

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.

Keywords: privacy; perceived control of information; community engagement; social support; online health community

1 **1.0 Introduction**

2 The evolution of Web 2.0 has facilitated the inception of different online platforms, where people
3 with similar interests and commonalities share their knowledge, ideas, experiences, opinions and
4 often establish a sense of duty towards the network members (Luo et al., 2020; Park et al., 2015).

5 The insurgence of these online platforms has shepherded the healthcare industry towards remarkable
6 transition and fostered an environment for different online health communities (OHCs) where patient
7 networking has turned out to be an essential part of the health care experience (Gage, 2013; Li et al.,
8 2018). Undoubtedly, these OHCs have remarkable potency to provide advantages for the healthcare
9 sector in many aspects, such as being accessible by a large audience, achieving high levels of
10 engagement, removing the location and physical access barriers (Griffiths et al., 2012; Laranjo,
11 2016; Welch et al., 2016). Besides, communities like PatientsLikeMe in the US; HealthUnlocked in
12 the UK; Ping A Good Doctor in China have certainly made it easier and faster to diffuse health-
13 related resources such as sharing information, offering emotional support, validation of experience
14 and treatment, and logistical help along with professional medical consultation and information
15 access. Such diffusion of health interventions through these platforms facilitated considerable
16 behavioural change in people seeking health information and self-healthcare management. For
17 example, individuals in the UK looking for health-related information online increased from 54% in
18 2018 to 63% in 2019 (Office for National Statistics, 2020). In fact, a nationwide survey in 2020
19 shows that 25.4% of people in the US intended to get cancer-related information online before going
20 to doctors or health care providers at first (HINTS, 2020). Therefore, OHCs have appeared to be an
21 unconventional collaborative platform in the healthcare industry, ensuring a suitable environment for
22 easy accessibility of information and offering different alternative routes for healthcare service
23 provisions.

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

27 decisions (Lin and Kishore, 2021; Wentzer and Bygholm, 2013). Hence, within an OHC's integrative
28 environment, social support plays a crucial role in individuals' healthcare management-related
29 behaviours (Greaney et al., 2018; Latkin and Knowlton, 2015). Nevertheless, irrespective of various
30 benefits, OHCs present challenges regarding privacy breach issues. For instance, 249.09 million
31 individuals are being affected directly or indirectly by healthcare data breaches between 2005 to
32 2019 (Seh et al., 2020). More recently, in May 2021 alone, 6,535,130 healthcare records were
33 exposed or compromised across 63 incidents in the US (HIPPA, 2021). These privacy breaches can
34 lead to reconstructing anyone's identity and can trigger prejudice, harassment, privacy invasion,
35 damage of personal information and even identity theft, putting individual safety at risk. Such
36 incidents highlight the importance of privacy control in OHCs. However, existing literature has
37 provided evidence of privacy related issues in different contexts, but scant attention has been paid to
38 the impact of privacy concerns in the OHCs context (Shirazi et al., 2021; Zhang et al., 2018). While
39 OHC literature has provided evidence on the impact of privacy concerns on trust (Bansal and Gefen,
40 2010), personal health information disclosure (Zhang et al., 2018), knowledge sharing intentions
41 (Dang et al., 2020), or antecedents of privacy calculus model (Kordzadeh et al., 2016), it provides
42 limited clues whether privacy concerns can influence individuals social support exchange behaviour
43 in OHC platforms. Therefore, investigating the impact of privacy concern drivers (i.e., perceived
44 control of information and privacy risk) on OHC members' social support exchange behaviour is
45 critical.

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

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

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

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

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

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

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

86 **2.0 Literature Review and Hypothesis Development**

87 ***2.1 Social support in OHCs***

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

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

108 Sarason et al. (1983: 127) broadly defined social support as "the existence or availability of
109 people on whom we can rely, people who let us know that they care about, value, and love us".
110 Alternatively, Cobb (1976: 300) defined social support as fitting to one or more of the following
111 three options: information leading the subject to believe that they are cared for and loved; esteemed
112 and valued; and belongs to a network of communication and mutual obligation. Thus, social support
113 can be defined as an exchange of resources between individuals (Shumaker and Brownell 1984),
114 reflecting a concept of support that is perceived to be beneficial by both the provider and receiver
115 (Yan and Tan, 2014). In such a sense, social support is not just a consequence of relationships; rather
116 it results from individuals' successful negotiation and mobilisation (Hajli et al., 2015; Offer, 2012),
117 which enable networking, communication, reliance, common understanding, mutual social protocols,
118 intangible information, and relationship exchanges. In fact, Wang et al. (2021a) identified that social
119 support for remotely working people during the COVID-19 pandemic had provided necessary
120 emotional and instrumental resources to handle unique challenges. Similarly, in OHCs, receiving
121 social support plays an important role in transforming individuals' health-related experiences (Li et
122 al., 2018) and empowers patients that improve their compliance to treatment and recovery
123 (DiMatteo, 2004). For example, social support has been shown to benefit patients who are
124 constrained by their conditions such as coronary disease (Waring et al., 2018), Alzheimer's disease
125 (White and Dorman, 2000), Huntington's disease (Coulson et al., 2007), cancer (Turner et al., 2001),
126 HIV/AIDS (Ranjit et al., 2020), or different disabling conditions (Frost and Massagli, 2008; Wicks et
127 al., 2010). Besides, social support found to improve patient's life quality (Li et al., 2016; Yao et al.,
128 2015) offer support for mothers who are suffering from postpartum depression (Evans et al., 2012),
129 and helping patients move to a healthier state who are suffering from different psychological issues

