provision strategies will promote their happiness, health-wellbeing, and socialization skills. Last, the insights in this study provide indicators on personalize care strategies, promotion of effective participation in OHCs, and collaborative information systems design in healthcare management.

## 5.2. Research Background and Literature Review

To understand the dynamic interactions between users' online information disclosure mechanisms and support response acceptance behaviors, we discuss the literature on online health communities and describe the disclosure decision-making model (DD-MM) framework, which informs the theorization of dynamic efficacy behaviors. We then propose a conceptual model that explains dynamic activities among variables in a system.

### 5.2.1. Online Health Communities

Online health communities (OHCs) create channels for personalized patient-healthcare management and provide a platform for sharing opinions regarding topics like health issues (e.g., Liu et al., 2020). Online communities in general provide a virtual space that enable people of common interests to communicate and provide support to each other (Kim et al. 2008) and it serves as a robust platform for information sharing among members, anonymous or known, with shared common interests (Sproull et al. 2007). Such shared interests typically include designing new products, debugging new software, writing new texts, or sharing an idea, and artwork (Yu et al. 2010). To a large extent, online communities operate on voluntary knowledge sharing between members with different motivations. Knowledge sharing is a communication process between two or more individuals characterized by exchanging personal knowledge to collectively create new knowledge (Van Den Hooff and De Ridder 2004). Findings indicate that knowledge sharing is often motivated by reputation, social interaction ties, trust, norms of reciprocity, identification, shared vision, shared language, community-related outcome expectations, and personal outcome expectations (Wasko and Faraj 2005). Specifically, online health communities (OHCs) create channels for personalized patient-healthcare management and provide a platform for sharing opinions regarding topics like health issues (S. Liu et al., 2020).

There has been a growing interest in examining different phenomena in OHCs because is the potential to facilitate healthcare delivery, enhance physician-patient interaction for easy access to professionals and for better healthcare service provision, and motivate user active participation for value generation, knowledge contribution, and information disclosure and support response activities (Hur et al., 2019; Yan et al., 2016; Zhang et al., 2017). This growing interest, however, requires different approaches in examining phenomena related to online health platform. This current study departs from prior research and contributes to the growing body of knowledge to understand users' disclosure mechanisms for enhancing support response acceptance and how the supports users receive can improve their disclosure abilities.

### 5.2.2. Information Disclosure and the Disclosure Decision-Making Model

Information disclosure is defined as the extent to which individuals are willing and confident to reveal sensitive and confidential information about their health conditions in online health communities (X. Zhang et al., 2018a). Information disclosure has received good coverage by information systems researchers (e.g., Zhang et al. 2018; Fan et al. 2014). The decision to disclose personal information is often intentional and carefully deliberated (Wakefield, 2013). An individual's decision to disclosure information has been explained using the DD-MM theoretical framework (e.g., Choi et al. 2016; Greene 2009). The DD-MM framework is a mechanism to study the process by which patients make disclosure decisions. Originally, the DD-MM outlines three components in the decision process: information assessment (a discloser's assessment of their health condition or the information under consideration for disclosure), receiver assessment (a discloser's evaluation of the expected response of disclosure target), and disclosure efficacy (a discloser's perceived effectiveness of information sharing or the confidence to disclose) (Greene, 2009a).

Disclosure efficacy in prior literature refers to an individual's ability to reveal information that achieves its intended purpose. Users in OHCs craft their messages covering length and breadth to engage their readers with the aim to receive a response. Consistent with prior research that has used multidimensional conceptualization of disclosure behavior to provide a more accurate description of individual behaviors (e.g., Knijnenburg et al. 2013), disclosure efficacy in this study is conceptualized as comprising of information density and information efficacy. Information density is the degree to which a patient in OHC platform discloses information that is sufficient in terms of depth/scope. Information efficacy refers to the succinctness of the disclosed information.

### 5.2.3 Response Efficacy (Support Response Acceptance)

Response efficacy is defined in literature as the degree to which an individual believes that the recommended response provided will be effective (Woon et al., 2005). Responsiveness are shown to constitute important outcomes of individuals' disclosure processing decisions (Blankespoor et al., 2020). The DD-MM has been extended to include the effect of disclosure on outcomes such as supportiveness (Torke et al., 2012). In the context of OHCs, the audience provide responses either by replying, or providing non-verbal gestures such as supportive, useful, and helpful votes to the discloser's message. In this study, we examine dynamic interactions between disclosure of and support response to disclosed information. In the next section, we propose a model that examines the two-way relationship. In this study, we conceptualize response efficacy as support response acceptance, which refers to the recognition of support response as useful, helpful, and beneficial (Lee et al. 2019).

## 5.3. User Disclosure and Response Behaviors Ecosystem

The literature on health communication suggests an interdependent relationship between disclosure efficacy and response efficacy although prior literature has not fully explored it. In fact, the DD-MM framework found that a participant's ability to share information is associated with the readiness to reveal information in the near future (Greene et al. 2012). Therefore, a participant's ability to provide effective feedback (response efficacy) is expected to be linked to the evaluation of user's disclosure ability. Based on the DD-MM framework, we argue that at the higher level, an individual's response efficacy increases with increased disclosure efficacy. Conversely, we propose that an increase in user's response efficacy will reduce information density and improve information efficacy. Below we drill down the discussions to explain the interdependent relationships between the dimensions of disclosure efficacy (information density and information efficacy) and response efficacy construct (support response acceptance).

### 5.3.1. Information Density and Support Response Acceptance

Information density is the amount of informational content being disclosed. The ability to manage health conditions with the expectation of receiving informational, emotional, and social support is seen in the depth of disclosure (Barak & Bloch, 2006). Messages that are effectively disclosed are considered helpful (Park et al., 2020). Disclosed information or posts that are deep, are considered to elicit positive and helpful support responses (Barak & Bloch, 2006). However, when the support response is acceptable or helpful, the discloser feels satisfied because the response provided fulfils their needs. Consequently, their ability to disclose dense information diminishes over time. This is because in subsequent disclosures, the user is no longer driven by emotions but rather influenced by the knowledge gained from the prior support response received. Hence, a change in information density will increase support response acceptance while a change in support response acceptance will reduce information density over time.

### 5.3.2. Information Efficacy and Support Response Acceptance

Information efficacy refers to the succinctness of the shared information. Information that is succinct adds quality to the user post and increases readability and understanding. Hence more acceptable support responses will be provided to disclosures that eases the reader's comprehension. Conversely, an increased number of support response acceptance to a user post is an indication the user did well by providing quality information that adds value to the readers. Thus, over time, as the support increases, the user is encouraged to do better and hence, information efficacy ability improves. We infer that in the online health community context, when the support response is acceptable, users tend to generate more value on the online platform by sharing more information and knowledge. Hence, users are more likely to further disclose more succinct information because of the enhanced satisfaction they derived earlier.

Based on the disclosure DD-MM framework and the literature presented above, we present a system that captures user information disclosure and support response dynamics in OHCs. The system includes information density, information efficacy, and support response acceptance components. Information density is operationalized as the total number of words a user post contains, Information efficacy is measured by the number of words per sentence of a post, and support response acceptance is measured by the total number of acceptable useful support votes a user post receives. The model in Figure 5.1 represents the interactions between the three variables in the system.

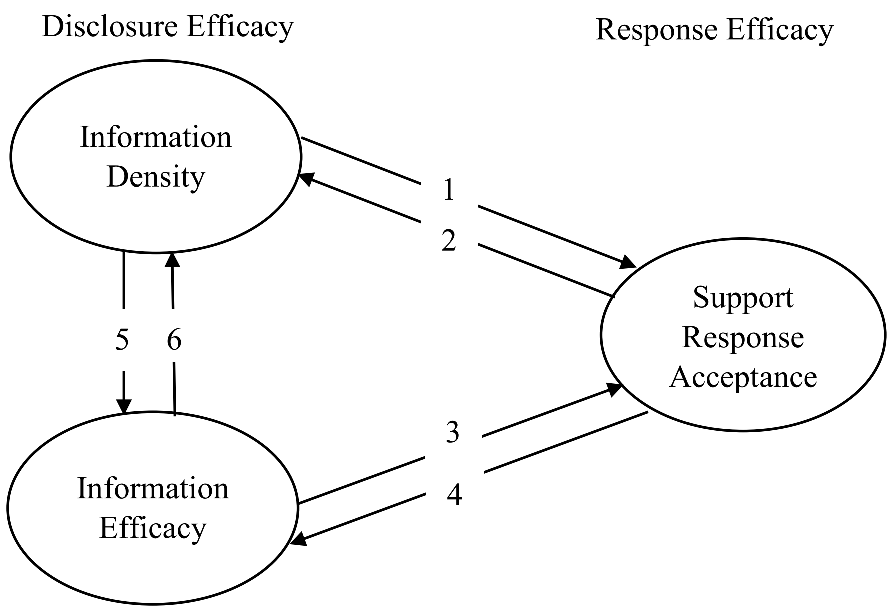



Figure 5. 1: System Model of User Disclosure and Response Behaviors in OHCs Over Time.

The model shows six causal relationships. Relationships 5 and 6 are not examined since our focus was on the effects of disclosure efficacy dimensions to support response acceptance. Based on the model, relationship 1 suggests that user information density will increase support response acceptance while an increase in support response acceptance will reduce user information density of a post over time (relationship 2). Relationship 3 suggests that user information efficacy can lead to increased support response acceptance while support response acceptance will improve the information efficacy of a user post in the long run (relationship 4).

## 5.4. Research Methodology

### 5.4.1. Data, Variables, and Measures

We utilize a data set that captures posts and the number of support responses to examine user information disclosure and response behavior dynamics in OHCs. The data comes from *inspire.com*, an OHC platform that constitutes the context of our study and provides a medium through which patients with illnesses can freely discuss and express themselves to their peers (e.g., Hur et al. 2019; Park et al. 2020). Our interest in studying user behaviors in OHCs is important because of the uniqueness that these platforms afford compared to other social platforms. For instance, OHCs have a broader functioning scope including the sharing of knowledge and information, provision of informational and emotional supports, and companionship activities. In OHCs, member ship is unique in the sense that users face emotional distress, are anxious, and tend to look for a context to disclose personal information freely and safely. Additionally, OHCs are unique in that participation is dynamic, interactive, but more volatile than other social networks (see Huang et al., 2019). Given these unique characteristics on OHCs, our analysis considers users posting and support response behaviors in a dynamic system while controlling for the volatility of users' disclosure and response habits over time. The daily was observed from March 2014 to February 2022. After data cleaning and transformation, we constructed a daily unbalanced data set of user observations spanning March 2014 to February 2022 with a final sample of 1028 observations for analysis.

