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Completed Research Paper

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Abstract

Online healthcare communities (OHCs) facilitate two-way interaction. Examining users' information disclosure-audience support response dynamics can reveal insights for fostering a supportive environment, community engagement, bond formation, knowledge sharing, and sustained participation in OHCs. We propose a structural vector autoregression (SVAR) model of user disclosure and response dynamics in OHCs. Based on the health disclosure decision-making model and daily time series data, we examine the two-way interaction of two dimensions of disclosure efficacy with audience support response acceptance. 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. Further, higher information efficacy leads to more support response acceptance with long run improved information efficacy. Theoretically, findings extend the disclosure decision-making model in OHCs. Practically, the results provide insights for OHC management to facilitate two-way dynamic users' interactions.

Keywords: Disclosure efficacy, information density, information efficacy, response efficacy, support response acceptance, online health communities, SVAR

Introduction

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

Although online health platforms present potential impacts by connecting information seekers--disclosers to support providers--responders (Chen et al. 2020), research is yet to explore users' information disclosure and support response acceptance behavior dynamics in OHCs. Considering that most of the users who visit online platforms share their personal health information in search for answers or support to their health needs (Lee et al. 2019), it is unclear from prior research how their disclosure behavior activities determines support response acceptance and vice versa. For example, it may be obvious an information seeker will receive a response to the question they pose but it is not certain that they will receive an acceptable, or helpful, or beneficial answer. On the contrary, users may decide to keep refining the information they disclose until they get the answers they want otherwise they 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 users understand that improving information disclosure increases responders' understanding leading to the expected response from the audience and that this process can be cyclical or dynamic.

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: *Is there a two-way interaction between users' online information disclosure behaviors and audience support response acceptance? If so, what is the nature of the two-way interaction?* To address our research question, we leverage the health disclosure-decision making model (DD-MM) as the theoretical lens (Choi et al. 2016; Greene 2009). 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 (Choi et al. 2016; Greene 2009).

The sample used for the analysis contains daily user observations (posts) for the period from March 2014 to February 2022 obtained from a popular online health community. Modeling a system of equations and relationships between user information disclosure and support response dynamics introduces endogeneity problems which limits the use of traditional econometric techniques as these tools may produce biased estimates (Luo et al. 2013). We utilize a time series data set for the analysis and test structural vector autoregression (SVAR) models. Our SVAR model captures three main variables in the causal system: information density, information efficacy, and audience response acceptance. Information density refers to the volume or density of informational content in a user online post measured as an aggregate of the number of words in an online message. Information efficacy is a user's ability to effectively convey a message in an online discussion post, measured as the number of words per sentence. Support response acceptance is defined as the tendency for the response to a user post to be helpful and beneficial.

The empirical analysis reveals interesting dynamics among the variables in the system of structural equations. First, we find that an increase in information density and information efficacy is associated with increase in 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 is associated with reduction in 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 clarity, preciseness, and quality of their subsequent posts.

The findings have the following contributions to the health information technology and the disclosure decision-making model (DD-MM) literatures (e.g., Choi et al. 2016; Greene 2009). 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 characteristics and support response acceptance behaviors can be modeled dynamically to produce helpful immediate audience support to meet discloser's needs and to improve the quality of disclosure in subsequent posts. This finding will not be revealed from traditional econometric techniques such as OLS models. Second, our results show that both dimensions of information disclosure efficacy elicit more acceptable response over time. Thus, this study presents disclosure efficacy as a multi-dimensional construct concept, which is an extension of the DD-MM framework, providing opportunities for future research using these subconstructs by studying their effects on other disclosure outcomes (Chaudoir and 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 characteristics and support response acceptance behaviors dynamically can produce varying effects. For example, in the long run, the helpfulness of the support response users receive could make them increase the quality of their posts while reducing the number of words per sentence and decreasing the volume of post. 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 personalized care strategies, promotion of effective participation in OHCs, and collaborative information systems design in healthcare management.