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

132 Social support is a construct embedded in online communities where individuals offer their
133 advice and know-how, answer to questions, provide recommendations and express their feeling of
134 attachment. Hence, existing literature has generally categorised social support into different forms,
135 such as informational, emotional, companionship, and instrumental support (Berkman et al.,
136 2000; Wortman and Conway, 1985). Despite being conceptualised multidimensionally (Lo, 2019),
137 there is an agreement that informational and emotional support are more fitting for online
138 community settings (Chen et al., 2019; Wang et al., 2021b). In particular, social support, such as
139 informational and emotional support, is vital and beneficial for OHC members for health-related
140 decisions and outcomes (Lin et al., 2016; Yan and Tan, 2014). Informational support refers to advise,
141 guidance, suggestions, experience, or knowledge (Liang et al., 2011; Yu et al., 2015). Informational
142 support through explaining symptoms, own experiences, and suggestions, can offer direction and
143 assistance to solve the health problems of online community members. Alternatively, emotional
144 support involves listening, encouragement, sympathy, empathy, concern, or trust to compensate for
145 negative emotions (Johnson and Lowe, 2015; Nadeem et al., 2019; Yoo et al., 2014). Emotional
146 support can provide patients with the experience of being loved, cared for, valued, and empathised.
147 Given the interactions that take place in online platforms, we conceive that such a collaborative
148 process of exchanging informational and emotional support likely to develop a sense of mutual
149 obligation within the community members and can increase their engagement and encouragement to
150 support others (Lin et al., 2015; Loane et al., 2015; Zheng et al., 2013). Thus, to assess the effect of
151 social support in OHCs, this study emphasises on the informational and emotional support.

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

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

168 ***2.2 Perceived control of information and perceived privacy risk***

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

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

194 Perceived control of information has been utilised to reflect an individual's innate fear of
195 potentially losing their private information. For example, studies have found that higher perceived
196 control of information plays a crucial role in reducing privacy concerns (Dinev and Hart, 2006; Xu et
197 al., 2011), which ultimately increases, such as online transactions, online social interactions, or civic
198 expressions (Jiang et al., 2013; Wang and Liu, 2019; Xu et al., 2012). With higher perceived control
199 of information, individuals produce a higher amount of self-disclosure and willingness to post/share
200 information online (Olivero and Lunt, 2004; Taddei and Contena, 2013). While OHC platforms have
201 made virtual health diagnosis and consultation very easy, OHC members are mostly anxious about
202 information leaks. This compromising disclosure can lead to damaging consequences such as
203 discrimination, presumption, humiliation, especially with sensitive issues related to psychological
204 disorders, physical incapacities, sexual diseases, drug abuse (Anderson and Agarwal,
205 2011; Obermeyer et al., 2011; Zhang et al., 2018). To increase information security and prevent
206 privacy invasions, OHC platforms offer different privacy policies and settings to control personal

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

210 ***H1_a**: Perceived control of information is positively related to the user's emotional support.*

211 ***H1_b**: Perceived control of information is positively related to the user's informational support.*

212 ***H1_c**: Perceived control of information is positively related to users' participation intention in*
213 *OHCs.*

214 Besides, privacy risk is another direct antecedent of privacy concerns (Li, 2012; Xu et al.,
215 2005). Due to the nature of online community platforms, it is easy to collect, distribute, and utilise
216 user's personal information, which ultimately increases the possibility of potential control loss over
217 personal information resulting in higher privacy risk. Thus, users' concerns or beliefs regarding the
218 degree to which they associate a high potential loss with sharing personal information have been
219 referred to as perceived privacy risk (Gerlach et al., 2015; Smith et al., 2011). Perceived privacy risk
220 can be a key predictor of users' online behaviour, and it can affect issues from trust to willingness in
221 disclosing personal information (Bugshan and Attar, 2020; Dinev and Hart, 2006; Malhotra et al.,
222 2004). Research has shown that OHCs give rise to inconvenient access, misappropriation, and
223 revelation of private health information (Li, 2013). These communities mainly count on
224 communication regarding personal health information with other users, creating secondary usage of
225 health data and posing serious privacy risks (Li, 2013; Safran et al., 2007). Therefore, users may not
226 be willing to take part in OHCs and disclose their personal health information. However, studies
227 (e.g., Cheung et al., 2015; Hallam and Zanella, 2017; Heravi et al., 2018) have found that perceived
228 privacy risks have limited or no impact on disclosing personal information. Li et al. (2018) have
229 observed that perceived risk does not affect health information sharing and seeking intentions within
230 certain study groups in their research. Privacy calculus theory shed light on such argument,
231 suggesting that individuals perform a calculus between the cost of privacy risk and benefit of