A time series data was collected on the user disclosures (posts) and support responses (votes) to measure information density, information efficacy, and support response acceptance. We employ text analytic technique via sentiment to obtain sentiment features in a user post to measure information density and information efficacy. Sentiment analysis output was obtained from the scores of the linguistic inquiry and word count (LIWC) text analysis program (Pennebaker et al., 2015). We measure *information density* as the total number of words in a user post with more words indicating higher information density of the post. *Information efficacy* is measured as the total number of words per sentence of a user post, with fewer words per sentence indicating higher information efficacy. *Support response acceptance* is directly observed on the platform and is operationalized as total number helpful or useful votes a user post receives. Table 5.1 presents the variable operationalization and descriptive statistics. When a user discloses health or personal information in an online platform, other users provide feedback in the form of votes of support. The "votes" to a user post in our context are synonymous to the "online gifts" that patients provide to physicians' online professional services, which has been used in previous research (e.g., Wang et al., 2020).

Table 5. 1: Construct Definition/Operationalization and Descriptive Statistics

| Variable | Definition | Analytic Method | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| INFODEN | The total number of words in a user online post | Sentiment analysis | 4.8996 | 1.3129 | 0.0000 | 7.9215 |
| INFOEFF | The total number of words per sentence in a user online post | Sentiment analysis | 0.0972 | 0.1828 | 0.0035 | 1.0000 |
| SUPPACC | The total number of useful support votes provided to a user post | Observed on the platform | 1.2386 | 1.5439 | 0.0000 | 6.8156 |

*Notes*: Descriptive statistics for daily data used in this study; INFODEN – information density, INFOEFF – information efficacy; SUPPACC – support acceptance; all variables are logged.

The time series graphs for user information density, information efficacy, and support response acceptance are presented in Figures 5.2-5.4 with some periodic patterns noticed in the data. The Figures show some surges and dips in years 2016, 2019, and 2021, which could be due to either implementation of platform policies or some health crisis. Specifically, in 2019, the COVID-19 pandemic generates unique features in our data, which saw an increase and a decrease in the information density, and an increase in the support response acceptance. Thus, we must consider the recent COVID-19 pandemic as an exogenous shock in our analyses. Research has shown that recent outbreaks of diseases such as Ebola poses a shock to healthcare systems and examining behaviors of health systems as a response to these contemporaneous shocks is import to determine their resilience in the face of crises (Llamzon et al., 2022).

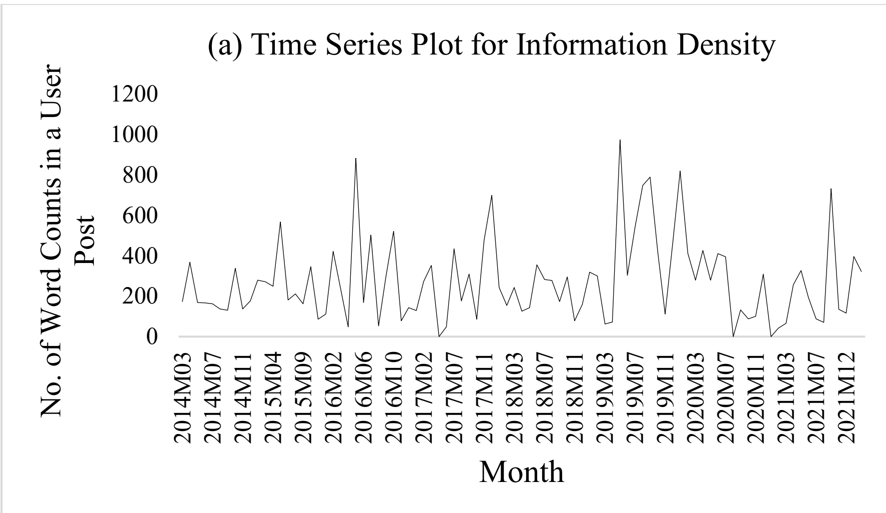



Figure 5. 2: Time Series Plot for Information Density

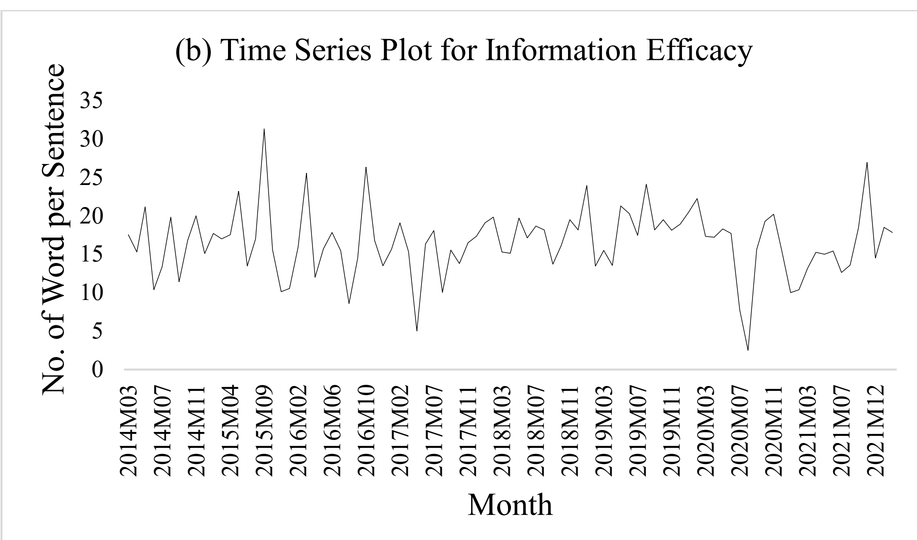



Figure 5. 3: Time Series Plot for Information Efficacy

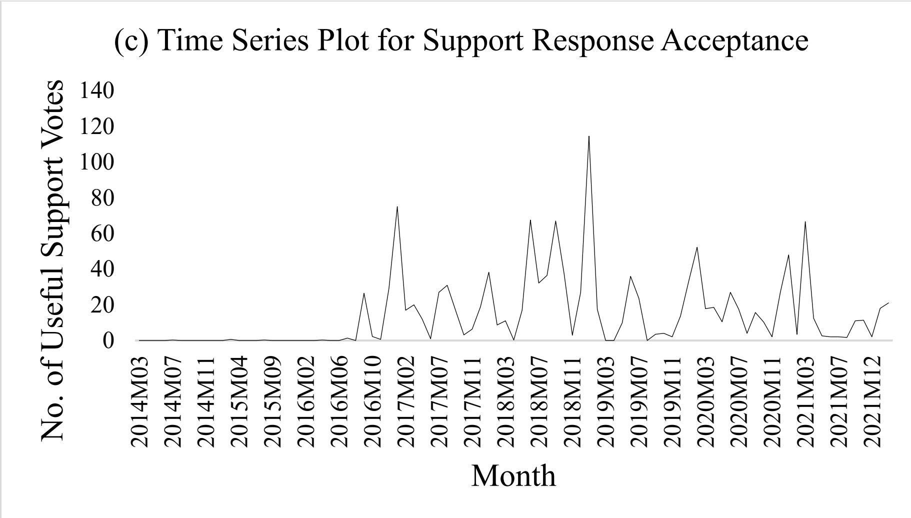



Figure 5. 4: Time Series Plot for Support Response Acceptance

### 5.4.2. VAR and SVAR Frameworks

The purpose of this study is to examine user dynamic behaviors in OHCs as presented in our conceptual model above. These behaviors are highly interrelated and endogenous. Thus, modeling such dynamics with causal effects over time entails the use of a more advanced technique that accounts for endogenous shocks in the system. The structural vector autoregression (SVAR) technique is better suited for modeling relationships between contemporaneous variables (Escobari & Sharma, 2020). SVAR models are derived from the standard vector autoregression (VAR) models, which are limited in their ability to describe contemporaneous relationships. Both VAR and SVAR can model the endogenous interdependence among variables in a system, but SVAR goes beyond that by imposing restrictions on the contemporaneous relationships while VAR does not. Variables in a SVAR model are estimated by regressing the variable on its own lagged (L) values and on lagged values of other variables. This helps to address lagged effects and reverse causality among the variables (Wang et al., 2020).

The challenge with SVAR models is how to identify purely exogenous shocks. To understand SVAR models, let's consider the following structural system of equations in (1),

$$AY_t = BY_{t-1} + \mu_t \tag{1}$$

where vector variable $Y_t$ depends on the lag variables of itself B and structural shocks $\mu_t$ (are normally distributed), A represents a matrix with diagonal normalized to 1 i.e., $\mu_t \sim N(0, I)$, and I is the identity matrix. Multiplying the SVAR model by inverse of matrix A (i.e., $A^{-1}$) gives:

$$A^{-1}AY_t = A^{-1}BY_{t-1} + A^{-1}\mu_t,$$

which implies $$Y_t = A^{-1}BY_{t-1} + A^{-1}\mu_t, \text{ where } A^{-1}A = I \tag{2}$$

Therefore, $$Y_t = CY_{t-1} + e_t, \tag{3}$$

where $C = A^{-1}B$ and $e_t = A^{-1}\mu_t$ indicate the link between structural shocks and the reduced-form VAR shocks. This means that matrix A is related to the forecast errors of the reduced-form VAR e and the structural shock $\mu_t$. These forecast errors are linear combinations of the structural shocks $\mu_t$, t is the time intervals in days. Figure 5.5 shows the outline on how to identify a SVAR model, which is the same as estimating the matrix A.

