Effect of Privacy Concerns and Engagement on Social Support Behaviour in Online Health Community Platforms

The growth of interactive technologies has fostered different online health communities (OHCs) where individuals share similar interests in health-related information and exchange social support to facilitate health outcomes. While OHCs offer a variety of benefits to society, it is challenged by surrounding issues of privacy concerns. Breach of privacy poses undesirable consequences for people, and thus privacy concerns can influence individuals' social support behaviour in OHC platforms. Moreover, willingness to engage in the community can be an outcome of prosocial behaviour, motivating people to offer additional social support on OHC platforms. Hence, addressing the role of engagement in a multi-actor online environment requires further attention. Drawing on social support theory, by examining the effects of privacy concerns, control of information, and community engagement, this study develops a framework to create an informed and sharing online community. Using survey data collected from different OHC platforms on Facebook, our study presents some interesting conclusions. Our results show that community engagement and privacy concerns can influence certain types of social support (i.e., information or emotional support), leading to OHC members' intention to participate. Our conceptual model and findings will inform both future research and policymakers.

1.0 Introduction

The evolution of Web 2.0 has facilitated the inception of different online platforms, where people with similar interests and commonalities share their knowledge, ideas, experiences, opinions and often establish a sense of duty towards the network members (Luo et al., 2020; Park et al., 2015). The insurgence of these online platforms has shepherded the healthcare industry towards remarkable transition and fostered an environment for different online health communities (OHCs) where patient networking has turned out to be an essential part of the health care experience (Gage, 2013; Li et al., 2018). Undoubtedly, these OHCs have remarkable potency to provide advantages for the healthcare sector in many aspects, such as being accessible by a large audience, achieving high levels of engagement, removing the location and physical access barriers (Griffiths et al., 2012; Laranjo, 2016; Welch et al., 2016). Besides, communities like PatientsLikeMe in the US; HealthUnlocked in the UK; Ping A Good Doctor in China have certainly made it easier and faster to diffuse health-related resources such as sharing information, offering emotional support, validation of experience and treatment, and logistical help along with professional medical consultation and information access. Such diffusion of health interventions through these platforms facilitated considerable behavioural change in people seeking health information and self-healthcare management. For example, individuals in the UK looking for health-related information online increased from 54% in 2018 to 63% in 2019 (Office for National Statistics, 2020). In fact, a nationwide survey in 2020 shows that 25.4% of people in the US intended to get cancer-related information online before going to doctors or health care providers at first (HINTS, 2020). Therefore, OHCs have appeared to be an unconventional collaborative platform in the healthcare industry, ensuring a suitable environment for easy accessibility of information and offering different alternative routes for healthcare service provisions.

One of the fundamental motives behind individuals engage in OHCs is social support (Wang et al., 2021b). Social support empowers OHC members who struggle with similar health challenges by offering knowledge, skills, and awareness to identify and engage in appropriate health-related

decisions (Lin and Kishore, 2021; Wentzer and Bygholm, 2013). Hence, within an OHC's integrative environment, social support plays a crucial role in individuals' healthcare management-related behaviours (Greaney et al., 2018; Latkin and Knowlton, 2015). Nevertheless, irrespective of various benefits, OHCs present challenges regarding privacy breach issues. For instance, 249.09 million individuals are being affected directly or indirectly by healthcare data breaches between 2005 to 2019 (Seh et al., 2020). More recently, in May 2021 alone, 6,535,130 healthcare records were exposed or compromised across 63 incidents in the US (HIPPA, 2021). These privacy breaches can lead to reconstructing anyone's identity and can trigger prejudice, harassment, privacy invasion, damage of personal information and even identity theft, putting individual safety at risk. Such incidents highlight the importance of privacy control in OHCs. However, existing literature has provided evidence of privacy related issues in different contexts, but scant attention has been paid to the impact of privacy concerns in the OHCs context (Shirazi et al., 2021; Zhang et al., 2018). While OHC literature has provided evidence on the impact of privacy concerns on trust (Bansal and Gefen, 2010), personal health information disclosure (Zhang et al., 2018), knowledge sharing intentions (Dang et al., 2020), or antecedents of privacy calculus model (Kordzadeh et al., 2016), it provides limited clues whether privacy concerns can influence individuals social support exchange behaviour in OHC platforms. Therefore, investigating the impact of privacy concern drivers (i.e., perceived control of information and privacy risk) on OHC members' social support exchange behaviour is critical.

Moreover, the collaborative environment of OHC has also transformed the nature of community engagement and, therefore, has received growing consideration in the existing literature. While engagement is considered critical for organisational settings in different industries (Shawky et al., 2020), it is also particularly crucial for the success and sustainability of OHC platforms (Gopalsamy et al., 2017; Young, 2013). A growing body of literature has given particular attention to engagement behaviour in the social media and online community contexts. For example, privacy concerns (Jozani et al., 2020), relational bonds (Kim and Kim, 2018), image interactivity (Cano et

al., 2017), social media affordance (Cabiddu et al., 2014), channel richness (Mirzaei and Esmaeilzadeh, 2021), social identity (Feng et al., 2021), and social support (Molinillo et al., 2020) have shown to influence users' engagement behaviour. However, little research has examined whether the willingness to engage in the community can explain and predict the community members' actual relevant behaviour (i.e., social support) (Cao et al., 2021; Wu et al., 2018). Specifically, community engagement from a prosocial point of view has rarely been examined in relation to the individuals social support providing behaviour in OHC platforms. Hence, in this study, we take a prosocial view of community engagement to examine its effect on OHC member's social support providing behaviour.

Given the preceding discussion, our study attempts to build a theoretical framework to examine how privacy concerns, engagement, and social aspects can affect individuals' intention to act on the support provided within the OHC platforms. By integrating the drivers of privacy concerns and social support theory, this study offers a better understanding of how individuals react to the privacy issue in OHCs. Our study also captures community engagement as a behavioural manifestation towards social support providing actions and conceptualises it as individuals' prosocial contributions to the OHCs (Ray et al., 2014; Wu et al., 2018). Specifically, we develop propositions on how privacy control concerns and prosocial intention through engagement can affect different social support offering behaviour in the OHCs that could influence individuals' intention to participate. We also believe that this study will help governments and health organisations develop a more informed social climate for engaging people in healthy communities. While OHCs can play a key role, we need to understand the elements that persuade people to participate in these platforms. Hence, this study seeks to address the following research questions:

RQ1: Whether privacy concerns affect individuals' social support offering behaviour in OHCs?

RQ2: What is the effect of community engagement on individuals' social support behaviour in OHCs?

RQ3: To what extent social support can influence an individual's health-related online community participation intentions?

The rest of this paper proceeds as follows. We first provide a theoretical background to this research and develop a conceptual model and hypotheses. We then discuss the method used, estimate the model, and test the hypotheses to examine the relationships between privacy concerns (i.e., perceived information control and privacy risks), community engagement, social support (i.e., information and emotional support), and participation intention. The paper concludes by discussing the findings, implications, and limitations.

2.0 Literature Review and Hypothesis Development

2.1 Social support in OHCs

OHC can be referred to as a virtual forum/internet-based platform where members share collective interests in health-related information, experiences and emotions and offer support to others within the community (Atanasova et al., 2018; Liu et al., 2018). OHCs represent a valuable platform for individuals to diffuse health-related resources, including informational support, logistical advocacy, emotional relief, caregiving strategies, and even financial donations for people who seek support to cope with illness or understand health issues better (Smith and Christakis, 2008; Thoits, 2011). According to Laireiter and Baumann (1992), such forms of assistance offered by online community members constitute social support. Previous studies (e.g., Mazzoni and Cicognani, 2014; Shirazi et al., 2021; Wang et al., 2021b) have shown that OHCs can incredibly influence patients' health-related behaviour and assist individuals to manage health-related uncertainties through additional social support. For instance, Liu et al. (2020) demonstrated that social support in OHCs is effective in helping users to improve their insights on the cause of the illness or lowering the uncertainty through verification of their interpretation of the illness. In addition, Park et al. (2020) stated that empathetic and encouraging messages in OHC could offer emotional and informational support through which members can manage uncertainties and enhance their mood or improve their health-related behaviour. In fact, social support in the OHC can obviate stigma and reduce barriers to access

support (Davison et al., 2000; Johnson and Ambrose, 2006). These social supports make community members feel more informed, more in control, and more able to manage their health conditions (Bronstein, 2017; Setoyama et al., 2011). Therefore, social support is considered as an indispensable experience for members in any OHC platform (Introne and Goggins, 2019).