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.

Online Health Communities

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 considerable 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). Online health communities focus on creating channels for personalized patient-healthcare management and provide a platform for sharing opinions on health issues (Liu et al. 2020).

There has been a growing interest in examining different phenomena in OHCs because it has the potential to facilitate healthcare delivery, enhance physician-patient interaction for easy access to professionals for better healthcare service provision, and motivate user active participation for value generation, knowledge contribution, 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 platforms. Table 1 provides a literature synopsis that focuses on information disclosures in online platforms or communities. This current study departs from prior research and contributes to the growing body of knowledge (which has primarily focused on antecedents, motivators, situational, and privacy factors that influence information disclosure) to understand users' disclosure mechanisms for enhancing support response acceptance and reciprocal improvement in user disclosure abilities.

Author, Year	Objective	Theory	Context / Technique	Findings
(Zhang et al. 2018)	To explore the antecedents and consequences of health information privacy concerns.	Integrated the dual calculus and protection motivation theories	Offline and online health communities / Hierarchical regression method	Users' health information privacy concerns, informational and emotional support, significantly influence personal health information disclosure intention.
(Zhou 2018)	To examine the factors influencing people's personal	Based on "motivation-	Online health (cancer) communities	In not so severe disease conditions, participants post their personal information to only obtain needed

	information disclosure behavior in OHCs.	risk" perspective	/ Hierarchical regress analysis	information. In severe situations, participants disclose personal information to obtain both needed information and emotional support, with emotional support prioritized. Additionally, participants risk losses to seek more useful information.
(Zhang 2015)	To examine the effect of technology adoption on a firm's voluntary information disclosure.	Adoption theories	Social media / K-means for cluster analysis	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.
(Ouyang et al. 2022)	To investigate the impact of the physician's self-disclosed information on the patient's decision and the moderating effect of the physician's online reputation.	The limited-capacity model of attention	Online health community / Regression analysis	Physician's emotion orientation has positive effect on patient's decision. Excessive quantity of information can raise barriers for patient's decision. Semantic topics diversity has negative effect on patient's decision. Online reputation has different moderating effect for each part.
(Esmaeilzadeh 2020)	To test the impacts of perceived transparency of privacy policy on cognitive trust and emotional trust and the effects of trust dimensions on the intention to disclose health information.	Theory of reasoned action (TRA), the technology adoption literature, and the trust literature	Health information exchanges (HIEs) networks / Structural equation modeling	Findings suggest that awareness about HIE security measures and sharing procedures encourage patients to be cognitively and emotionally involved with the HIE system. Consequently, when the trust is formed, patients become more likely to disclose health information.
(Wakefield 2013)	To explore the roles of positive and negative affect on users' trust and privacy beliefs that relate to the online disclosure of personal information.	Cognitive consistency theory (Balance theory and Congruity theory)	Social networking websites / Partial least squares	Results indicate that positive affect has a significant effect on users' website trust and privacy beliefs that motivate online information disclosure, and this effect is more pronounced for users with high internet security concerns.
(Cao et al. 2018)	To study peer disclosure of sensitive personal information in online social communities modeled as the imposition of a negative	Social networks analysis	Online social communities	A nudge decreases user participation and information contributions, but it also reduces the total privacy harm and sometimes increases social welfare by driving some users out of the community.

	externality on other people.			
(Li et al. 2010)	To examine how an individual's decision-making on information disclosure is driven by competing situational benefits and risk factors.	Social contract theory and Privacy calculus	E-commerce transaction context / Experimental web design	Results show that information disclosure is the result of competing influences of exchange benefits and two types of privacy beliefs (privacy protection belief and privacy risk belief). In addition, the effect of monetary rewards is dependent upon the fairness of information exchange.
(Anderson and Agarwal 2011)	To explore the impact of emotion linked to one's health condition on willingness to disclose.	Privacy boundary theory, Privacy calculus, Communication privacy management theory	Digital healthcare setting / Quasi-experimental survey methodology	Results suggest that contextual factors related to requesting stakeholder and the purpose for the requested information. 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.
(Wang et al. 2020)	To investigate physicians' online-offline behavior dynamics using data from both online and offline channels.	Online health communities' participation literature	Online health communities / Structural vector autoregression technique	Results show that physicians' online activities can lead to a higher service quantity in offline channels, whereas offline activities may reduce physicians' online services because of resource constraints. Results also show that the more offline patients physicians serve, the more articles the physicians will likely share online.