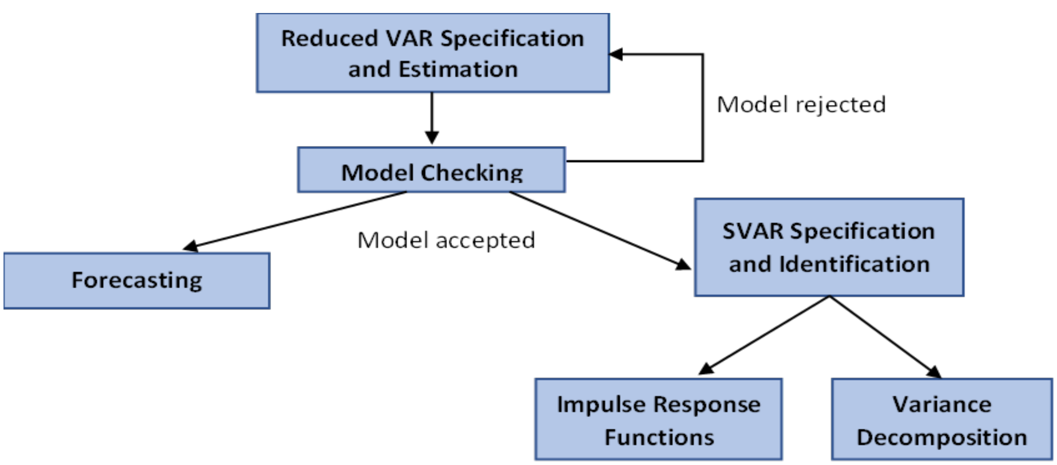



Figure 5. 5: An Outline for SVAR Identification

### 5.4.3. Empirical Models Specifications

Our research framework shows three variables in the system, but we were interested in studying only the effects of information density and information efficacy on support response acceptance. Therefore, in the specification of our structural models, we constructed a system of equations as shown in equation (7). As presented in Table 1, we measured information density as the total number of words in a user post, information efficacy as the total number of words per sentence, and support response acceptance as the total number of useful support votes a user post receives. Using a SVAR to model the interactions between these variables helps to systematically provide insights to answer our research questions of understanding user information disclosure characteristics and support response behaviors dynamics. All variables were log transformed to normalize the overdispersion and skewness in the data. The matrix forms of our model are specified as shown in the following equations.

$$A * \begin{bmatrix} SUPPACC_t \\ INFODEN_t \\ INFOEFF_t \end{bmatrix} = \alpha_i + B * \begin{bmatrix} SUPPACC_{t-1} \\ INFODEN_{t-1} \\ INFOEFF_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \tag{7}$$

where $SUPPACC_t$, $INFODEN_t$, and $INFOEFF_t$ are logged values of support response acceptance (number of useful support votes), information density (number of word count of a post), and information efficacy (number of words per sentence), respectively. The $\alpha_{i\text{'s}}$ i = 1, 2, 3 are all constants to be estimated. Matrix A contains the variances of the error term (that is, it assumes the covariance matrix is diagonal) and it describes the contemporaneous relationships between the observable variables in the system. The lagged effects of the variables in the systems is denoted by matrix B and $\varepsilon_{it}$ (i = 1, 2, 3) are the structural shocks or innovations in the system.

### 5.4.4. Model Identification – Imposing Short-run and Long-run Restrictions

Different types of restrictions can be used to identify SVAR models including short-run and long-run restrictions. Research suggests that both restrictions can be applied at the same time (e.g., Bjørnland & Leitemo, 2009). To impose restrictions, the identifying scheme must be of the form:

$$e_t = A^{-1}B\mu_t,$$

implying that

$$Ae_t = B\mu_t \qquad (8).$$

This is called the AB-model - a mixture of the A- and B-model (see Amisano & Giannini, 2012), where $e_t \sim N(0, I)$, B must contain at least (n(n−1)/2 restrictions (n is the number of endogenous variables in the system). By imposing structure on the matrices, A and B, we impose restrictions on the structural VAR in equation (1) above.

For our analysis, we develop the matrices A and B as described below.

$A = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix}$ $B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix}$ where A is known as the lower unit triangular matrix with a recursive structure and B is a diagonal matrix.

## 5.5. Empirical Analysis and Results

### 5.5.1. Diagnostic Checks

We used Eviews as the statistical tool for analysis, which was performed using daily time series data. In the analysis, we ordered the variables from the most exogeneous to endogenous. So, INFOEFF was considered the most exogeneous because the number of sentences and words per sentence add up to make the post dense. Next is INFODEN, followed by SUPPACC. In estimating the SVAR model, we first estimate the standard VAR model, select the appropriate lag length using a lag length criteria (AIC, SC, HQ), re-estimate the VAR using the correct lag length, check model stability, impose the restrictions on the estimated VAR, and then estimate the SVAR. Before following this process, we performed some diagnostic tests including 1) correlation matrix to assess multicollinearity, 2) unit root test to determine stationarity of the series, and 3) autocorrelation test to ensure the residuals are not autocorrelated. Details of these tests are shown in the appendices section.

The correlation matrix (see Appendix A1) indicate that the factors had no issue of multicollinearity with each other, but each construct was strongly correlated with itself. We verify that the three series are stationary by testing the presence of a unit root using the Augmented Dickey-Fuller (ADF) method. From the ADF test results (see Appendix A2), we reject the null hypothesis of a unit root in the series at conventional significance levels and conclude that the series are stationary at levels. Hence, we can proceed to estimate the Structural Vector Autoregression (SVAR). We do not need to difference the series. We then proceeded to select the lag length for the VAR model. Lag length is selected based on Hannan-Quinn information criterion (HQ), Schwarz information criterion (SC), Akaike information criterion (AIC), and Final prediction error (FPE). Based on the results, the lag selection criteria test in Table 5.2 show that the best lag is selected under the AIC is of order 6.

Table 5. 2: Lag Selection Criteria

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | -2824.07 | NA | 0.05128 | 5.54328 | 5.55777 | 5.54878 |
| 1 | -2773.65 | 100.440 | 0.04728 | 5.46207 | 5.52004 | 5.48408 |
| 2 | -2718.05 | 110.449 | 0.04315 | 5.37068 | 5.47213* | 5.40920 |
| 3 | -2690.58 | 54.3966 | 0.04162 | 5.33447 | 5.47940 | 5.38950 |

Table 5.2, cont.

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | -2665.42 | 49.6740 | 0.04032 | 5.30279 | 5.49120 | 5.37433 |
| 5 | -2644.96 | 40.2879 | 0.03942 | 5.28031 | 5.51220 | 5.36836* |
| 6 | -2631.36 | 26.6845* | 0.03907* | 5.27130* | 5.54666 | 5.37586 |
| 7 | -2623.77 | 14.8530 | 0.03918 | 5.27406 | 5.59291 | 5.39513 |
| 8 | -2619.43 | 8.47756 | 0.03954 | 5.28319 | 5.64551 | 5.42077 |

*Notes*: * indicates lag order selected by the criterion, HQ: Hannan-Quinn information criterion, SC: Schwarz information criterion, AIC: Akaike information criterion, FPE: Final prediction error, LR: sequential modified LR test statistic (each test at 5% level).

**5.5.2 SVAR Estimation**

From the above results, we then proceed to estimate the VAR model using 6 lags. The VAR results are omitted since the focus is on SVAR. But we need to estimate the VAR first before estimating the SVAR models. Table 5.3 shows the results of the estimated SVAR models. The results show that the SVAR model is just-identified. Note that the estimates are derived by imposing restrictions on the AB-model shown. The estimated model is given by Ae = Bu, where E[uu'] = I, with the recursive unit triangular A matrix and B diagonal matrix as shown. Coefficients $a_{21}$ is the effects of information efficacy on support response acceptance, $a_{31}$ is the effects of information density on support response acceptance, and $a_{32}$ is the effects of the lag of support response acceptance on itself. Additionally, the B diagonal matrix coefficients: $b_{11}$, $b_{22}$, and $b_{33}$ represent the effects of the lag of information density, information efficacy, and support response acceptance on themselves, respectively. The coefficients are valid at the 95% confidence interval level with $p < 0.000$.

Table 5. 3: SVAR Estimates

Structural VAR is just-identified

Model: Ae = Bu where E[uu'] = I

A =

| | | |
|---|---|---|
| 1 | 0 | 0 |
| $a_{21}$ | 1 | 0 |
| $a_{31}$ | $a_{32}$ | 1 |

B =

| | | |
|---|---|---|
| $b_{11}$ | 0 | 0 |
| 0 | $b_{22}$ | 0 |
| 0 | 0 | $b_{33}$ |

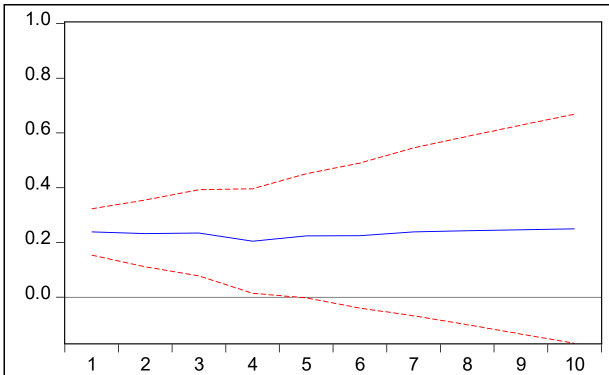
| | Coefficient | Std. Error | z-Statistic | Prob. |
|---|---|---|---|---|
| $a_{21}$ | 0.104196 | 0.002801 | 37.20102 | 0.0000 |
| $a_{31}$ | -0.587137 | 0.046318 | -12.67610 | 0.0000 |
| $a_{32}$ | -3.882273 | 0.337145 | -11.51514 | 0.0000 |
| $b_{11}$ | 1.304251 | 0.028848 | 45.21061 | 0.0000 |
| $b_{22}$ | 0.116784 | 0.002583 | 45.21061 | 0.0000 |
| $b_{33}$ | 1.258711 | 0.027841 | 45.21061 | 0.0000 |

Note: Model: Ae = Bu where E[uu'] = I, A – recursive unit triangular matrix, B – diagonal matrix, $a_{21}$– $b_{33}$ are estimated SVAR coefficients; *** $p < 0.001$.