Sarason et al. (1983: 127) broadly defined social support as "the existence or availability of people on whom we can rely, people who let us know that they care about, value, and love us". Alternatively, Cobb (1976: 300) defined social support as fitting to one or more of the following three options: information leading the subject to believe that they are cared for and loved; esteemed and valued; and belongs to a network of communication and mutual obligation. Thus, social support can be defined as an exchange of resources between individuals (Shumaker and Brownell 1984), reflecting a concept of support that is perceived to be beneficial by both the provider and receiver (Yan and Tan, 2014). In such a sense, social support is not just a consequence of relationships; rather it results from individuals' successful negotiation and mobilisation (Hajli et al., 2015; Offer, 2012), which enable networking, communication, reliance, common understanding, mutual social protocols, intangible information, and relationship exchanges. In fact, Wang et al. (2021a) identified that social support for remotely working people during the COVID-19 pandemic had provided necessary emotional and instrumental resources to handle unique challenges. Similarly, in OHCs, receiving social support plays an important role in transforming individuals' health-related experiences (Li et al., 2018) and empowers patients that improve their compliance to treatment and recovery (DiMatteo, 2004). For example, social support has been shown to benefit patients who are constrained by their conditions such as coronary disease (Waring et al., 2018), Alzheimer's disease (White and Dorman, 2000), Huntington's disease (Coulson et al., 2007), cancer (Turner et al., 2001), HIV/AIDS (Ranjit et al., 2020), or different disabling conditions (Frost and Massagli, 2008; Wicks et al., 2010). Besides, social support found to improve patient's life quality (Li et al., 2016; Yao et al., 2015) offer support for mothers who are suffering from postpartum depression (Evans et al., 2012), and helping patients move to a healthier state who are suffering from different psychological issues

(Pollard and Kennedy, 2007; Yan and Tan, 2014). Therefore, given the role of online social support, it has become an important aspect of OHC related studies.

Social support is a construct embedded in online communities where individuals offer their advice and know-how, answer to questions, provide recommendations and express their feeling of attachment. Hence, existing literature has generally categorised social support into different forms, such as informational, emotional, companionship, and instrumental support (Berkman et al., 2000; Wortman and Conway, 1985). Despite being conceptualised multidimensionally (Lo, 2019), there is an agreement that informational and emotional support are more fitting for online community settings (Chen et al., 2019; Wang et al., 2021b). In particular, social support, such as informational and emotional support, is vital and beneficial for OHC members for health-related decisions and outcomes (Lin et al., 2016; Yan and Tan, 2014). Informational support refers to advise, guidance, suggestions, experience, or knowledge (Liang et al., 2011; Yu et al., 2015). Informational support through explaining symptoms, own experiences, and suggestions, can offer direction and assistance to solve the health problems of online community members. Alternatively, emotional support involves listening, encouragement, sympathy, empathy, concern, or trust to compensate for negative emotions (Johnson and Lowe, 2015; Nadeem et al., 2019; Yoo et al., 2014). Emotional support can provide patients with the experience of being loved, cared for, valued, and empathised. Given the interactions that take place in online platforms, we conceive that such a collaborative process of exchanging informational and emotional support likely to develop a sense of mutual obligation within the community members and can increase their engagement and encouragement to support others (Lin et al., 2015; Loane et al., 2015; Zheng et al., 2013). Thus, to assess the effect of social support in OHCs, this study emphasises on the informational and emotional support.

Nevertheless, online platforms pose undesirable consequences such as personal information breaches (Malhotra et al., 2004), theft usurpation, and disclosure of security-sensitive information (Featherman et al., 2010; Suh and Han, 2003), financial fraud (Demetis, 2020; Saridakis et al., 2016). Most of the time, OHC's members need to disclose personal information such as geographic location,

telephone number, real name, thus increase the potential risks of information theft and privacy invasion (Lambert et al., 2012; von Muhlen and Ohno-Machado, 2012). Additionally, OHC patients may need to address their health issues in further detail with health professionals, doctors, or other patients (Bansal and Gefen, 2010; Li et al., 2018), increasing the risk of private information exposure. As a result, users of online platforms have a great privacy concern regarding the use of their personal health information and the degree of control they have over their health information (Bansal and Gefen, 2010). Previous studies (e.g., Li et al., 2020; Li et al., 2018; Metzger, 2006) suggested that the ability to control personal information and privacy risk assessment plays an important role in deciding whether to seek/share/disclose information. Thus, given several privacy concerns triggered by patients when dealing with online health information, we must further explore the role of perceived risk and information control on patients' health information seeking/sharing intentions.

2.2 Perceived control of information and perceived privacy risk

Managing online privacy is a constant challenge that people experience while interacting, disclosing, or discussing their personal information online. Especially, people are sensitive to personal health information and want to have control over their information because of privacy and security concerns. Controlling personal information is critical for online user's privacy management, as the ability to control is deeply rooted in the concept of privacy (Heravi et al., 2018; Xu et al., 2012). In fact, individuals perceive privacy through the degree of their belief in control over what information is shared, how data is collected, and whom it is shared with (Malhotra et al., 2004; Xu et al., 2011). While most people have little or false sense of control over how their data is being used, and shared (Cavusoglu et al., 2016; Jozani et al., 2020), usually, most people try to evaluate the extent of control they have over it (Foxman and Kilcoyne, 1993). Such evaluations over the control of information are referred to as 'perceived control of information', where individuals perceive they can control the use of their own information.

Perceived control can influence attitudes, intentions (Averill, 1973; Skinner, 1996), and behaviours of online platform users more than actual control (Hajli and Lin, 2016). For instance, Wang and Liu (2019) state that when people perceive high control over their shared information, they are willing to post more information online. Similarly, perceived control of information drives users' intensity to use online platforms and intention to publicly share more information (Cavusoglu et al., 2016; Jordaan and Van Heerden, 2017). Sometimes higher perceived control of information even leads to an unnecessary revelation of private information (Brandimarte et al., 2012). Alternatively, a sense of losing control over information can induce information removal or a negative attitude towards information sharing (Sheng et al., 2019; Taddei and Contena, 2013). Therefore, the prominence of control of information seems to be a vital factor influencing privacy concerns among online social platform users (Hanna et al., 2010). Besides, it implies that higher perceived control of information will be more likely to allow individuals to feel protected and encourage seeking and sharing health-related information on online platforms.

Perceived control of information has been utilised to reflect an individual's innate fear of potentially losing their private information. For example, studies have found that higher perceived control of information plays a crucial role in reducing privacy concerns (Dinev and Hart, 2006; Xu et al., 2011), which ultimately increases, such as online transactions, online social interactions, or civic expressions (Jiang et al., 2013; Wang and Liu, 2019; Xu et al., 2012). With higher perceived control of information, individuals produce a higher amount of self-disclosure and willingness to post/share information online (Olivero and Lunt, 2004; Taddei and Contena, 2013). While OHC platforms have made virtual health diagnosis and consultation very easy, OHC members are mostly anxious about information leaks. This compromising disclosure can lead to damaging consequences such as discrimination, presumption, humiliation, especially with sensitive issues related to psychological disorders, physical incapacities, sexual diseases, drug abuse (Anderson and Agarwal, 2011; Obermeyer et al., 2011; Zhang et al., 2018). To increase information security and prevent privacy invasions, OHC platforms offer different privacy policies and settings to control personal

information and protect users' privacy (Jozani et al., 2020; Saridakis et al., 2016). Such perceived control of information can decrease an individual's discretion and help them disclose information within the online community (Acquisti et al., 2015; Cavusoglu et al., 2016). Therefore, we propose:

H1$_a$: Perceived control of information is positively related to the user's emotional support.

H1$_b$: Perceived control of information is positively related to the user's informational support.

H1$_c$: Perceived control of information is positively related to users' participation intention in OHCs.

Besides, privacy risk is another direct antecedent of privacy concerns (Li, 2012; Xu et al., 2005). Due to the nature of online community platforms, it is easy to collect, distribute, and utilise user's personal information, which ultimately increases the possibility of potential control loss over personal information resulting in higher privacy risk. Thus, users' concerns or beliefs regarding the degree to which they associate a high potential loss with sharing personal information have been referred to as perceived privacy risk (Gerlach et al., 2015; Smith et al., 2011). Perceived privacy risk can be a key predictor of users' online behaviour, and it can affect issues from trust to willingness in disclosing personal information (Bugshan and Attar, 2020; Dinev and Hart, 2006; Malhotra et al., 2004). Research has shown that OHCs give rise to inconvenient access, misappropriation, and revelation of private health information (Li, 2013). These communities mainly count on communication regarding personal health information with other users, creating secondary usage of health data and posing serious privacy risks (Li, 2013; Safran et al., 2007). Therefore, users may not be willing to take part in OHCs and disclose their personal health information. However, studies (e.g., Cheung et al., 2015; Hallam and Zanella, 2017; Heravi et al., 2018) have found that perceived privacy risks have limited or no impact on disclosing personal information. Li et al. (2018) have observed that perceived risk does not affect health information sharing and seeking intentions within certain study groups in their research. Privacy calculus theory shed light on such argument, suggesting that individuals perform a calculus between the cost of privacy risk and benefit of

disclosing information, where if potential gain overtakes the cost, individuals are willing to disclose information (Culnan and Armstrong, 1999; Kokolakis, 2017). Despite studies show that individuals exhibit discrepancies between their intentions to protect privacy and self-disclosure behaviour (i.e., privacy paradox), it is apparent that privacy concerns significantly reduce the disclosure of personal information (Baruh et al., 2017; Koohikamali et al., 2017). Hence, the impact of perceived privacy risk remains an open question and warrants further investigation, especially in the OHC context.