Table 1. Sample Prior on Information Disclosures in Online Platforms / Communities

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 (Zhang et al. 2018).

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 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 2009).

Information efficacy refers to a user's ability to effectively convey a message. Effective messages stem from the succinctness of the disclosed information. According to a recent study people would benefit from a concise and precisely defined model of word reading (Davis et al. 2021). Base on the DD-MM framework, when users in an online health community disclose information that precisely and clearly describe their health conditions, it increases readability and comprehensibility in the audience. The more users are understood, the more effective and helpful the response from the audience will be. Hence, information that is effectively disclosed will increase support response acceptance.

Audience Response Efficacy (Support Response Acceptance)

Response efficacy is defined in the literature as the degree to which an individual believes that the recommended response provided will be effective (Woon et al. 2005). Responsiveness is shown to constitute important outcome 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. Response efficacy, thus, is an evaluation of how helpful and beneficial the support response mitigates the discloser's needs. In this study, we examine dynamic interactions between disclosure of information 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).

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 (Greene 2009). In fact, a study using the DD-MM framework found that a participant's ability to share information is associated with the readiness to reveal information in future (Greene et al. 2012). 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 (support response acceptance).

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 and 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 and Bloch 2006). When the support response is acceptable or helpful, the discloser feels satisfied because the response provided fulfils their needs. Consequently, users' ability to disclose dense information diminishes over time. That is, in subsequent disclosures, the user is no longer driven by emotions but 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.

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.

Using 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. We then propose a conceptual model that explains dynamics among variables in the system of equations (see Figure 1).

The model in Figure 1 represents the interactions between the three variables in the system. The model shows four causal relationships.