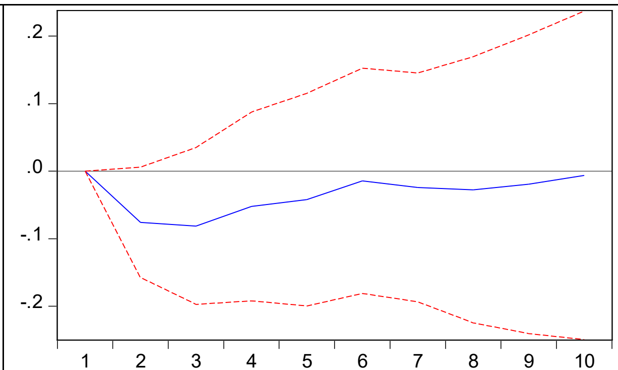
To assess the stability of our SVAR models, we tested for stability and for autocorrelation of the residuals. The result of the stability test (see Appendix A3) shows that none of the eigenvalues is even close to one; the Eigenvalues ranged from 0.480382 to 0.936638. Thus, VAR satisfies the stability condition. The Correlogram (see Appendix A4) outcomes indicate that most of the lag p-values are greater than 0.05. Therefore, we cannot reject the null of no residual autocorrelation at the 5% conventional significance level; so, we have no evidence to contradict the validity of our VAR estimation.

### 5.5.3. Impulse Response Functions Results

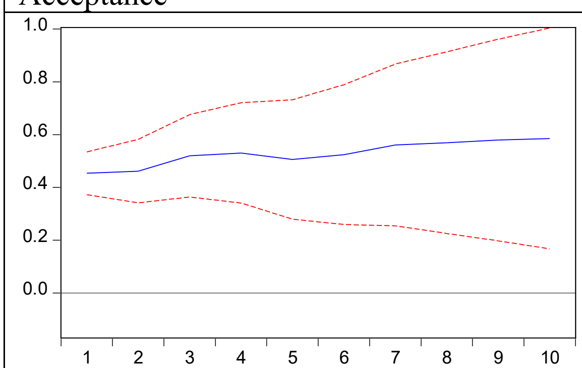
The goal of this study is to examine user dynamics in OHCs, and the impulse response functions (IRFs) provide a better picture in explaining the relationships between the variables in the system over time. IRFs help us to understand the dynamic interactions among variables in a system. The IRF measures the reaction of the system to a shock of interest and is derived from the estimated SVAR model. Since the terms of the residual series may be serially correlated, an orthogonal IRF provides the most appropriate approach for estimating the model (Sims, 2008). The IRFs graphs are shown in Figure 5.6 (a-d), and they represent the impulse response functions for a SVAR of support response, information density, and information efficacy. These IRFs Figures (a) to (d) show the impact of a one standard deviation shock to support response and vice versa.



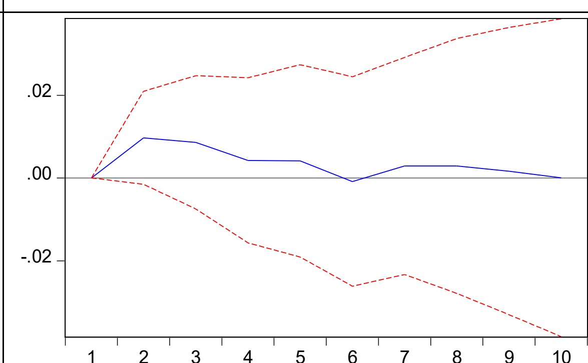

(a) Information Density to Support Acceptance




(b) Support Acceptance to Information Density




(c) Information Efficacy to Support Acceptance




(d) Support Acceptance to Information Efficacy

Figure 5. 6: Participants' Online Disclosure and Response Dynamics

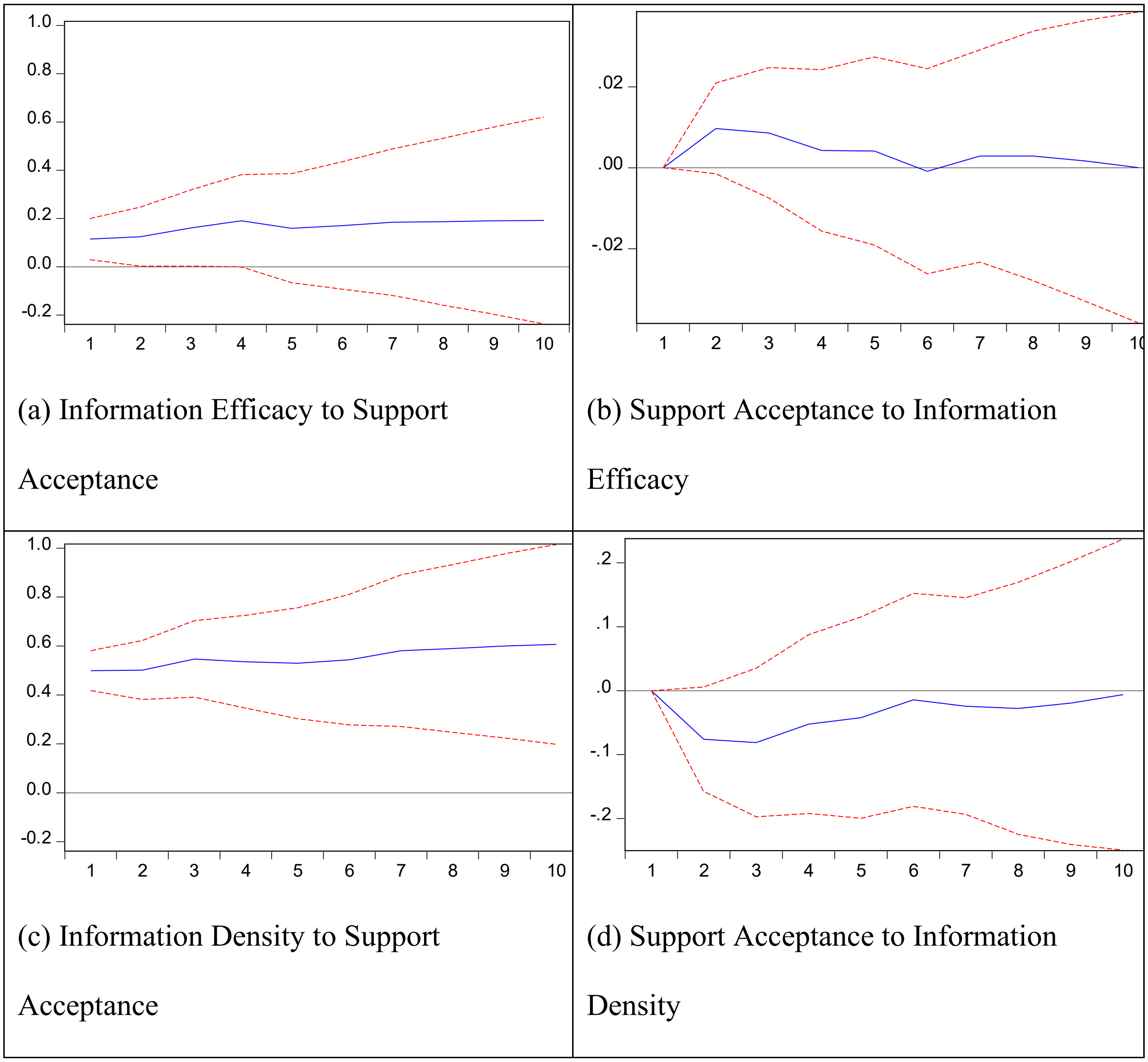
*Notes*: Blue line represents the effect of the impulse on response; red line is the 95% confidence interval band.

The IRF graphs of the first row of Figure 5.6 present how participants' online information disclosure behavior characteristic (information density - INFODEN) affects the total number of support responses provided to user post in the online health community and vice versa. Figure 5.6 (a) indicates that a unit shock to information density, that is, the total number of words in a user online post can generate a positive response in the total number of accepted support responses provided (SUPPACC) and that such positive effect remains significant from the days 2 to 5, and then remain constant over time. Figure 5.6 (b) shows that a unit shock in the total number of support responses acceptance provided, has no first-period impact on information density. The zero-immediate effect is because of the restrictions imposed when estimating the SVAR model. The result also shows that the effect of a unit shock on information density is non-significant (although the confidence interval band includes the zero line), decreases, and remains stable from day 2 to 3. But the effect gradually dies down after day 7.

The IRF graphs of the second row of Figure 5.6 represent how participants' online information disclosure behavior characteristic (information efficacy - INFOEFF) affects the total number of support responses provided to user post in the online health community and vice versa. Figure 5.6 (c) shows that a unit shock to the information efficacy of an online post, that is, the total number of words per sentence of a user post will lead to an in the number of support response acceptance provided and such positive impact remains significant and slightly increases over time. Figure 5.6 (d) shows that a unit shock in the total number of support responses acceptance provided, has no first-period impact on information efficacy. However, the effect is non-significant although it is within the zero line. The zero-immediate effect is because of the restrictions imposed when estimating the SVAR model. The result also shows that the effect increases up to day 3 but the effect of the unit shock on information efficacy decreases from days 3 to 6 and gradually dies down after day 7. The above findings demonstrate the dynamics of participants' online information disclosure and support response behaviors over time. In summary, the above findings demonstrate the dynamics of participants' online information disclosure and support response behaviors over time.

### 5.5.4. Robustness Checks and Additional Analyses

Even though the stability analysis validates the results of the SVAR estimates, the ordering of the variables in the system of equations matters due to endogeneity issues. Information density and information efficacy measures are derived from the user post, which means that endogeneity between them is highly expected. Thus, to ensure that our findings are robust, we perform some robustness checks and conduct additional analyses. Prior research recommend following the Cholesky ordering (i.e., reordering or flipping the variables being fed into the system (Cheng et al. 2016). In the ordering of variables in our SVAR model and IRFs, we consider two permutations of the variables. The results of the first permutation following the ordering INFODEN, followed by INFOEFF, and then SUPPACC are shown in Figure 4 above. In the second permutation, we start with INFOEFF, followed by INFODEN, and then SUPPACC. We consider this second permutation to ensure the results are unchanged or whether there are any changes. The new IRF results are shown in Figure 5.7(a-d).