Perceived privacy risk denotes the perceptions and beliefs of people about the potential loss of control over data about themselves (Bélanger and Crossler, 2011; Tseng and Wang, 2016). Such perceived privacy risks have been found to negatively affect an individual's behaviours and decisions toward using online sites (Chang and Tseng, 2013; Van Slyke et al., 2006). Moreover, the privacy risks can have a negative impact on an individual's information seeking and sharing intentions (Dinev and Hart, 2005; Krasnova et al., 2010). Even perceived privacy risk can be critical in terms of individuals decisions concerning information-sharing behaviour on blogs (Chai et al., 2011) and online civic engagement (Wang and Liu, 2019). Besides, the nature of online platforms makes the private data easily collectable, distributable, and usable without users' consents (Hajli and Lin, 2016). Hence, higher perception of privacy risk can negatively impact online users' informational and emotional support seeking intentions.

H2$_a$: Perceived privacy risk is negatively related to the user's emotional support.

H2$_b$: Perceived privacy risk is negatively related to the user's informational support.

2.3 Engagement in OHCs

The concept of engagement has recently gained importance because of the dominance of online platforms and their user's growing intention to seek online social support. Higgins (2006: 422) generically defined engagement as "to be involved, occupied, and interested in something." However, the concept of engagement has been subjected to various interpretations beyond the notion of involvement and participation (Azer et al., 2021; Brodie et al., 2019). Existing literature defined

engagement as a psychological or motivational construct reflecting an individual's behavioural investment to accomplish their roles. For instance, Kahn (1990) defined engagement as individuals' being emotionally connected, cognitively vigilant, and physically involved in a role that reflects their thinking, creativity, beliefs, and values and promotes their relationship with other group members. Similarly, Brodie et al. (2013) conceptualised engagement as a context-dependent, multidimensional concept of a psychological state that comprises emotional and behavioural investment in the process of relational exchange. In contrast, engagement has also been defined as motivation (intrinsic/extrinsic) to interact and cooperate with community members (Algesheimer et al., 2005; Baldus et al., 2015). These definitions promote individuals' behaviour of delivering instantaneous value for others, but they go more than fulfilling a sense of duty and show prosocial behaviours that are emergent, virtuous, helpful, conscientious, innovative, and interpersonally collaborative (Ray et al., 2014; Rich et al., 2010). In this study, we take a prosocial contribution standpoint towards defining engagement in OHCs.

Prosocial behaviour is described as voluntary behaviour primarily aimed at benefitting others (Eisenberg et al., 2015). It is driven by the intrinsic and/or extrinsic motives such as altruism (desire to benefit others with no concern for self), egoism (desire to benefit the self), collectivism (desire to benefit collective members of a valued group) and/or principlism (desire to benefit others to uphold moral principles) (Batson et al., 2011; Slattery et al., 2019). These motives are underpinned by different sentiments such as promoting self-identity (Caprara and Steca, 2005; Ray et al., 2014), or feeling good about oneself through helping others (Fu et al., 2017; Lavertu et al., 2020), or expecting reciprocal benefits (Grant and Dutton, 2012; Yang et al., 2020). Therefore, the fundamental rationale behind prosocial behaviour can be seen to be self-serving, mutually beneficial, or socially acceptable. Consequently, a prosocial exchange may occur over different behaviour, such as giving, lending, or sharing (Belk, 2010; Harvey et al., 2020). To facilitate these behaviours, members try to create, contribute, or consume online content (Dolan et al., 2019; Van Doorn et al., 2010), show commitment (Wiertz and de Ruyter, 2007; Zheng et al., 2015), engage in interaction (Brodie et al.,

2021; Wirtz et al., 2013), co-create and/or collaborate (Azer and Alexander, 2018; Laroche et al., 2012), and participate (Algesheimer et al., 2005; Brodie et al., 2019) in the online communities. In this process, engaged individuals believe that their contributions bring impact and share a sense of belongingness, mutual responsibilities, specific beliefs, and develop obligations towards fellow members in the community (Algesheimer et al., 2005; Muniz and O'guinn, 2001). Considering this prosocial perspective, we define engagement as an individual's voluntary behaviour driven by intrinsic or extrinsic motives that are perceived to be personally meaningful, socially beneficial, and emotionally connected towards the community.

Despite having various conceptualisations of engagement, we define engagement as a form of behaviour because most studies agree that contributing to communities reflects the behavioural dimension of the engagement (e.g., Azer et al., 2021; Dolan et al., 2016; Oliveira et al., 2016; Shawky et al., 2020; Wu et al., 2018). In addition, Calder and Malthouse (2008) believed that engagement is a motivational force that drives an individual's behavioural response as a consequence of engagement. Besides, prosocial behaviour comprises a wide class of behaviour from involving costs for the self and resulting in benefits for others (Wittek and Bekkers, 2015); thus, we identify engagement as a mutually dependent process. Moreover, active contribution in online communities through disseminating personal information, experiences, and knowledge emphasises the interactive, two-way nature of community engagement and reflects its behavioural dimensions (Brodie et al., 2013; Wu et al., 2018). Therefore, this study focuses on the behavioural aspect of engagement in an OHC context as a collaborative process.

Several studies have examined user engagement and participation in online communities. For example, Khan (2017) found that user engagement is driven by motivations such as information giving and seeking, relaxing entertainment, social interaction and self-status seeking in social media platforms. Also, Shahbaznezhad et al. (2021) identified that rational, emotional, and transactional content and online platform contribute to positive user engagement. Besides, OHC studies have explored different factors influencing users' engagement. Feng et al. (2021) identified that the

community factors' social identity and perceived effectiveness played a significant role in influencing engagement in the OHC platform. Further, Mirzaei and Esmaeilzadeh (2021) showed that perceived channel richness and perceived social support positively influence OHC engagement. These studies show various factors influence engagement intentions in online platforms and offer copious evidence that engagement is an integral element in any online community context. However, further research is needed to investigate whether community engagement can explain and predict the individuals' social support providing behaviour in OHCs.

Online community provides a collaborative platform (Faraj et al., 2011; Mirzaei and Esmaeilzadeh, 2021), which allows community engagement and social relationship development as well as empowers its members through information exchange (Househ et al., 2014; Liang et al., 2011; Lowe and Johnson, 2017). Previous studies (e.g., Chou et al., 2009; McKenna and Bargh, 1998; Meier et al., 2007) show that member's participation in online support groups provides both informational and emotional benefits regarding a wide range of health conditions and illnesses. For instance, involved health community members seek informational support regarding medical experiences, treatment history and suggestions, disease diagnosis and prevention, health risk assessment advice from doctors (Gibbons et al., 2011; Oh, 2012; Xiao et al., 2014). Also, community members can provide emotional support, increasing community members' ability to fight stress, depression, loneliness, emotional hardships, bad moods, and continue treatment regimens (Lieberman and Goldstein, 2005; Menon et al., 2014; van Uden-Kraan et al., 2008). In other virtual community contexts, Cao et al. (2021) showed that engagement intention positively influences content creation, contribution, and consumption behaviour. Also, Molinillo et al. (2020) identified that engaged customers are likely to co-construct unique experiences by exchanging information and knowledge (i.e., willingness to co-create) on social commerce websites. Furthermore, Ray et al. (2014) showed that the exchange of information is driven by the greater sense of engagement that inspires community members to help others in a meaningful way. Besides, in a qualitative study, Azer et al. (2021) capture that engaged social community platform users to manifest informational,

supportive, inspiring, and emotional behaviour during the COVID-19 pandemic. Therefore, it is likely that an increase in community engagement would lead to an increase in the social support received from OHCs. Therefore, we posit the following two hypotheses:

H3$_a$: Community Engagement has a positive effect on users' emotional support.