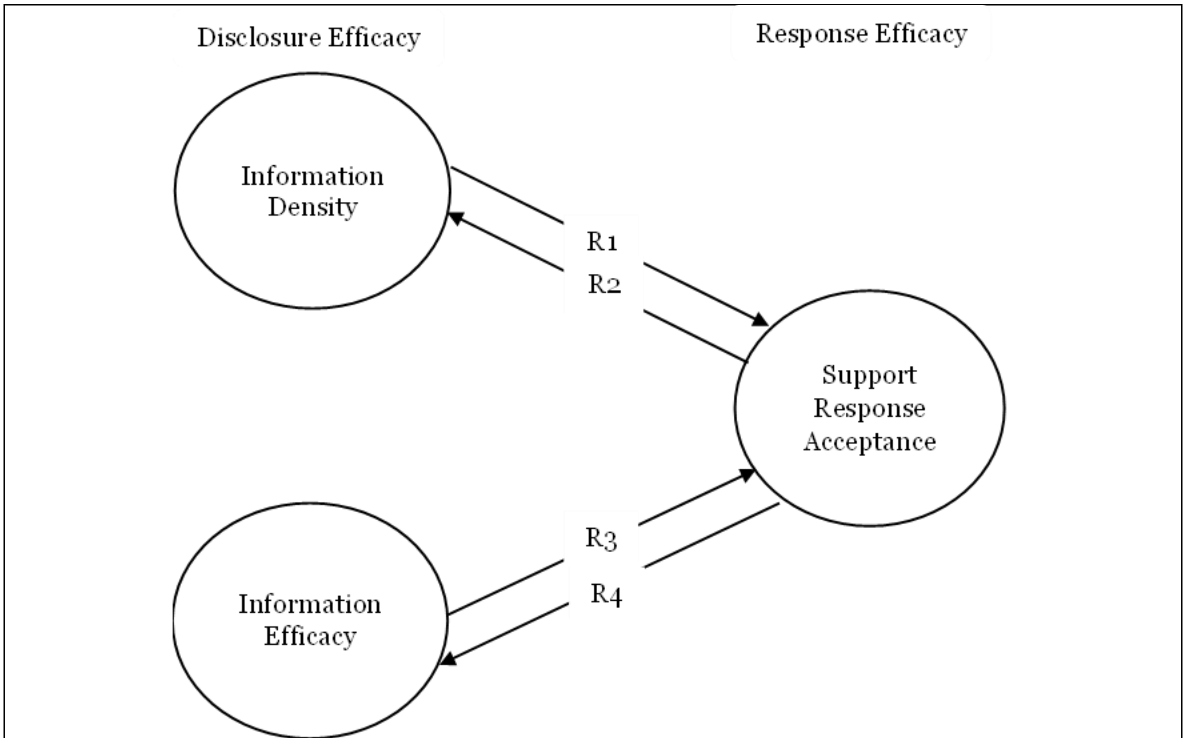


Figure 1. System Model of User Disclosure and Support Response Behaviors in OHCs

Based on the model, relationship 1 (R1) 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 (R2)). Relationship 3 (R3) 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 (R4)).

Research Methodology

Data, Variables, and Measures

We utilize a data set that captures posts and the number of support responses to examine user information disclosure characteristics and support response acceptance 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, membership 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 data from the cancer support community on inspire.com for the period March 2014 to February 2022 was recorded. After 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.

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 linguistic inquiry and word count (LIWC), text analytic tool, to extract the key variables for the study (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 of helpful or useful votes a user post receives. Table 2 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).

Variable	Definition	Analytic Method	Mean	Std. Dev.	Min.	Max.
INFODEN	The total number of words in a user online post.	Text analytics	4.8996	1.3129	0.0000	7.9215
INFOEFF	The total number of words per sentence in a user online post.	Text analytics	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

Table 2. Construct Definition/Operationalization and Descriptive Statistics

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

The time series data for user information density, information efficacy, and support response acceptance indicate some periodic patterns in the data possibly due to implementation of platform policies or some health crisis, or other major events. These events cause exogenous shocks in the data.

The recent COVID-19 pandemic for example, is considered as an exogenous shock in our analyses. Research has shown that recent outbreaks of diseases such as Ebola pose a shock to healthcare systems and examining behaviors of health systems as a response to these contemporaneous shocks is important to determine their resilience in the face of crises (Llamzon et al. 2022). Figure 2 shows a typical example of information disclosure and support response in OHCs.

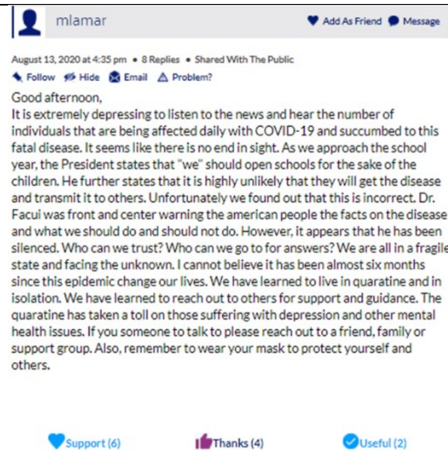


Figure 2. Scenario of User Information Disclosure and Audience Support Response

Vector Autoregression (VAR) and Structural VAR (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 exogenous shocks in the system. The structural vector autoregression (SVAR) technique is better suited for modeling relationships between contemporaneous variables (Escobari and 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 values and on lagged values of other variables. This helps to address lagged effects and a recursive relationship among the variables (Wang et al. 2020).