(a) Information Efficacy to Support Acceptance

(b) Support Acceptance to Information Efficacy

(c) Information Density to Support Acceptance

(d) Support Acceptance to Information Density

Figure 5. 7: Impulse Response Graphs for Robustness Check (Impulse to Response)

*Notes*: Blue line represents the effect of the impulse on response; red line is the 95% confidence interval band.

Following the ordering in the second permutation, we estimate the new SVAR model and plot the IRFs graphs. Based on the IRF analysis, we find that all the results remain unchanged. The results show that show that both information efficacy and information density maintain their positive and significant impacts on support response acceptance (Figure 5(a) and 5(c)), respectively. Meanwhile, the positive impact of information efficacy on support response acceptance remained the same (Figure 5(b)) as well as the negative impact of information density on support response acceptance (Figure 5(d)), but the effects were insignificant.

In addition to the impulse response functions in Figure 4 and Figure 5, we investigated and found other important interactions among participants' disclosure characteristics and the different types of response votes (support votes, thanks votes, and useful votes) that a user post receives as shown in Chapter V Appendices A5, A6, and A7. For example, in Appendix A5, Figure (a), we discover that a unit shock to the information density in a post has a positive and significant effect on support votes and the effect is stable from day 1. This positive impact increases significantly from day 2 to 4 and thereafter, remains stable over time. It is interesting to note that we also see similar patterns of a unit shock in information density on thanks votes and useful votes. Most of the results in this section did not show any significant difference from the previous IRFs, confirming that our results are stable and robust. Details of the IRFs for these additional analysis are presented in the appendices (see Appendix A5-A7).

## 5.6. Discussions

From the results of the impulse response functions, we found that the number of words in a user post increases the number of useful support votes the post receives. This result reveals that individuals' information density disclosure strategy can slightly increase the level of support response acceptance to their posts. That is, when disclosers provide more details about themselves or about their health conditions, this will increase the number of supportive responses to address their disclosure needs. This, ties with previous research on individuals' initial motivation for sharing personal information on online platforms, which is to seek for some type of informational, or emotional support, or companionship to manage their health crises (Chen et al., 2019; Huang et al., 2019; S.-Y. Lee et al., 2019). On the contrary, we found that support response acceptance reduces the number of words in a user post. The result shows that participants as support response increase, information density is zero and non-significant for about two days. But the impact of the shock is felt again from the third day. This means that when individuals get enough support that address their disclosure needs, they tend to feel satisfied and may stop posting lengthy messages until they experience other symptoms or disease conditions, which brings them back after three days. This can be explained by the economic theory of diminishing marginal utility, which describes the negative value derived from an increase in consumption (Easterlin, 2005).

Furthermore, we found that the number of words per sentence increases support response acceptance. This result suggests that the information efficacy of users' online posts can increase the level of supports received significantly. This result means that the fewer the number of words per sentence, the stronger the information efficacy. Linguistic research models of text reading and comprehension emphasize the ability for individuals to construct succinct sentences that improve long term memory (Bean & Steenwyk, 1984). When a user post contains fewer number of words per sentence, it prevents the introduction of multiple concepts or concerns in the sentences, thereby, improving reading and reducing the potential of having grammatical errors that interfere with understanding user posts to provide appropriate support. On the other hand, we find that the number of acceptable support responses a user post receives has a positive impact on the number of words written per sentence. That is, the result shows that as participants' support response acceptance increase, information efficacy is zero and non-significant initially. But the impact of the shock is felt again from the second day. This means that when individuals get enough support that address their disclosure needs, they tend to improve on the efficacy of their post by writing fewer words per sentence although the effect diminishes after day 6.

## 5.7. Implications and Conclusion

In this paper, we developed a SVAR model and IRFs to study users' dynamic information disclosure characteristics and support response acceptance behaviors in OHCs. The SVAR model was estimated by a maximum likelihood procedure. Three endogenous variables were identified based on the DD-MM framework to best explain the data. Our results offered several insights into the driving forces behind users' online behaviors and, hence, demonstrated the usefulness and value of online health communities in facilitating user information sharing characteristic and support provision. Despite the sizeable body of research on information disclosure and the motivational factors that impact different types of supports in OHCs, there is less attention paid to the user dynamics between user information disclosure characteristics and support response acceptance. A recent study that mirrors our research rather focuses on examining physicians' online and offline activities (L. Wang et al., 2020b). This current study departs from prior literature and is unique in that physicians engage in online activities because of frequent platform users (patients) and studying these users' online behavior dynamics is important not only to facilitate physician healthcare delivery but for the users' health welfare and continuity of the online platforms. Thus, our study makes some main contributions to the literature on user information disclosure/response behaviors in OHCs, as well as practical implications for OHCs' management and healthcare technologies.

First, by studying the online information disclosure characteristics and support response activities of users who suffer from various diseases, we revealed the benefits of online health communities in helping users improve their health conditions. We show these behaviors can be modeled dynamically to provide interesting insights not possible using regression techniques. Second, our results prove that dimensions of information disclosure efficacy can be treated as multi-construct concept, which is an extension of the DD-MM framework, thus, providing opportunities for future research (Chaudoir & Fisher, 2010). Third, the increasing effects of information density and information efficacy on support response acceptance indicate that modeling users' online disclosure and response behaviors dynamically can reveal the importance of studying the role of disclosure efficacy in generating positive feedback from other users to help them improve their health conditions. Finally, to the best of our knowledge, our study is the first to examine user information disclosure and support response behavior dynamics and reveals the importance of online health platforms in supporting healthcare delivery and management (Fichman et al., 2011b). Combining theoretical and data validation in this study, the findings of this study signify the potential of being generalizable and applicable to other research contexts.

Practically, the results show that effective online disclosure engages responders to contribute value and knowledge on the platform while good support responses enhance positive feelings and emotions in the disclosers. In addition, effective support provision can increase satisfaction and learning, hence, management can use this as a proxy to encourage passive users, thereby, reducing lurking behaviors. Next, our model suggest that users can boost their efficacy behaviors on the OHC platform so that their disclosure and support response provision strategies will promote their happiness, health-wellbeing, and socialization skills. Last, the insights in this study provide indicators on personalize care strategies, promotion of effective participation in OHCs, and collaborative information systems design in healthcare management.

This study has some limitations and opportunities for future research. First, the analysis was performed using a daily time series data sample, results may not reflect other samples with weekly, monthly, quarterly, or yearly time series data. Using data samples with these different time periods will be necessary to validate and improve the results. Second, our estimated model shed some light about user dynamic activities on OHC platforms using time series data, which focuses on observing a single user at multiple time intervals. While the results are stable in this current study, we belief that conducting the analysis using a panel data that focuses on observing multiple individuals at multiple time intervals could be a great opportunity for future research. Third, only one online health community was explored. Examining different platforms could change the findings and/or reveal new insights for patient-centered care management.

CHAPTER VI

CONCLUSION

## 6.1. Recap of Objective

Motivated by the importance of numerous supportive benefits that online health communities provide to patients and other users who join these platforms, the need for a richer understanding of individuals' information disclosure, participation, and response behaviors, and how disclosure aligns with response behaviors, the theses in this dissertation set out to address these research questions:

*1. a) What situational factors influence effective participant personal health information disclosure in online health community forums? b) What participant information disclosure mechanisms elicit effective community response in online health community forums?*

*2. a) How do the dimensions of social presence theory (intimacy, immediacy, efficiency, and non-verbal communication) in patients' initial postings interchange to predict an individual's overall participation behavior in an online health community? b) How do the dimensions of social presence theory in patients' initial postings interact to influence an individual's giving or receiving participation behavior in an online health community?*

*3. a) What factors promote two-way communication in online health communities? b) Is there a two-way relationship between users' information disclosure and response behaviors in online health communities?*

To investigate these research question, I drew from some basic assumptions that have been taken for grant in prior research when dealing with users' information disclosure, participation, and response behaviors in online health communities.

First, prior literature has assumed that the support provided to the information users disclosed in OHCs is satisfactory and helpful. However, the act of sharing information does not guarantee that patients will consider the support as useful, beneficial, or satisfying. An effective outcome of OHC support should maximize the discloser's after-disclosure gratification. In assessing this claim, I leveraged insights from the disclosure decision-making model framework to develop a two-stage model, which first identifies those situational factors that influence individuals' information disclosure behaviors and then explores how these behaviors affect the effectiveness of the responses. I analyzed the model and test the hypotheses using ordinary least squares for the first stage and a two-stage least squares regression for the second stage. Results show support for most of the hypotheses, thereby, providing valuable insights for research and practice. The findings are detailed in Chapter 3.

Second, online health communities (OHCs) require effective two-sided communication between disclosers and responders. However, previous research has mostly modeled OHCs as one-way communication medium by examining the influence of information disclosure on response stakeholders receive. I argue that over time, active and sustained communication between individuals in the online community and maximum contributions to the online platforms depend on the degree of effective two-way relationship between disclosers and responders.

Using a longitudinal sample, I applied a vector autoregression technique to assess the bidirectional relationship between individuals' efficacy behaviors in online health communities. As postulated, I found evidence to support the two-way interaction disclosure efficacy and response at the upper level. Additionally, drilling down to the interactions between the dimensions of disclosure and response efficacy, I found that information density and information persuasiveness had a two-way relationship. Meanwhile, the rest of the relationships were unidirectional. These results also suggest some valuable implications for theory and practice. Comprehensive description of the findings is outlined in Chapter IV.

Third, participation in prior studies has mostly been lumped as an aggregate of a user’s overall activity on the platform; that is, how many messages the user posts or how often the user post and replies to messages and the amount of support that they also receive. Notwithstanding, a user's evaluation of an initial message can influence content generation (giving) and substance utilization (receiving) distinctively by participation because of their impression or enthusiasm of the message. I used social presence theory as the basis to understand how users form first impressions through their messages in online platforms, which consequently impact their level of participation through either giving or receiving. Social presence is the ability to utilize online media to send meaningful gestures while connecting with peers in an online platform. From this theoretical perspective, this last part of the dissertation focused on examining how the dimensions of an individual’s social presence interact to impact their giving or receiving participation. The complete discoveries of the decision tree approach to investigate the research problem in this part of the dissertation are provided in Chapter V.