H3$_b$: Community Engagement has a positive effect on users' *informational support.*

2.4 Social support and intention to participate

Social support is a critical element of human interaction (Rozzell et al., 2014) and significant indicator that leads to experiencing social benefit (Vicary and Fraley, 2010). According to Vaux (1988), it is a process of seeking, offering, and evaluating supportive behaviours, regularly projected through the exchange of verbal and nonverbal messages. Online social support helps users with their intangible needs, such as emotional and informational support (Coulson, 2005; Madjar, 2008). Especially, people need emotional and informational support because of their health-related issues (Schaffer et al., 2008) and such support may attract individuals to be more active and participative in online community platforms (Liang et al., 2011). According to Hsu et al. (2012) dependable and responsive exchange of information will lead to better community involvement. Besides, Li et al. (2018) show that people get benefits from informational and emotional support that ultimately increase their intention to share health information in the online social network communities. Therefore, social support has a significant effect on the individual's psychological state (Hajli et al., 2015), which may affect an individual's willingness to participate/act on the support received in OHCs. So, we propose that:

H4: Emotional support positively affects users' online community participation intention.

H5: Informational support positively affects users' online community participation intention.

Based on the discussion above, we present our conceptual model in Figure 1. This model aims to understand the impact of privacy concerns and community engagement on social support behaviour, contributing to members' intention to participate in OHC platforms.

3.0 Research Method

3.1 Data Collection

We collected primary data through different OHCs. We invited 1000 random users from healthcare-based online platforms where members can collaborate with others in the group to share information and offer immediate responses to deliver health-related solutions. With a response rate of 20.2%, we have received 202 usable questionnaires from several healthcare-based pages such as the CDC, Act Against AIDS, CDC Tobacco Free, CDC en Espanol, CDC Emergency, Million Hearts, NIOSH, Weight of the Nation, Veto Violence, and Start Talking Stop HIV. The sample population for this study are members who had been involved in any of the healthcare-based pages mentioned above. Table 1 provides demographical information about our participants.

3.2 Measurements

All the items for each indicator were adapted from previous research, and some statements were modified to fit the current research context. All items used a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Items for perceived privacy risk were adapted from Pavlou et al. (2007) and Hajli and Lin (2016) that measure individual's subjective evaluation with regard to what happens to the disclosed information, whereas items of perceived control of information were adapted from Krasnova et al. (2010) and Hajli and Lin (2016) that attempts to assess perception regarding the possibility of managing subject's own information. Items for community engagement were adapted from Algesheimer et al. (2005), Hajli and Lin (2016), and Baldus et al. (2015) to measure users' effort to interact with others and willingness to refer potential users who need support. In addition, two key concepts measured the social support indicator, i.e., informational and emotional support for which the items were adopted from Hajli (2014). Finally, the dependent variable intention to participate

was measured by capturing individuals' tendencies to act on support received from the OHC. We asked participants to consider their behaviour and activities on the online health platforms while answering questions. Table 2 provides further description and information regarding each construct and related items.

<div style="text-align: center;">Insert Table 2 here</div>

4.0 Data Analysis and Results

Structural equation modelling (SEM) is a distinct technique that implies a confirmatory approach to assess multiple relationships for developing a model (Hair et al., 2013; Tabachnick and Fidell, 2013). As a result, to assess the conceptual model and its related hypotheses, structural equation modelling (SEM) has been used as an analytical technique, and the data have been analysed with IBM AMOS 26.0 software. First, we have carried out some preliminary assessments to determine the plausible context of the distribution and understand the data's appropriateness for multivariate analysis. Second, we have assessed the measurement model to determine the reliability and validity of theoretical constructs. Third, we examine the common method variance (CMV). Fourth, we have measured the structural model by estimating the significance of the causal relationships among the constructs. Results from each analysis are presented in the following.

4.1 Preliminary Analysis

Prior to structural equation modelling, we have carried out various analyses to establish a logical context of the distribution and identify the data's appropriateness for multivariate analysis. At first, we have calculated the normality assessment of distributions of variables using a z-score by dividing the skewness and kurtosis values by their standard errors. At a conservative statistical significance level of 0.01, the z-score values show that not all variable falls between the threshold values of $\pm$ 2.58. Further analyses using Shapiro-Wilk and Kolmogorov-Smirnov tests ($p < .05$) also illustrate that the distributions of variables violate the normality assumption. Besides, we have also assessed the multivariate normality by using Mardia's coefficient of multivariate kurtosis, which indicated that

the dataset was multivariate non-normal.

Given that the data are multivariate non-normal, to fix this problem, a Bollen–Stine bootstrap (n=2000 at 95% bias-corrected confidence interval) has been performed to achieve stronger accuracy in confidence intervals (Nevitt and Hancock, 2001; Schumacker et al., 2015). Moreover, the detrimental effects of nonnormality and underestimating variance disappear with sample sizes over 200 (Tabachnick and Fidell, 2013; Waternaux, 1976). Therefore, with a sample size of N=202, non-normal distributions of variables do not impose any constraints derived from the normality assumption.

To identify potential outliers in the dataset, the Mahalanobis distance method (Mahalanobis D^2) has been used. The results illustrate that all observation values of D^2/df (df=5) are less than the threshold value of 4.0, exhibiting no characteristics of outliers in the dataset (Hair et al., 2013). Levene's test of equality of variance also shows that homogeneity of variances is present. Besides, Variance Inflation Factor (VIF) analysis indicates no evidence of multicollinearity issue, as VIF values are between 1.001 to 1.260, well below the cut-off point of 4.0, and tolerances are more than 0.10 ranging from 0.79 to 0.99 (Pallant, 2016). Finally, potential non-response bias has also been assessed by comparing the early and late respondents (Armstrong and Overton, 1977). We have split the data based on the response order of the survey before and after the first seven days as a dividing point. The results show no statistically significant difference between these two groups at a 95% confidence level, supporting that non-response bias does not appear to be an issue in this study.

4.2 Measurement Model Analysis

At first, by assessing causal relationships between the observed variables and the underlying latent variables, we have assessed the validity of the measurement model. Thus, to assess the unidimensionality of the constructs and the underlying latent variables, we have performed confirmatory factor analysis (CFA). The combinations of fit statistics for CFA illustrate that chi-square/degrees of freedom x^2/df = 1.504, standardised root mean square residual (SRMR) = 0.054, root-mean-square error of approximation (RMSEA) = 0.050 with pclose = 0.484, comparative fit

index (CFI) = 0.974, Tucker–Lewis index (TLI) = 0.969, incremental fit indices (IFI) =0.975, have

met the requirements of recommended values (Bagozzi and Yi, 1988; Bentler and Bonett,

1980; Brown, 2006), thus exhibiting a good fit to the collected data.

Also, convergent validity has been used to determine the construct validity by assessing

Cronbach's alpha (**α)**, standardised factor loading estimates (FL), average variance extracted (AVE),

and composite reliability (CR) values (Fornell and Larcker, 1981; Hair et al., 2013). Cronbach alpha

is commonly used to assess internal consistency as it involves correlating inter-item responses to

determine whether principal items are measuring the same domain (Rattray and Jones,

2007; Tabachnick and Fidell, 2013). The results in **Table 2** illustrate that for each variable, the alpha

values are above 0.70, ensuring high reliability (ranging from 0.722 to 0.970) (Bollen and Lennox,

1991; Sarantakos, 2013). Standardised factor loading estimates for all variables are statistically

significant at p<0.001 and range from 0.765 to 0.848, which exceeds the minimum criterion of 0.50.

Besides, composite reliability values range from 0.744 to 0.970, which are greater than the

commonly accepted cut-off value of 0.70 and ensure construct reliability. Finally, the average

variance extracted (AVE) for each variable exceeded the recommended benchmark of 0.50 (See

Table 3). These results confirm that the research has sufficient reliability and convergent validity.

Next, the following techniques have measured the discriminant validity of the scales. First, the

results show that the square root of AVE for each construct (bold letter on the diagonal in **Table 3**) is

higher than the correlation between any pair of distinct constructs (Fornell and Larcker, 1981).

Second, none of the correlation coefficients exceeds the threshold value of 0.70 (Sepasgozar et al.,

2019; Yukl et al., 2008). Finally, all maximum-shared squared variances (MSV) for the factors are

smaller than the AVE. These results presented in **Table 3** show that all latent variables differ

sufficiently from each other and thus provide evidence of discriminant validity (Urbach and

Ahlemann, 2010).

Insert Table 3 here

4.3 Common Method Variance

While researchers report different post-hoc statistical tests for CMV bias, disagreement remains regarding the application of the most appropriate approach (Malhotra et al., 2017; Simmering et al., 2015). Thus, we have used three different statistical analyses to assess the severity of CMV in the study. First, Harman's single factor test extracted six factors explaining 79.29% of the variance and un-rotated factor solution shows that the first factor explains only 17.38% of the variance, which is below the threshold of 50%, showing the potential bias for common method variance is low (Harman, 1976; Podsakoff et al., 2003). Second, a partial correlation technique using a marker variable has been used to assess the influence of common method variance. The results show that adjusted correlations were only slightly deviated from the unadjusted correlations with unchanged significance levels, thus showing that common method variance is very unlikely to contaminate the results (Lindell and Whitney, 2001).