The challenge with SVAR models is how to identify purely exogenous shocks. To understand SVAR models, let us 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, BY_{t-1} and normally distributed structural shocks μ_t i.e., $\mu_t \sim N(0, I)$, A represents a lower triangular matrix with diagonal elements normalized to 1, while B is a diagonal matrix, t is the time intervals in days, and I is the identity matrix. Pre-multiplying equation (1) by the inverse of matrix A (i.e., A^{-1}) gives:

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

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

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_t and the structural shock μ_t. These forecast errors are linear combinations of the structural shocks μ_t. The SVAR model is identified by estimating the matrices A and B.

Empirical Models Specifications

Our research framework shows three variables in the system, and we are interested in studying the effects of information density and information efficacy on support response acceptance and vice versa. Therefore, in the specification of our structural models, we construct the system of equations (4). The unit of analysis is user interaction which is analyzed using users' posts and support responses. As presented in Table 2, 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 acceptance behavior 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.

$$A\begin{bmatrix} SUPPACC_t \\ INFODEN_t \\ INFOEFF_t \end{bmatrix} = \alpha_i + B\begin{bmatrix} SUPPACC_{t-1} \\ INFODEN_{t-1} \\ INFOEFF_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \end{bmatrix} \quad (4)$$

where $SUPPACC_t$, $INFODEN_t$, and $INFOEFF_t$ are logged values of support response acceptance, information density, and information efficacy, respectively. The α_i, for 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 μ_{it} (i = 1, 2, 3) are the structural shocks or innovations in the system.

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 and Leitemo 2009). To impose restrictions, the identifying scheme must be of the form:

$$Ae_t = B\mu_t \quad (5)$$

Equation (5) is called the AB-model - a mixture of the A-and B-model (see Amisano and Giannini 2012). This is the Cholesky decomposition, and it is one method of identifying the impulse-response functions. 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.

$$A = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \text{ and } B = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \quad (6)$$

where A is known as the lower unit triangular matrix with a recursive structure and B is a diagonal matrix.

Empirical Analysis and Results

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 the Akaike information criterion (AIC), the Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ), and Final prediction error (FPE). We use the selected lag length, check model stability, impose the restrictions on the estimated VAR, and then obtain 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.

The correlation matrix (Table 3) indicates that the factors are unlikely to have issues with multicollinearity with each other, but each construct strongly correlates 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.

Variables	INFODEN	INFOEFF	SUPPACC
INFODEN	1.000		
INFOEFF	-0.7661	1.000	
SUPPACC	0.1544	0.0719	1.000

Table 3. Correlation Matrix

From the ADF test results (Table 4), we reject the null hypothesis of a unit root in the series at conventional significance levels and conclude that the series are all stationary in levels. Hence, we do not need to difference them.

		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	

Table 4. Unit Root Test: Augmented Dickey Fuller (ADF) Test

We proceed to estimate the Structural Vector Autoregression using HQ, SC, AIC, and FPE to select the appropriate lag length. The lag selection criteria presented in Table 5 show that the optimal lag is of order 6 as selected by the AIC.

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
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

Table 5. Lag Selection Criteria

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

Structural Vector Autoregression (SVAR) Estimation

We proceed to estimate the VAR model using six lags. The VAR results are not reported since the focus is on the SVAR. Table 6 shows the results of the estimated SVAR model. As our estimates are derived by imposing restrictions on the AB-model discussed above, the SVAR is just-identified. The estimated model is given by $e_t = A^{-1}u_t$, with the recursive unit triangular A matrix and B diagonal matrix as shown. The lower triangular coefficients for the A matrix: a_{21} is the effect of information efficacy on support response acceptance, a_{31} is the effect of information density on support response acceptance, and a_{32} is the effect 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 $p < 0.000$.

Parameter	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***

Table 6. SVAR Estimates

Notes: AB-Model: $e_t = A^{-1}u_t$, A – recursive unit triangular matrix, B – diagonal matrix, a_{21}, a_{31}, a_{32}, b_{11}, b_{22}, and b_{33} are estimated SVAR coefficients; *** $p < 0.001$.