## 6.2. Contributions

This dissertation advances and enhances research and makes contributions to practice in several ways. I summarize and briefly discuss the key contributions from the previous three chapters of this dissertation subsequently.

### 6.2.1. Implications for Research

This dissertation demonstrates the boundaries of the DD-MM through its applicability in the OHC context. Second, I conceptualize both disclosure efficacy and response efficacy as multidimensional concepts, which provide granular insights into how the different subconstructs differentially influence disclosure and response efficiency outcomes. Specifically, disclosure efficacy is categorized into two dimensions – information density and information breadth. Evidence from our results show that each of these dimensions leads to a novel outcome (response efficacy – information persuasiveness and response persuasiveness), extending the DD-MM framework. By conceptualizing both disclosure efficacy and response efficacy as multidimensional constructs, this study supports the notion that complex phenomena can be broken down into smaller units, which offer granular understanding of such phenomena otherwise not present in unidimensional analysis. Lastly, this study unveiled different information sharing behaviors based on the stigmatization labeling of the diseases.

The findings have the following implications for disclosure decision-making model (DD-MM) and information systems healthcare literature: 1) not all dimensions of information disclosure elicit audience response, 2) supportive response is viewed differently by information receivers, 3) proper disclosure engages readers and increases site traffic while good responses enhance positive feelings and emotions in the disclosers, and 4) our model can boost patients' efficacy behaviors on the OHC platform so that their disclosure and response provision strategies will promote their happiness, health-wellbeing, and socialization skills.

### 6.2.2. Implications for Practice

The findings regarding dimensions of disclosure efficacy can help managers improve the experience of participants in OHC. Managers may offer participants tools such as customizable auto-complete text features relevant to the OHCs context to improve the breadth of the sentences in the post. Such effort will reinforce the usefulness of the auto-complete features in other technologies. Second, management can design the text fields, with suggested number of words to motivate participants to improve the information density of a post.

The result enlightens managers as to the two-way cause and effect of online users' efficacy behaviors. Based on our proposed framework, OHC management can be confident that users' past disclosure and response behaviors can be leveraged as a yardstick to assess users' sustained commitment on the platform. Moreover, the findings provide insights for operators of OHCs to enhance participation by 1) designing the OHC to encourage creative expression of feelings and to heighten comprehension of the posts; 2) providing indicators on the OHC platforms that ascertain whether the response was actually beneficial to the discloser and whether the disclosed message was well understood by the responder; and 3) suggesting that the model can aid patients (both disclosers and responders) to boost the chances that disclosure and response provision will promote their health and welfare.

## 6.3. Limitations and Future Research

This dissertation has some limitations that require further investigation. In Table 6.1, I summarize these limitations and outline some opportunities for future research.

Table 6. 1: Summary of Limitations and Future Research Opportunities

| Component | Limitation | Future Research Direction |
|---|---|---|
| Generalizability and validation | Only one online health community platform was chosen for the study. | Testing the propositions and models on a cross-section of other platforms could provide some new and interesting findings. Moreover, using non-health platforms could help to validate the current results. |

Table 6.1, cont.

| | | |
|---|---|---|
| Scope of study | Study examined only two communities in the online platform with stigmatized and non-stigmatized disease types. | Extending the scope of coverage of disease types will be important to grasp a rounded picture of the findings. Additionally, future research could conduct the analysis for stigmatized diseases and non-stigmatized diseases separately for better understanding. Consideration of other disease types will improve the study. |
| Sample size | Limited samples considering the analytic focus of the research. | Although the study showed some good results, a larger sample size is needed considering that the focus of the research is analytics. |
| Data | Study was conducted using secondary online data. | It will be useful to collect primary data from interviews and surveys to test the concepts and outcomes under investigation. |
| Causation | Some results of this work do not establish causal links between the constructs. | Carrying out an experimental study or a design science approach could provide additional insights on how to improve online health communication. |
| Study type | Participation was examined using cross sectional sample. | Although users' participation behavior can be investigated with some few days when they register on the platform, active and sustained participation in online communities is better assessed over a longer period. Thus, a longitudinal study is imperative to capture users' continuous participation. |

## 6.4. Conclusion

Inspired by the importance of online health communities to foster a supportive environment, community engagement, trust, knowledge sharing, and sustained participation through a two-way interaction between disclosers and responders, this dissertation advanced literature on users' information disclosure, participation, and response behaviors by conceptualizing situational factors that influence disclosure efficacy and its impact on response efficacy at the granular level, and theorizing the two-way interaction between the two efficacy behaviors. Based on the disclosure decision-making model, I empirically tested the proposed models, and the analyses reveal some important findings users' participation in online health communities.

Overall, the insights of this dissertation provide indicators on the enhancement of user disclosure and response behaviors in online health communities, enabling personalize care strategies through knowledge and support acquisition, promotion of effective and continuous participation in online health communities through giving and receiving supports, and collaborative information systems design in healthcare management from a two-way communication perspective by disclosers and responders in online communities.

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APPENDIX A

APPENDIX A

RECEIVING PARTICIPATION

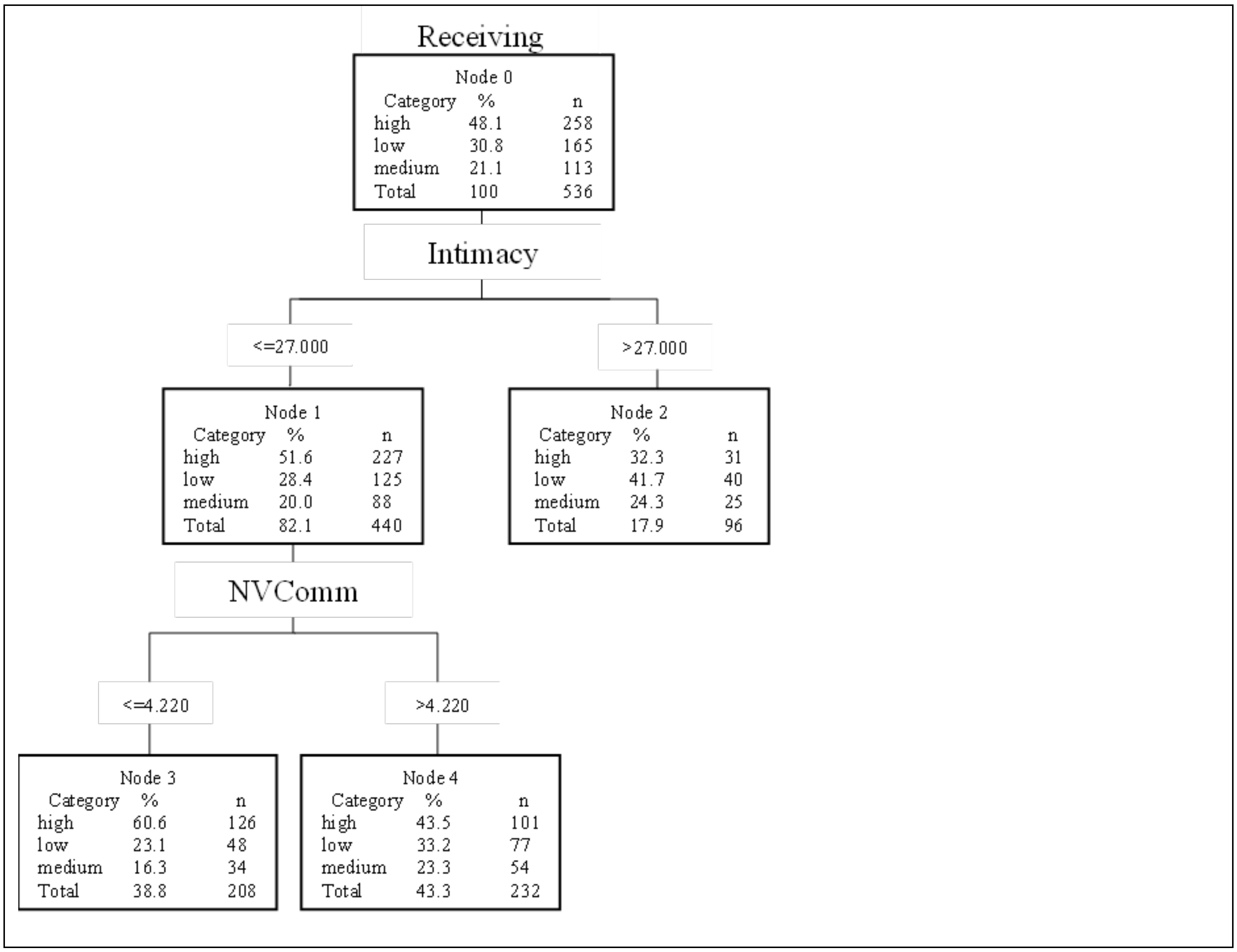


Figure 6. 1: Classification Decision Tree Diagram for Receiving Participation.

Table 7.1 shows the set of candidate hypotheses that were abducted from the sibling nodes.

Table 7. 1: Abduction of Sibling Rule Hypotheses for Receiving.

| Backend Condition | Set of sibling nodes | Receiving = *High* | | Abduct? | Candidate sibling rule hypothesis |
|---|---|---|---|---|---|
| | | Proportion (N) | | | |
| | 1 | 0.516 | 440 | **Yes** $p = 0.0001 < 0.05$ | *Intimacy* impacts *Receiving Participation* |
| | 2 | 0.323 | 96 | | |
| *Intimacy* < 27.0 | 3 | 0.606 | 208 | **Yes** $p = 0.0001 < 0.05$ | If *Intimacy* < 27.0, Then Nonverbal communication impacts Rece*iving Participation* |
| | 4 | 0.435 | 232 | | |

For the hypothesis abduction and evaluation using difference of proportion test, given two proportions $p_1$ and $p_2$, and similar samples $n_1$ and $n_2$, we can use the difference of proportion test to calculate the Z-score for the sibling rules that occur in pairs. For example, consider the pair of candidate sibling rules for Receiving:

- *If INTIMACY <= 27.000, then Receiving Participation is high with relative frequency (proportion)* $p_1 = 51.6\%$ *number of cases* $n_1 = 440$.
- *If INTIMACY > 27.000, then Receiving Participation is high with relative frequency (proportion)* $p_2 = 32.3\%$ *number of cases* $n_2 = 96$.