Third, a confirmatory factor analysis (CFA) marker technique recommended by Williams et al. (2010 has been used to identify potential CMV impact on the study results. The results presented in **Table 4** show that the test for Method-C Model (constrained model) resulted in a significant chi-square difference of Δx^2=34.557 at Δdf=6, which indicates that there is shared CMV between the latent marker variable and substantive variable indicators. Next, a model comparison between Method-U (unconstrained model) and the Method-C model shows a significant chi-square difference of $\Delta x2$=53.472 at Δdf=20, showing CMV is not affecting all substantive constructs related correlations equally (Malhotra et al., 2017). Finally, to assess whether the correlations are significantly biased by marker variable method effects, a comparison of the Method-U and Method-R has been performed. The chi-square difference test resulted in a non-significant difference of Δx^2=2.619 at Δdf=15, which shows that the presence of CMV does not spuriously inflate or skew the relationships between the substantive variables (Shuck et al., 2017; Williams et al., 2010). Thus, the above three different analyses indicate CMV does not pose any concerns for the results.

4.4 Structural Model Analysis

After confirming the measurement model fit and related validity issues, the study proceeds to the second step of SEM, identifying and assessing the theorised structural model. The results show that the structural model meets all the requirements for a good model fit. With respect to the threshold values, the absolute fit measures are x^2/df =1.046; RMR = 0.019, SRMR = 0.023 and RMSEA = 0.015 with a pclose of 0.571, which meets the requirements. In addition, incremental fit measures also illustrate good model fit by exceeding the cut-off value of 0.90, where CFI = 0.999, TLI = 0.996, and IFI = 0.999. Hence, with the evidence of a good model fit, the study progresses to test the proposed hypotheses.

4.5 Hypothesis Testing

The H_{1a} predicts the relationship between perceived control of information and emotional support (β_{H1a} = 0.522, t-value = 8.814, p <0.001), which was significant. However, in terms of H_{1b}, we did not find any significant relationship between perceived control of information and informational support (β_{H1b} = -0.004, t-value = -0.073, p = 0.942). Thus, *Hypothesis 1$_a$* has been supported, but *Hypothesis 1$_b$* has been rejected. Moreover, the surprising result shows that the relationship between perceived control of information and intention to participate (β_{H1c} = .000, t-value = 0.006, p = 0.996) is non-significant, rejecting Hypothesis *1$_c$.* With regard to research hypotheses H_{2a} and H_{2b}, results show the relationships between perceived privacy risks, emotional support, and informational support. Perceived privacy risk shows no significant relationship with emotional support (β_{H2a} = -0.079, t-value = -1.291, p = 0.197), indicating *Hypothesis H2$_a$* is rejected. While the result suggests that the perceived privacy risk has a significant positive influence on providing informational support (β_{H2b} = 0.428, t-value = 6.730, p <0.001), this study hypothesised the relationship inversely. Hence, *Hypothesis H2$_b$* is also rejected. In hypotheses H_{3a} and H_{3b}, results again show that community engagement has no relationship with emotional support (β_{H3a} = -0.103, t-value = -1.675, p = 0.094),

while informational support has a significant relationship with it (β_{H3b} = 0.157, t-value = 2.460, p = 0.014), indicating the acceptance of *Hypothesis 3ᵦ* and rejection of *Hypothesis 3ₐ*. The relationships between emotional support, informational support, and intention to participate variables are supported in the path analyses. The results show that emotional support (β_{H4} = 0.332, t-value = 4.273, p <0.001) and informational support (β_{H5} = 0.147, t-value = 2.227, p = 0.026) influence intention to participate, confirming both the *Hypotheses 4* and *Hypotheses 5*. **Figure 2** and **Table 5** show regression coefficients, squared multiple correlations (R^2), t-values and related p-values for each path hypothesised.

Insert Figure 2 here

Insert Table 5 here

4.6 Multi-group Analysis

After evaluating the structural model, the study performs a multi-group analysis to identify the difference in the model between two different groups. A chi-square difference test shows the results of gender-based subgroup analysis (x^2/df = 13.783, df = 9, p= 0.130) and indicates no significant difference between the groups. However, scholars (e.g., Yuan and Bentler, 2004; Yuan and Chan, 2016) argue that the chi-square difference test can be problematic and unable to control Type I or Type II errors. Besides, the chi-square difference test is directly affected by sample size (Hair et al., 2013) and for large samples, even inconsequential differences may become significant. Hence, even a chi-square test shows an insignificant difference; the base model can still be substantially different between the groups. So, a comparison between the paths for each group has been performed. Results in **Table 6** shows that out of 9 different paths, only three paths have a significant difference between the groups. Analysis confirms that community engagement has a greater negative effect on male respondents toward emotional support than female respondents. Whereas the result shows that community engagement has a greater positive effect on male respondents toward informational

support than female respondents. This shows that male respondents place significantly greater importance on informational support while communicating on health community platforms than female respondents. Moreover, the analysis also highlights a significant difference between informational support and intention to participate in the groups. The result reveals that male respondents place significantly greater importance on providing informational support than offering emotional support when participated in OHCs.

Insert Table 6 here

5.0 Discussion

Drawing on social support and prosocial behaviour theory, our research tests a new model that aims to provide a better understanding of the three research questions related to consumer behaviour in online communities, examining the role of privacy concerns, control of information, and community engagement with people's participation in OHCs. One of the interesting key findings of this research is that the perceived privacy risk has a positive influence on seeking informational support, which intriguingly differs from most of the existing literature. While other studies found at least no significant relationships between perceived privacy risk and Chinese people's intention to seek health information (Li et al., 2018); personal information disclosure (Heravi et al., 2018); motives for using online platforms or online expressions (Lin and Liu, 2012; Wang and Liu, 2019), none of the studies found a positive relationship. Our finding identifies that when people perceive more privacy risk, they are more willing to explore information in OHCs. One possible justification behind such a relationship may be that crisis situations inflict more urgency on information-seeking needs (Park et al., 2019). For instance, Azer et al. (2021) found that community members offer unfiltered information during the COVID-19 crisis to others, which is inherently unpredictable and unprecedented. Moreover, Zhao and Liu (2021) reported that the perceived severity of societal level risks stimulates individual information-seeking behaviour. Hence, an uncertain environment can trigger the need for an individual to seek information, as it allows them to gain adequate knowledge about a situation to make informed decisions (Superio et al., 2021). As a result, considering between

privacy risk and health crisis or the extent of health information required by an online member, whether to seek/share personal information can result from subjective evaluations of importance. A further alternative explanation of such a positive relationship can be that people tend to think the online platform services are reliable (Hu et al., 2010), and with considerable experience of using the platforms can help to dominate privacy concerns of people, enabling them to attain a higher level of information seeking behaviour (Alsmadi and Prybutok, 2018). Hence, ensuring specific and correct information with suitable user experience within these platforms could be an important mission for healthcare communities and even for governments.

Our findings also shed light on the matter that the benefit of informational and social needs leads to the continued active participation of users in OHCs despite the risk that personal information might be compromised. For instance, Zhu et al. (2021) show that individuals pay more attention and give importance to the perceived benefit of using mobile health applications rather than the privacy risk concerns. Furthermore, Church et al. (2017) identified that online social network exchange benefits suffices to override privacy risk concerns. Besides, different other studies (e.g., Hallam and Zanella, 2017; Li et al., 2019; Xu et al., 2009) have also shared a similar view that individuals trade privacy to accrue benefits. For instance, Alsmadi and Prybutok (2018) stated that users might also decide to deal with some of their security and privacy concerns to get the various benefits of the online platform services. Besides, Turner et al. (2001) found that online communities where participants are vulnerable sometimes compromise privacy concerns to get needed social support. Hence, the perceived benefit can have a greater impact on users' information support seeking/sharing intention than privacy concerns, referring to the perspective of privacy calculus and supporting the existence of the privacy paradox in the OHC context. Moreover, cultural/norms can play a very significant influence, as Li et al. (2018) demonstrate that perceived risk on people's intentions to share health information online platforms may differ based on cultural differences. Thus, this finding calls for a further re-examination of the common belief that privacy risk may decline informational support seeking behaviour in online platforms.

Interesting enough, the study did not find any relationships of perceived risk or community engagement with emotional support within OHCs. One of the reasons behind such a finding may be that previous treatment experiences can discourage patients from communicating emotional support within the support groups (Emrick, 1989). For example, Yoo et al. (2018) demonstrated that alcoholics who have received many treatments are disinclined to talk about emotional issues further in virtual community groups because they already feel emotionally overwhelmed. According to Yoo et al. (2018), the severity of patients' illnesses may inhibit them from participating in supportive communication because they spend so much time and energy dealing with their diseases' emotional and physical challenges. Since effects of emotional messages also do not unfold in the same way for all individuals (Bodie and Burleson, 2008; Yoo et al., 2014), our finding suggests that patients/members of OHC sometimes may seek only informational supports, rather than seeking emotional supports.