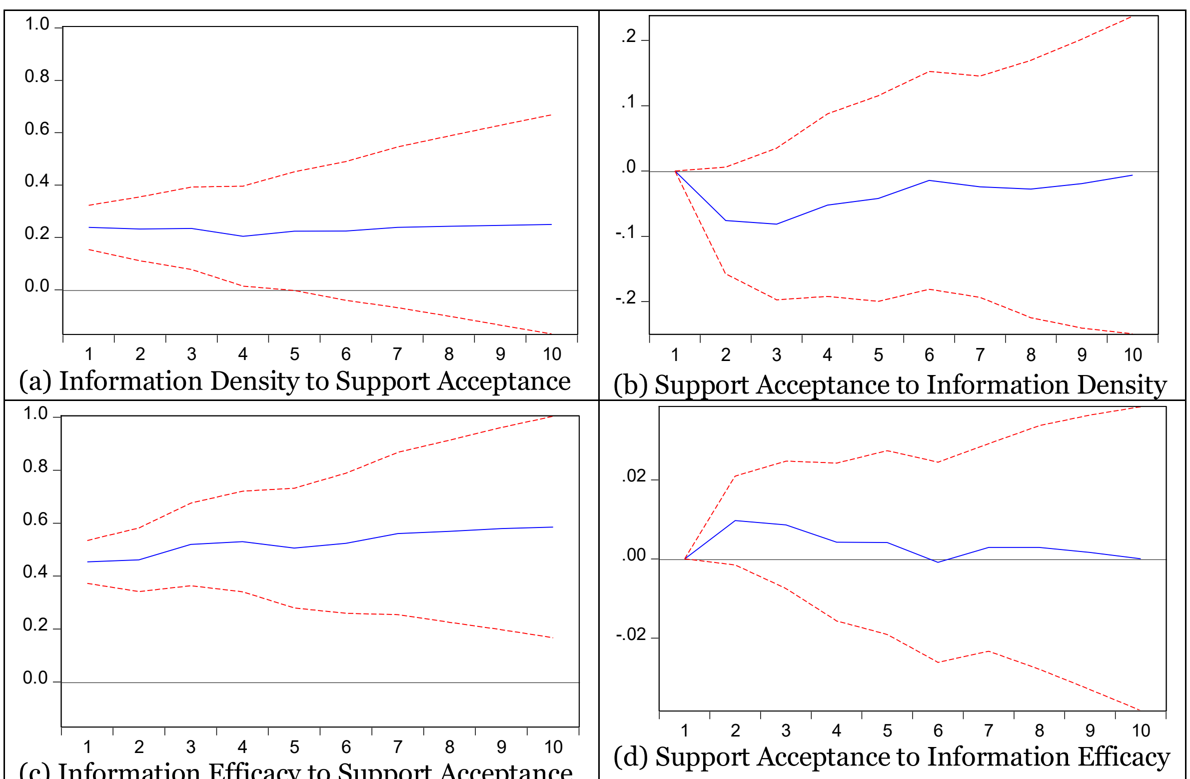
To assess the stability of our SVAR models, we assessed for stability and for autocorrelation of the residuals. The result of the stability test (see Appendix A3) shows that all the eigenvalues are less than one; the Eigenvalues ranged from 0.480382 to 0.936638. Thus, VAR satisfies the stability condition. 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.

Impulse Response Functions (IRFs) Results

The goal of this study is to examine user dynamics in OHCs, and the impulse response functions (IRFs) provide a graphical explanation of the relationships among 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. To allow for the possibility that there could still be some autocorrelation in the residuals, we estimate an orthogonal IRF, which provides the most appropriate approach for estimating the model (Sims 2008). The IRFs graphs are shown in Figure 3 (a-d), and they represent the impulse response functions for a SVAR of support response acceptance, information density, and information efficacy. For example, figure (a) shows the impact of a one standard deviation shock of information density on support acceptance.