Applying the formula for $Z = \{(p_1-p_2)/\text{Sqrt}\{[p_1(1-p_1)/n_1]+[p_2(1-p_2)/n_2]\}\}$, we find that for the sample pair of sibling rules, $p_1 = 0.516$, $p_2 = 0.323$, $n_1 = 440$, and $n_2 = 96$,

$Z = \{(0.516-0.323)/\text{Sqrt}\{[0.516(1-0.516)/440]]+[0.323(1-0.323)]/96\}\} = 0.193/0.0533 = 3.6210$

Thus $P(Z) = P(3.6210) = 0.00014$, which is significant at $P < 0.05$. Table 7.2 validates results.

Table 7. 2: Validation by Comparison of Results of Phase 1 and Phase 2

| ID | Hypothesized Relationship | Phase 1 | Phase 2 | Comments |
|---|---|---|---|---|
| $H_{1, P}$ | NVC has a significant impact on participation. | Significant | Significant | Same |
| $H_{2, P}$ | INT has a significant impact on participation. | Significant | Significant | Same |
| $H_{3, P}$ | EFF has a significant impact on participation. | Non-significant | Significant | Different |
| $H_{1, M}$ | NVC moderates the relationship between EFF and participation. | Significant | Significant | Same |
| $H_{2, M}$ | NVC moderates the relationship between INT and participation. | Significant | Significant | Same |
| $H_{1, G}$ | INT has a significant impact on giving. | Significant | Significant | Same |
| $H_{2, G}$ | EFF has a significant impact on giving. | Significant | Significant | Same |
| $H_{3, M}$ | INT moderates the relationship between EFF and giving. | Significant | Significant | Same |
| $H_{1, R}$ | INT has a significant impact on receiving. | Significant | Significant | Same |
| $H_{2, R}$ | NVC has a significant impact on receiving. | Significant | Significant | Same |
| $H_{4, M}$ | INT moderates the relationship between NVC and receiving. | Significant | Significant | Same |

*Notes: INT – intimacy; EFF – efficiency; NVC – nonverbal communication; NA: not applicable*

APPENDIX B

## APPENDIX B

## ADDITIONAL ANALYSIS AND IRFS

Table 8. 1: Correlation Matrix

| Correlation | INFODEN | INFOEFF | SUPPACC |
|---|---|---|---|
| INFODEN | 1.000 | | |
| INFOEFF | -0.7661 | 1.000 | |
| SUPPACC | 0.1544 | 0.0719 | 1.000 |

*Note*: Correlations between variables SUPPACC – support acceptance, INFODEN – information density, INFOEFF – information efficacy. Correlations values are below 0.5 level indicating variables are not autocorrelated.

Table 8. 2: Unit Root Test: Augmented Dickey Fuller (ADF) Test

| | | **t-Statistics** | | | **Prob.*** |
|---|---|---|---|---|---|
| | | INFODEN | INFOEFF | SUPPACC | |
| **Augmented Dickey-Fuller test statistic** | | -29.7988 | -14.5067 | -5.42368 | 0.0000 |
| **Test critical values:** | 1% level | -3.43649 | -3.43651 | -3.43653 | |
| | 5% level | -2.86414 | -2.86415 | -2.86416 | |
| | 10% level | -2.56820 | -2.56821 | -2.56822 | |

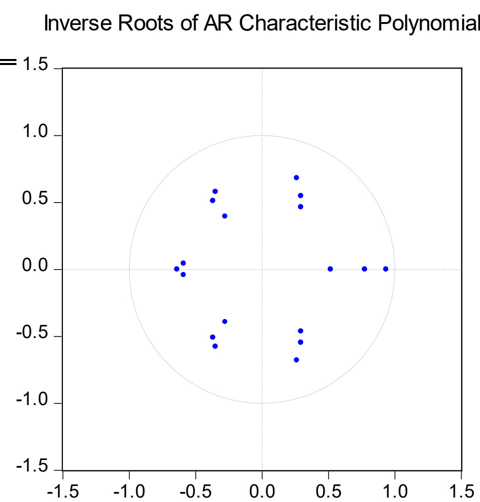
*Notes*: Null Hypothesis: INFODEN has a unit root; *MacKinnon (1996) one-sided p-values; Lag Length: 0 (Automatic - based on SIC, maxlag=21); The ADF statistic value is -8.639180 and the associated one-sided p-value is 0.0000. In addition, the critical values are reported at the 1%, 5% and 10% levels. Notice here that the statistic value t_alpha is less than the critical values so that we reject the null hypothesis at conventional test levels.

*Conclusion of ADF Test*: From the ADF test results, we reject the null hypothesis of a unit root in the INFODEN, INFOEFF, and SUPPACC series at conventional significance levels, and conclude that the series are stationary at levels. Hence, we can proceed to estimate the Structural Vector Autoregression (SVAR). We do not need to difference the series.

Table 8. 3: Inverse Root Test, Roots of Characteristic Polynomial

Endogenous variables: INFODEN INFOEFF SUPPACC

| Root | Modulus |
|---|---|
| 0.936638 | 0.936638 |
| 0.775411 | 0.775411 |
| 0.263547 + 0.679939i | 0.729228 |
| 0.263547 - 0.679939i | 0.729228 |
| -0.348242 - 0.578331i | 0.675084 |
| -0.348242 + 0.578331i | 0.675084 |
| -0.638085 | 0.638085 |
| -0.367311 - 0.511381i | 0.629625 |
| -0.367311 + 0.511381i | 0.629625 |
| 0.295148 - 0.547543i | 0.622026 |
| 0.295148 + 0.547543i | 0.622026 |
| -0.589056 - 0.042883i | 0.590614 |
| -0.589056 + 0.042883i | 0.590614 |
| 0.295256 - 0.464634i | 0.550509 |
| 0.295256 + 0.464634i | 0.550509 |
| 0.518218 | 0.518218 |
| -0.275830 + 0.393300i | 0.480382 |
| -0.275830 - 0.393300i | 0.480382 |




No root lies outside the unit circle.
VAR satisfies the stability condition.

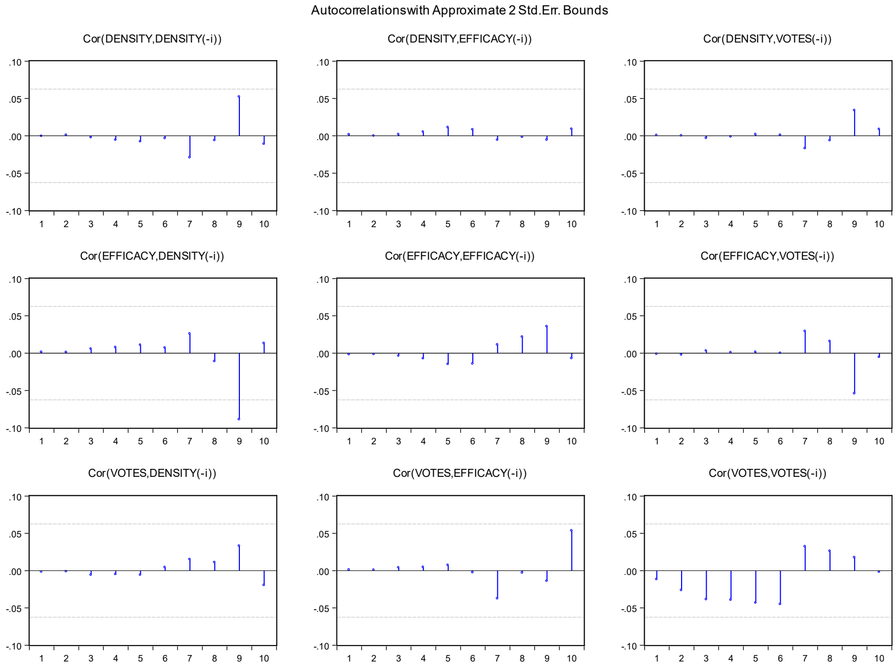



Figure 7. 1: Correlogram for Autocorrelation Within 2 Standard Error Bounds

Notes: Correlogram displays the autocorrelations series in a group up to the specified order of lags. In the above graph, the correlations are very low (the y axis goes from -0.10 to +0.10) and don't seem to have a pattern. The dotted lines are confidence bands - the approximate two standard error bounds computed as [+-2/srt(T)], T is the period in days, that tells us that the correlation is statistically significant.