This finding also shed light on how people's wellbeing may be better understood when they become more willing to explore information in OHCs. The term wellbeing first appeared in 1948 through the World Health Organization's (WHO) definition of health, which is "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO, 1948, p.1). Statham and Chase (2010) suggest that the emergence of this definition was to give a de-medicalized view of health and encourage the government to understand the various factors that link to poor health rather than disease and infirmity, such as the physical, mental and social wellbeing of individuals. However, the worldwide knowledge and development of wellbeing have resulted in confusion and complications to its meaning, with Forgeard et al. (2011, p.81) suggesting this "has given rise to blurred and overly broad definitions of wellbeing". To add to this, its development has created objective and subjective views of wellbeing, with objective wellbeing measured by hard facts (e.g., income, educational achievement, housing, life expectancy) and subjective wellbeing relating to an individual's personal perspective of life (e.g. happiness, quality of life, satisfaction) (Statham and Chase, 2010). As community engagement and privacy concerns can influence certain types of

social support, leading to OHC members' intention to participate, we can argue that the benefit of informational and social needs and the continued active participation of users in OHCs also reflect their subjective wellbeing relating to their personal perspectives of life.

Furthermore, the different online platform has distinctive features, which provide users with various gratifications. For instance, Zhang and Jung (2019) did not find emotional support to be a motivational factor for WeChat health community engagement because such a platform may be desirable for providing informational support rather than emotional support. Additionally, as community engagement may require users to constantly co-create information with their peers, the additional strain might limit their emotional and social resource sharing behaviour (Bowman, 2016; Shensa et al., 2016). Besides, variation in characteristics such as disease severity and time since treatment received can vary the urge for emotional support (Coughlin, 2008; Crossley, 2003). However, such investigation lived out of the scope of our study and thus warranted further investigation.

Our research additionally finds that people are willing to seek emotional support when perceived control of information is high, showing the extent to which individuals' ability to control information can help them feel comfortable to seek online social support, which is supported in other types of online communities (Hajli and Lin, 2016). Other research (e.g., Wang et al., 2019) also argue that perceived privacy risks and perceived control of information are key factors to encourage people to co-create value and participate in online communities. As such, our research also suggests that ability to control information or control online privacy allows people to have full control over their private information, which ultimately encourages people to seek social support and further participate in OHC platforms. In addressing the first research question, our analyses found that different privacy concerns will have a different impact on exchanging social support in OHC platforms, as perceptions of privacy concerns are context specific (Kehr et al., 2015). Additionally, the subjective nature of privacy concern, the pervasive expansion of online platforms, involvement of multiple parties, the nature of data disclosure and related ethics made it challenging to determine

the effects of the contradictions between individuals' privacy concerns and behaviours (Jang and Sung, 2021; Jozani et al., 2020). While OHC users can act in their interests, their perception of privacy risk and control of information influence their ethical perceptions, which in turn affects their subsequent behaviours (Wang et al., 2020). Moreover, ethical issues related to privacy concern will prevail as long as the information is shared (Hajli and Lin, 2016), but providing a mechanism of privacy protection to enhance the sense of assurance and new security policies can help to reduce users' perceived privacy related ethical concerns (Shirazi et al., 2021). Hence, ethical companies should collaborate with OHC users to increase their control over shared information and privacy to build a trustworthy environment (Wang et al., 2020). This could be an important factor in the continuous and sustainable use of OHC platforms. Overall, the results also contribute to online ethics related issues by showing how we can build an ethical digital environment for triggering users' social support and OHC participation behaviour.

Our result also shows that community engagement leads to informational support for community members. This finding is aligned with previous studies examining the links between community engagement and social support exchange behaviour. People show their interest to go to OHCs and share their experiences and information about health-related issues, which can be a valuable source of knowledge for others, leading individuals to act on the information provided within the health community (Lin and Kishore, 2021). For instance, Shao (2009, p.10) stated that information seeking "is driven by people's desire to increase awareness and knowledge of one's self, others, and the world". In addition, Johnston et al. (2013) state that the more involved the individual is with the community, the more likely they are to gain information by having access to new information and hearing redundant experiences that reinforce the credibility of the information. This may suggest that information provided through community engagement can lead to more information seeking behaviour, providing personal benefits to individual participants (Nambisan, 2011). Besides, Azer et al. (2021) found that community engagement leads users to engage in informative behaviour, such as individuals who want to support others, raise awareness, and/or keep

everyone updated by supplying information. Hence, our findings fit well with our second research question, supporting the role of prosocial behaviour in adopting socially beneficial initiatives. We found that OHC's offer a collective platform to facilitate a rich profusion of engagement and collaboration through sharing and creating information to assist with a specific health condition, or disease, generating possible solutions, and recommending treatments.

Another key finding of our research is that social support encourages more people to participate in OHCs. This finding is in line with the social support literature (e.g., Chiu et al., 2006; Wang, et al., 2017; Zhang et al., 2018), inferring that expected social supports are powerful predictors of an individual's intention to take part in OHC platform. For instance, Mirzaei and Esmaeilzadeh, (2021) show that informational and emotional support plays essential roles in enhancing an individual's intention to participate in OHC platform. When people seek or receive informational support and emotional support, they are likely to act on the support received on the OHC platform. Wang et al. (2021) found that users' experience in seeking and receiving social support predicts their successive OHC participation. It makes them feel they belong to a network of communication with a shared purpose and such sense encourages them to offer the same supports for others. According to Shumaker and Brownell (1984), receiving social supports from others in the community can provide a sense of fulfilment and mutual obligation, which can motivate them to provide similar support to other community members. Thus, high emotional and informational support levels can result in a better chance of engagement with people in OHCs to share or find valuable information, experience, and emotions. With respect to our third research question, our analyses find evidence that the quantity and the quality of support in the form of informational and emotional support has a significant influence on an individual's health-related online community participation intention.

Finally, this paper also tries to identify the difference between gender regarding the importance they place on perceived control and privacy risks in their decisions about information seeking and online community participation intentions. While there is no such difference between men and

women overall, the study found that men place significantly greater importance than women on informational support in terms of community engagement and intention to take part in OHCs. The finding is supported by a study conducted by Lin et al. (2016). Our study also shed light on the argument (e.g., Kristiansen et al., 2010) that variation in characteristics such as sex can alter the type of social support required.

6.0 Theoretical and practical implications

6.1 Theoretical contributions

This study supplements privacy-related literature with several novel insights. The current study focuses on social support, which has been inadequately investigated as an outcome of information disclosure in previous research (Shirazi et al., 2021; Zhang et al., 2018). The first contribution of this study is the conceptualisation of people's participation in health communities with drivers to encourage people by integrating social support theory. The findings provide evidence of the notion that social support is a key element of online communities to build communal relationships. Our research is among the first few studies that aim to facilitate people's intention to participate in OHCs by investigating people' reactions to their control of information and privacy concerns. It also contributed to existing research by identifying that community engagement encourages certain social support behaviour in the OHC platforms. From our understanding, this is the first study that examines community engagement from a prosocial standpoint to understand an individual's social support behaviour in OHCs.

Second, the study contributes to the existing research by recognising that users participate in online communities to attain social support in the form of informational and emotional support (Kordzadeh and Warren, 2017; Yan and Tan, 2014). Benefits from such social supports that users value the most can be self-representation, social control, social capital, social validation, perceived usefulness, or self-clarification (Jiang et al., 2013; Lee et al., 2013; Shibchurn and Yan, 2015). We show that relative importance plays a crucial role in information privacy and social support, where negative consequences are rationally evaluated against possible social outcomes.

Third, the study also emphasises those rational considerations concerning the privacy calculus may be bounded by psychological limitations (Kehr et al., 2015), where decision-making regarding privacy concerns is assumed to be irrational. For instance, specific online community factors might mislead rational decisions regarding privacy concerns (i.e., lots of privacy settings being provided), individuals might become delusional regarding whom they interact with or share their information (Acquisti, 2009; Masur, 2018: 95). As a result, individuals behave irrationally and show dissonance between perceived privacy concerns and actual privacy behaviours. Therefore, our findings also lend support for explaining paradoxical privacy behaviours from an irrational decision-making perspective. However, this study supports a hybrid tactic to overcome such a paradoxical situation as Barth and de Jong (2017) proposed. According to Barth and de Jong (2017), this paradoxical behaviour can be avoided if both rational and irrational processes can be implemented into designing (frontend and backend interface) so that decision-making ultimately becomes self-determined.