The IRF graphs of the first row of Figure 3 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 (a) and vice versa (b). Figure 3 (a) indicates that a unit shock to information density, that is, the total number of words in a user online post generates a positive response in the total number of accepted support responses provided (SUPPACC) and that such positive effect remains statistically significant up to four days. After day four, while the effect is still positive, it is no longer statistically significant. Figure 3 (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-contemporaneous 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 beyond day one is not statistically significant as the confidence interval band includes the zero line.



(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 3. Participants' Online Disclosure and Response Behavior Dynamics

Notes: Blue line represents the effect of the impulse on response; red line is the 95% confidence interval band. The horizontal axis is measured in days.

The IRF graphs of the second row of Figure 3 present 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 (c) and vice versa (d). Figure 3 (c) shows that a unit shock to the information efficacy of an online post, leads to an increase in the number of support response acceptance. This positive effect remains statistically significant for over 10 days. Figure 3 (d) shows that a unit shock in the total number of support responses acceptance provided, has no first-period impact on information efficacy. The effect is non-significant as the confidence bands include the zero line. The zero-contemporaneous effect is because of the restrictions imposed when estimating the SVAR model. While not statistically significant, the results show that the effect increases up to day three and then decreases from days 3 to 6 and gradually dies down after day 7. In summary, the above findings demonstrate the dynamics of participants' online information disclosure and support response behaviors over time.

Robustness Checks

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 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 3 above. In the second permutation, we start with INFOEFF, followed by INFODEN, and then SUPPACC. We consider this second permutation to assess whether the results hold. The new IRF results are shown in Figure 4.