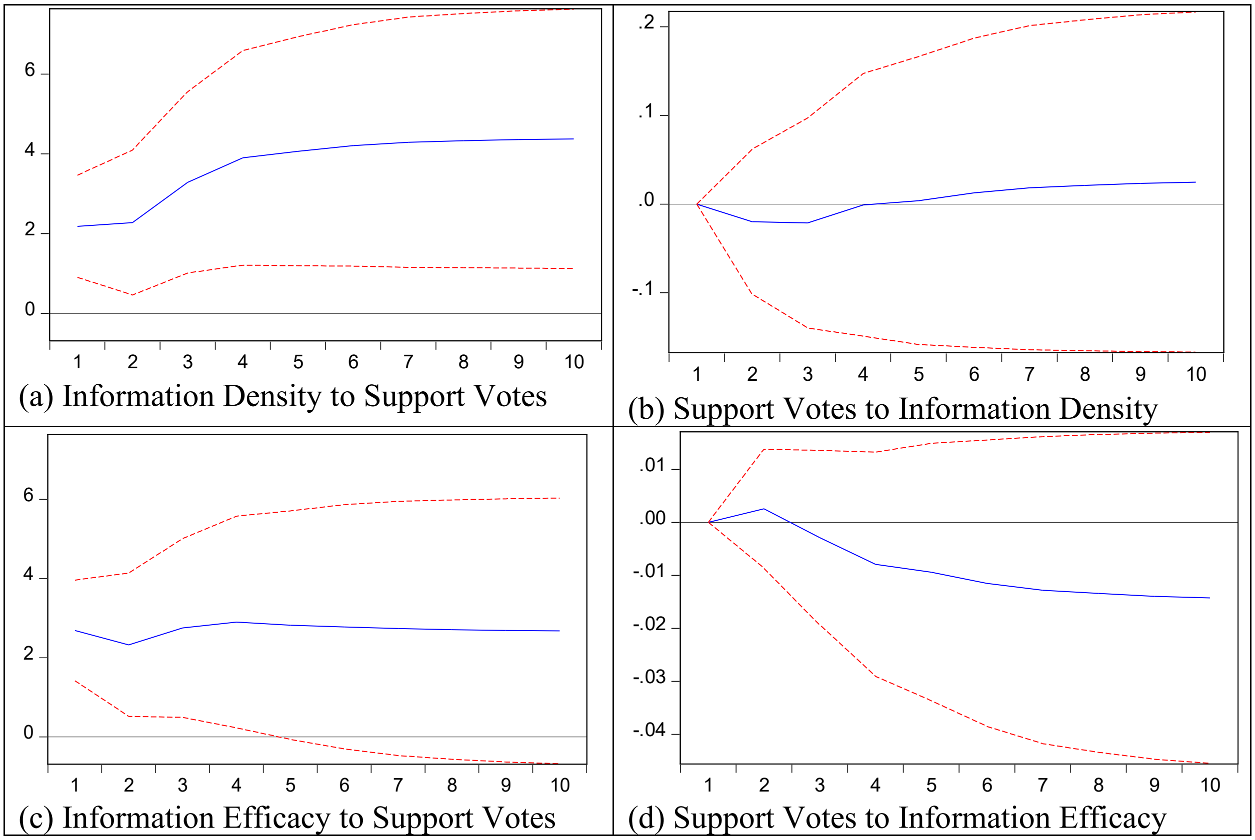
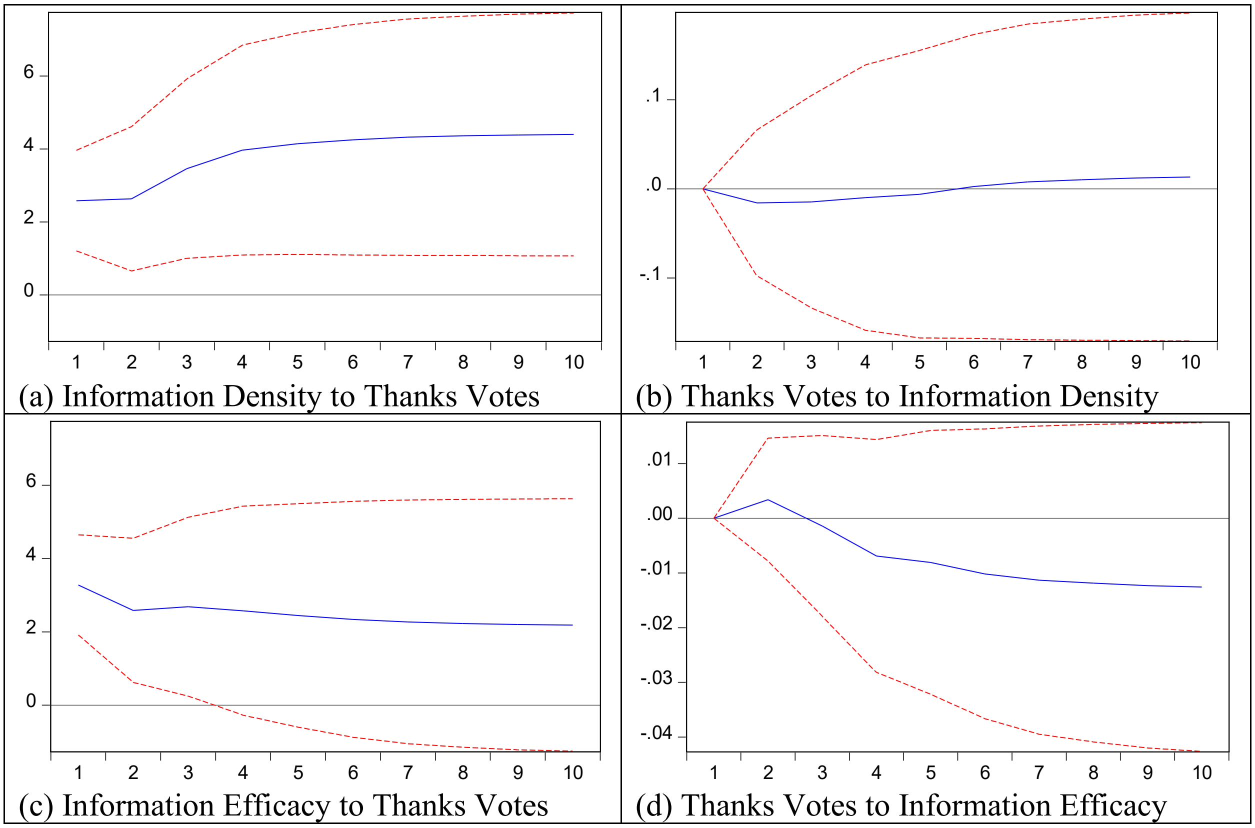
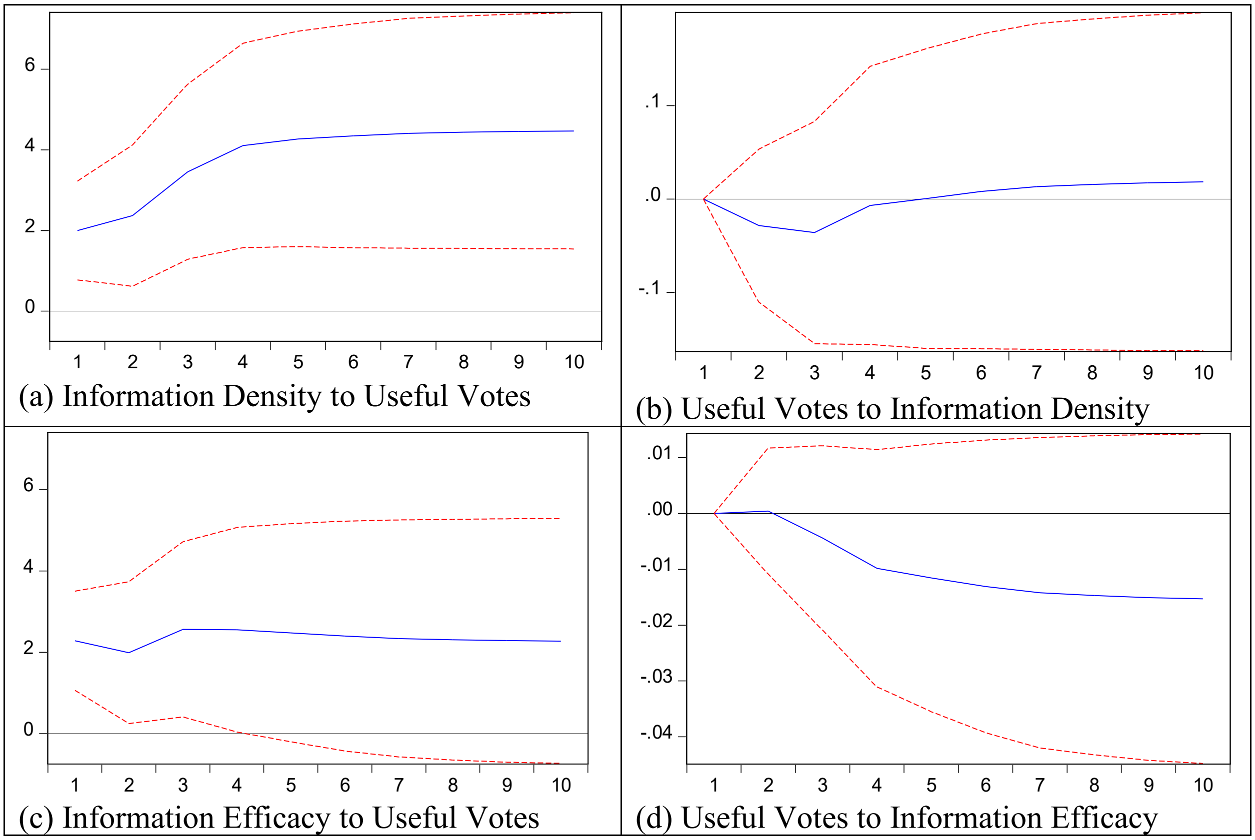


Figure 7. 2: Participants' Online Disclosure and Support Votes Behavior Dynamics




(a) Information Density to Thanks Votes
(b) Thanks Votes to Information Density
(c) Information Efficacy to Thanks Votes
(d) Thanks Votes to Information Efficacy

Figure 7. 3: Participants' Online Disclosure and Thanks Votes Behavior Dynamics




(a) Information Density to Useful Votes

(b) Useful Votes to Information Density

(c) Information Efficacy to Useful Votes

(d) Useful Votes to Information Efficacy

Figure 7. 4: Participants' Online Disclosure and Useful Votes Behavior Dynamics

## BIOGRAPHICAL SKETCH

Manga, Ade Joseph, PhD, earned his Doctor of Business Administration in Information Systems in July 2022 from the Robert C. Vackar College of Business & Entrepreneurship at the University of Texas Rio Grande Valley. He has a MSc. degree in Business Analytics from the University of North Texas, an MBA from Midwestern State University, and a BSc. degree in Mathematics and Computer Science from the University of Buea, Cameroon.

His research interests are in business intelligence and analytics, health information technology systems, and security policy compliance. His research focuses on online health communities, specifically investigating individuals' information disclosure, participation, and response behaviors in online health platforms.

He has published peer-reviewed papers in Hawaii International Conference on System Sciences (HICSS), Americas Conference on Information Systems (AMCIS), PACIS, and IFIP. He has reviewed for journals including the European Journal of Information Systems (EJIS), International Journal of Information Management (IJIM), Information Technology for Development (ITD), Information Systems Frontiers (ISF), and International Journal of Health Information Systems and Informatics (IJHISI). He has also served as an ad-hoc reviewer for International Conference of Information Systems (ICIC), Hawaii International Conference on System Sciences (HICSS), and Americas Conference on Information Systems (AMCIS).

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