Finally, our result shows that individuals perceived control of information do not have any effect on their OHC participation. Even though previous research presented counterarguments, we argue that the perceived control of information and online participation intention are abstract and cognitively distant constructs. We believe that, despite security concerns, when online community users provide social support or participate in online community activities, it does not necessarily indicate that users do not take actions to protect their privacy rather, it can be the case that they have configured a better strategy for their privacy management (Chen, 2018). From a people perspective, this study shows that people can be relational actors talented at acting in their own interests. However, the environment with privacy control and protection is also vital for individuals for offering social support.

6.2 Practical contributions

Current research suggests some significant practical implications for both online community moderators and users. As the study confirms informational and emotional support to be central for online community participation, community platforms should increase informational support and

enhance informational accuracy. Our research suggests that if OHCs and government can provide a trustworthy platform, where people can find adequate and accurate information regarding health care issues/treatment, people are likely to seek/share informational support in OHCs rather than make the physical facilities overwhelmed their presence. Moreover, these health communities should offer and endorse an empathetic environment, which eases and inspires people to seek/share delicate health-related problems and acquire emotional support. Online communities should also develop a user-centred system to direct the patients towards relevant chat rooms/threads/virtual health specialists so that they can get engaged in focused health discussions and receive more benefit/value from taking part in those virtual groups. Besides, an automated system should strengthen a user's privacy awareness and privacy knowledge with a user-friendly interface design that empowers patients to make well-informed decisions to take part in OHCs. Finally, OHC platforms should consider the impact of males and females assigning different importance to social support factors. Since males emphasise more about informational support, OHCs can focus on designing a holistic spatial layout and technologically functional platform, so that people can save time and effort searching for information.

7.0 Limitations and future research direction

This paper develops a new framework to highlight the role of privacy risk, privacy control of information, and community engagement on individual's participation intention on OHC platforms. A theoretical model is developed based on social support theory and tested using survey data from OHC users. The results provide strong support for a practical model to identify people's intention to participate in OHCs. Although this study includes its theoretical and practical contribution, the findings must be interpreted while considering its limitations, suggesting further theoretical and empirical extensions. The main limitation of this research is the sample size. Having a larger sample from different OHCs can better understand people's behaviour on these platforms. Future research should test this model with a new dataset from a wider population. Especially, new research needs to apply this framework with data from people involved with the COVID-19 epidemic to see how

pandemic situations influence the patients' information sharing and seeking behaviour. Third, we note that relatively little research has examined how cultural/normative influences shape patient's online community participation behaviour. On online platforms, their virtual community norms mainly affect user's participation (Chiu et al., 2006; Zhou, 2011) or country cultures (Li et al., 2018; Wang and Liu, 2019). Hence, given that cultures/norms can affect user participation behaviour, future research should examine how factors interact with social support issues to influence users' online participation intention. Fourth, the current study focuses on the degree of social support, while examining the contents of the social support issues in OHCs could be an interesting avenue for future research. Besides, examining the role of government can also be a new idea for future research. This is critical in the era of pandemic and epidemics, when governments are asking people to manage the health issues by staying home and getting basic health supports through online platforms.

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Figure 1: Research Framework
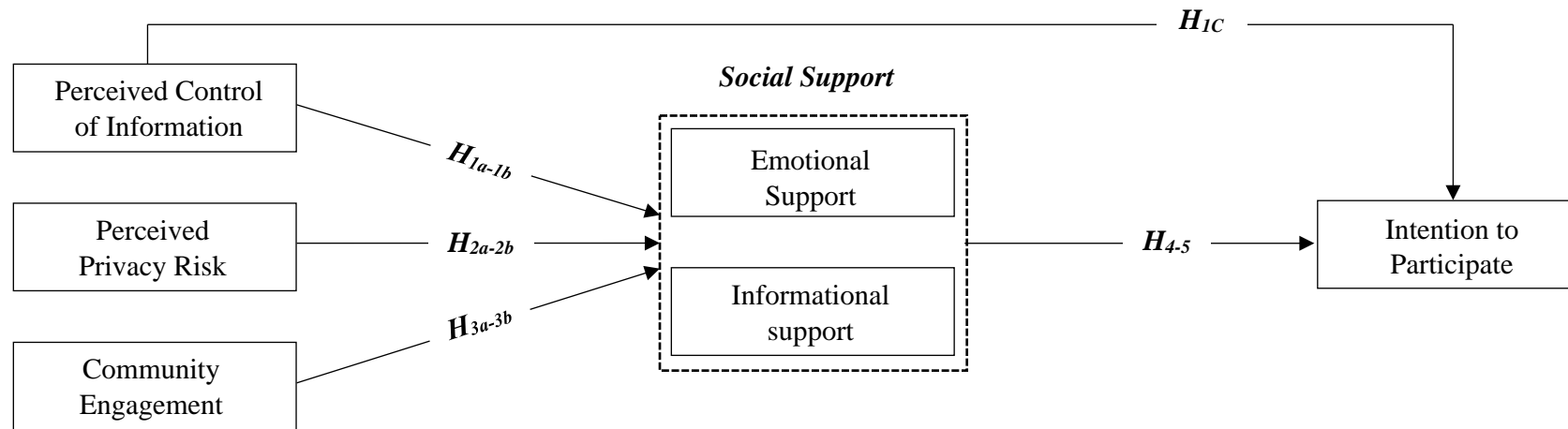
Figure 2: Estimation Results for the Structural Model

Significant path

Not significant path

*P< 0.05; *** P< 0.001; n.s = not significant
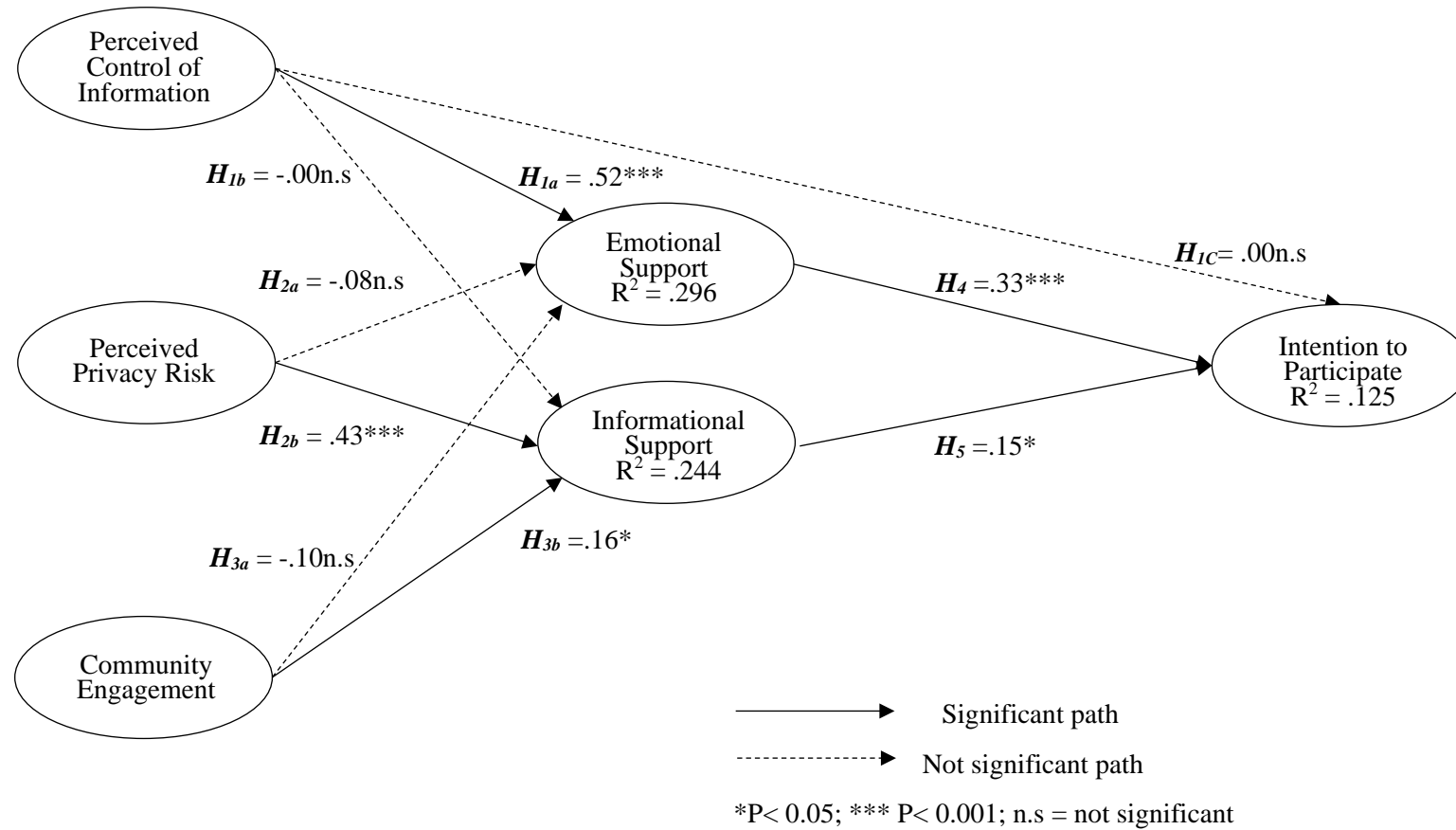
Table 1: Demographic Background (N=202)