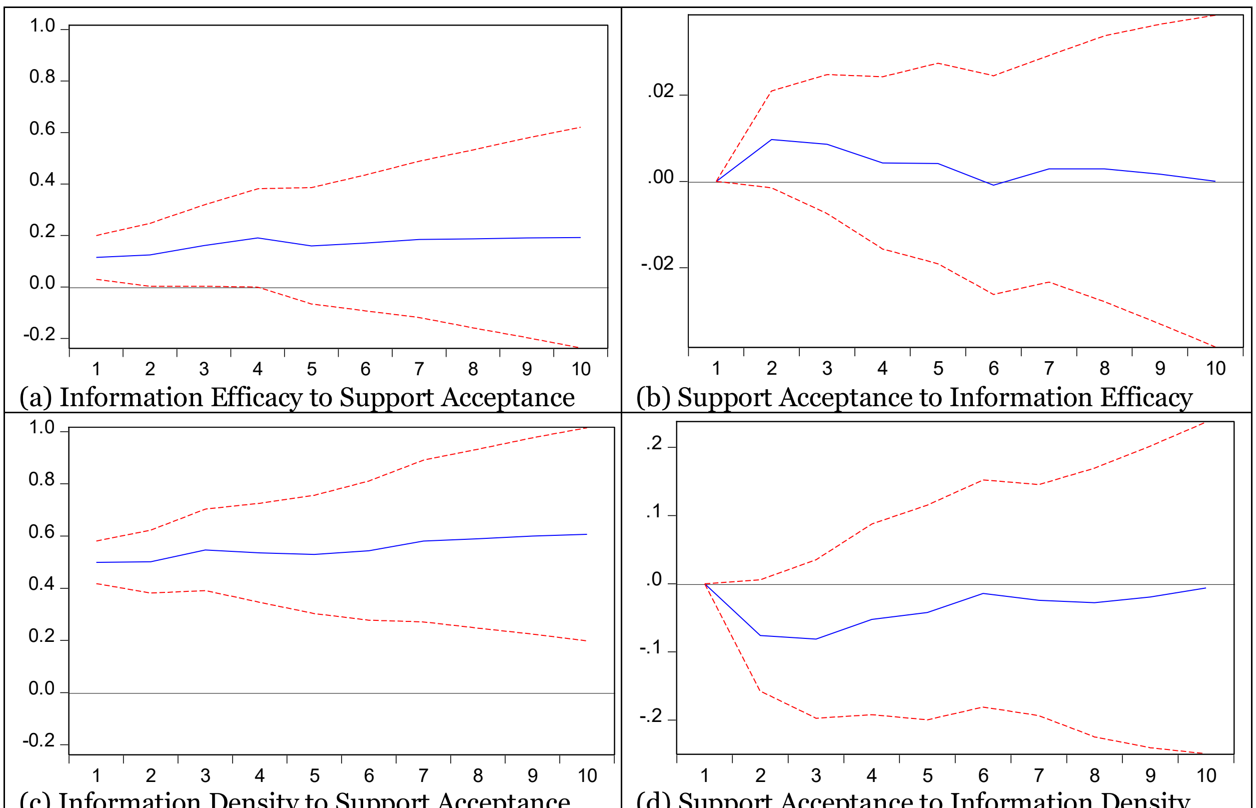


Figure 4. Impulse Response Graphs for Robustness Check (Impulse to Response)

Notes: Blue line represents the effect of the impulse on response; red line is the 95% confidence interval band. The horizontal axis is measured in days.

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 are qualitatively the same. The results show both information efficacy and information density maintain their positive and statistically significant impacts on support response acceptance (Figure 4 (a) and 4 (c)), respectively. Meanwhile, the positive impact of information efficacy on support response acceptance remained the same (Figure 4 (b)) as well as the negative impact of information density on support response acceptance (Figure 4 (d)), with the effects being not statistically significant.

Discussions

From the results of the impulse response functions, we find 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; Lee et al. 2019).

On the contrary, we find that support response acceptance reduces the number of words in a user post. The result shows that 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 addresses 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 and 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 increases, 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 six.

Implications

In this paper, we develop a SVAR model and IRFs to study users' dynamic information disclosure characteristics and support response acceptance behaviors in OHCs. We estimate various SVAR models via maximum likelihood. 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, demonstrate 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 diverse types of supports in OHCs, the dynamics between user information disclosure characteristics and support response acceptance has received little attention. Similar to prior research that examined healthcare providers' online-offline dynamic activities (Wang et al. 2020), this current study explores deeper the dynamic interaction among healthcare information seekers and responders. Thus, our study makes contributions to the literature on user information disclosure/response behaviors in OHCs, as well as practical implications for OHCs' management and healthcare technologies.

Despite the fact user participation on OHCs is a dynamic phenomenon, prior research has provided partial explanation of user participation by examining static factors such as antecedents, motivators, situational, and privacy factors (e.g., Li et al. 2010). The current study provides a more comprehensive theoretical explanation of the dynamic interaction between information disclosure and support response acceptance that otherwise would not have captured reciprocal improvement in user disclosure abilities. Furthermore, our study extends the DD-MM framework by expanding the intervening mechanism information density and information efficacy, that enables the exploration of the relative effects of these mechanisms. Thus, future research could revisit prior research that investigated the intervening variable at the higher level that resulted for new insights on inconclusive findings(Chaudoir and Fisher 2010; Fichman et al. 2011).

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 personalized care strategies, promotion of effective participation in OHCs, and collaborative information systems design in healthcare management.

Conclusion and Future Research Direction

This study outlines three 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 intervals will be necessary to validate and improve the results. Second, our estimated model sheds 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 believe that conducting the analysis using a panel data that focuses on observing multiple users at multiple time intervals could be a fantastic 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. Thus, future research should consider testing our model using data from other online health platforms. Major events such as the recent health pandemic, COVID-19, can significantly influence users' information sharing behavior online. Future research would examine the proposed study model with pre and post pandemic user data to shed more insights that can inform the design of OHCs.

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