Demographic	Range	Frequency	Percentage %
Gender	Male	116	57.4
	Female	85	42.1
	Prefer not to answer	1	.50
Age	17-23	8	4.0
	24-29	44	21.8
	30-39	55	27.2
	40-49	67	33.2
	50-59	23	11.4
	60-above	3	1.5
	Prefer not to answer	2	1.0
Educational Level	Diploma	2	1.0
	Some undergraduate work	50	24.8
	Bachelor's degree	25	12.4
	Some graduate work	91	45.0
	Postgrad's degree	29	14.4
	Doctorate/professional degree	5	2.5
Country	UK	87	43.1
	USA	115	56.9

Table 2: Constructs and Items with Descriptive Statistics, Factor Loadings, and Reliability Scores

Indicators	Items	M	SD	FL	Variance	α
Perceived Control of Information adapted from Krasnova et al. (2010) and Hajli and Lin (2016)						
PCI2	Privacy setting allows me to have full control over the information I provide on online health communities.	4.67	1.20	0.886		
PCI1	I feel in control over the information I provide on online health communities.	4.69	1.34	0.740	9.13 %	0.822
PCI3	I feel in control of who can view my information on online health communities.	4.68	1.21	0.717		
Perceive Privacy Risk adapted from Pavlou et al. (2007) and Hajli and Lin (2016)						
PPR3	I suspect that my privacy is not well protected by online health communities.	5.99	1.47	0.986		
PPR1	I am concerned that online health communities are collecting too much personal information about me.	5.97	1.49	0.984	6.89 %	0.964
PPR2	I'm worried that unknown third parties will access my personal information on online health communities.	5.72	1.54	0.880		
Community Engagement adapted from Algesheimer et al. (2005), Hajli and Lin (2016), and Baldus et al. (2015)						
CEG2	I am willing to recommend an application or online health communities with multimedia functions that are worth trying to help my friends in my favourite online health community.	5.14	1.59	0.833		
CEG1	I will ask my friends in forums and communities to provide me with their health information and suggestions.	5.04	1.56	0.702	5.94 %	0.772
CEG3	I am willing to share my own information and experience of online health communities, applications, or website with my friends in my favourite online health community through ratings and reviews.	5.39	1.45	0.649		
Informational Support adopted from Hajli (2014)						
IS1	In my favourite online health community, some people would offer suggestions when I needed help.	5.49	1.65	0.987		
IS3	When faced with difficulties, some people in my favourite online health community would help me discover the cause and provide me with suggestions.	5.47	1.66	0.975	19.6%	0.970
IS2	When I encountered a problem, some people in my favourite online health community would give me information to help me overcome the problem	5.49	1.62	0.906		

Emotional Support adopted from Hajli (2014)

		M	SD	FL		
ES2	When faced with difficulties, some people in my favourite online health community comforted and encouraged me.	3.54	1.44	0.882		
ES1	When faced with difficulties, some people in my favourite online health community are on my side with me.	3.70	1.58	0.829		
ES3	When faced with difficulties, some people in my favourite online health community listened to me talking about my private feelings.	3.99	1.38	0.820	6.87%	*0.886*
ES4	When faced with difficulties, some people in my favourite online health community expressed interest and concern in my well-being.	3.45	1.35	0.725		

Intention to Participate (New items)

		M	SD	FL		
IP2	If my friends offer information about their health care experience in my favourite online health community, I would act on them.	4.94	1.71	0.798		
IP1	If my friends ask for advices about a health-related problem in my favourite online health community, I intent to share it with them.	4.64	1.63	0.780		
IP3	If I need health information, I would consider the experiences of my friends in my favourite online health community.	4.90	1.37	0.775	17.5%	*0.843*
IP4	If a professional nurse offers advice based on his/her experience in my favourite online health community, I would act on them.	4.63	1.40	0.688		

Note: M = Mean, SD = Standard Deviation, FL = Standardised Factor Loadings, α = Cronbach's Alpha

Table 3: Convergent and Discriminant Validity

Variables	CR	AVE	MSV	1	2	3	4	5	6
1. Perceived Privacy Risk	0.966	0.905	0.215	**0.951**					
2. Perceived Control Information	0.826	0.615	0.221	-0.016	**0.784**				
3. Community Engagement	0.774	0.536	0.058	0.238	-0.007	**0.732**			
4. Emotional Support	0.888	0.666	0.221	-0.110	0.470	-0.111	**0.816**		
5. Informational Support	0.970	0.916	0.215	0.463	-0.012	0.242	-0.094	**0.957**	
6. Intention Participate	0.846	0.580	0.080	0.046	0.149	-0.088	0.284	0.105	**0.762**

Note: AVE = Average Variance Extracted; CR = Composite Reliability; MSV = Maximum Shared Squared Variance

Table 4: Model Comparison for CFA Model with Marker Variable

Model	$x^2(df)$	CFI	RMSEA (90% CI)	LR of Δx^2	Model comparison
CFA with marker variable	335.48 (231)	0.964	0.047 (.036, .058)		
Baseline	335.48 (235)	0.965	0.046 (.034, .057)		
Method-C	370.04 (241)	0.955	0.052 (.041, .062)	34.557, $df = 6$, p< .001	vs. Baseline
Method-U	316.57 (221)	0.967	0.046 (.034, .057)	53.472, $df = 20$, p< .001	vs. Method-C
Method-R	319.18 (236)	0.971	0.042 (.029, .053)	2.619, $df = 15$, p= .999	vs. Method-U

Note: CFA = Confirmatory Factor Analysis; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; LR = Likelihood Ratio Test; C = Constrained; U = Unconstrained; R = Restricted.

CFA marker model = CFA with a marker variable, *Baseline model* = marker variable having fixed factor loadings and fixed error variances with unstandardized factor loadings and error variances obtained from the CFA marker model, *Method-C model* = constrained model where the substantive item factor loadings from marker variable have been constrained to be equal, *Method-U model* = unconstrained model, where the substantive item factor loadings from marker variable have been freely estimated, and *Method-R model* = restricted model, where the substantive factor correlations of Method-U have been restricted to their values obtained from the Baseline model.

Table 5: Results of Hypothesis Testing

Hs	Path Directions			Std. β	Std. error	t-value	p-value	Results
H_{1a}			Emotional Support	0.522	0.068	8.814	***	Supported
H_{1b}	Perceived Control of Information	$\rightarrow$	Informational Support	-0.004	0.123	-0.073	0.942	Rejected
H_{1c}		$\rightarrow$	Intention to Participate	0.000	0.086	0.006	0.996	Rejected
H_{2a}	Perceived Privacy Risk	$\rightarrow$	Emotional Support	-0.079	0.040	-1.291	0.197	Rejected
H_{2b}			Informational Support	0.428	0.071	6.730	***	Rejected
H_{3a}	Community Engagement	$\rightarrow$	Emotional Support	-0.103	0.068	-1.675	0.094	Rejected
H_{3b}			Informational Support	0.157	0.122	2.460	0.014	Supported
H_4	Emotional Support	$\rightarrow$	Intention to Participate	0.332	0.074	4.273	***	Supported
H_5	Informational Support			0.147	0.037	2.227	0.026	Supported

Table 6: Multi-Group Analysis Between Male and Female Groups

Path Directions	Male path coefficient	Female path coefficient	Male-Female significant difference	Relationship Interpretation
Group Difference (Chi-square difference)	x2/df = 13.783, *df*=9, p= .130			There is no difference between the male and female group
	(Std. β, p-value)	(Std. β, p-value)	p-value	
PPR→ES	-0.046, p = .564	-0.166, p = .084	.397	There is no difference
PPR→IS	0.386, p < .001	0.483, p < .001	.612	There is no difference
CEG→ES	-0.223, p = .005	0.110, p = .262	.012	The relationship is only significant for Male.
CEG→IS	0.297, p < .001	-0.039, p = .710	.023	The relationship is only significant for Male.
PCI→ES	0.522, p < .001	0.554, p < .001	.604	There is no difference
PCI→IS	-0.063, p = .424	0.020, p = .835	.529	There is no difference
ES→IP	0.378, p < .001	0.269, p = .030	.466	There is no difference
IS→IP	0.192, p = .027	0.071, p = .498	.326	The relationship is only significant for Male.
PCI→IP	-0.026, p = .797	0.026, p = .830	.743	There is no difference

Note: PPR = Perceived privacy risk, CEG = Community engagement, PCI = Perceived control of information, ES = Emotional support, IS = Informational support, IP = Intention to participate