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

238 Perceived privacy risk denotes the perceptions and beliefs of people about the potential loss of
239 control over data about themselves (Bélanger and Crossler, 2011; Tseng and Wang, 2016). Such
240 perceived privacy risks have been found to negatively affect an individual's behaviours and decisions
241 toward using online sites (Chang and Tseng, 2013; Van Slyke et al., 2006). Moreover, the privacy
242 risks can have a negative impact on an individual's information seeking and sharing intentions
243 (Dinev and Hart, 2005; Krasnova et al., 2010). Even perceived privacy risk can be critical in terms of
244 individuals decisions concerning information-sharing behaviour on blogs (Chai et al., 2011) and
245 online civic engagement (Wang and Liu, 2019). Besides, the nature of online platforms makes the
246 private data easily collectable, distributable, and usable without users' consents (Hajli and Lin,
247 2016). Hence, higher perception of privacy risk can negatively impact online users' informational
248 and emotional support seeking intentions.

249 *H2_a: Perceived privacy risk is negatively related to the user's emotional support.*

250 *H2_b: Perceived privacy risk is negatively related to the user's informational support.*

251 **2.3 Engagement in OHCs**

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

257 engagement as a psychological or motivational construct reflecting an individual's behavioural
258 investment to accomplish their roles. For instance, Kahn (1990) defined engagement as individuals'
259 being emotionally connected, cognitively vigilant, and physically involved in a role that reflects their
260 thinking, creativity, beliefs, and values and promotes their relationship with other group members.
261 Similarly, Brodie et al. (2013) conceptualised engagement as a context-dependent, multidimensional
262 concept of a psychological state that comprises emotional and behavioural investment in the process
263 of relational exchange. In contrast, engagement has also been defined as motivation
264 (intrinsic/extrinsic) to interact and cooperate with community members (Algesheimer et al.,
265 2005; Baldus et al., 2015). These definitions promote individuals' behaviour of delivering
266 instantaneous value for others, but they go more than fulfilling a sense of duty and show prosocial
267 behaviours that are emergent, virtuous, helpful, conscientious, innovative, and interpersonally
268 collaborative (Ray et al., 2014; Rich et al., 2010). In this study, we take a prosocial contribution
269 standpoint towards defining engagement in OHCs.

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

283 2021; Wirtz et al., 2013), co-create and/or collaborate (Azer and Alexander, 2018; Laroche et al.,
284 2012), and participate (Algesheimer et al., 2005; Brodie et al., 2019) in the online communities. In
285 this process, engaged individuals believe that their contributions bring impact and share a sense of
286 belongingness, mutual responsibilities, specific beliefs, and develop obligations towards fellow
287 members in the community (Algesheimer et al., 2005; Muniz and O'guinn, 2001). Considering this
288 prosocial perspective, we define engagement as an individual's voluntary behaviour driven by
289 intrinsic or extrinsic motives that are perceived to be personally meaningful, socially beneficial, and
290 emotionally connected towards the community.

291 Despite having various conceptualisations of engagement, we define engagement as a form
292 of behaviour because most studies agree that contributing to communities reflects the behavioural
293 dimension of the engagement (e.g., Azer et al., 2021; Dolan et al., 2016; Oliveira et al.,
294 2016; Shawky et al., 2020; Wu et al., 2018). In addition, Calder and Malthouse (2008) believed that
295 engagement is a motivational force that drives an individual's behavioural response as a consequence
296 of engagement. Besides, prosocial behaviour comprises a wide class of behaviour from involving
297 costs for the self and resulting in benefits for others (Wittek and Bekkers, 2015); thus, we identify
298 engagement as a mutually dependent process. Moreover, active contribution in online communities
299 through disseminating personal information, experiences, and knowledge emphasises the interactive,
300 two-way nature of community engagement and reflects its behavioural dimensions (Brodie et al.,
301 2013; Wu et al., 2018). Therefore, this study focuses on the behavioural aspect of engagement in an
302 OHC context as a collaborative process.

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

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

316 Online community provides a collaborative platform (Faraj et al., 2011; Mirzaei and
317 Esmailzadeh, 2021), which allows community engagement and social relationship development as
318 well as empowers its members through information exchange (Househ et al., 2014; Liang et al.,
319 2011; Lowe and Johnson, 2017). Previous studies (e.g., Chou et al., 2009; McKenna and Bargh,
320 1998; Meier et al., 2007) show that member's participation in online support groups provides both
321 informational and emotional benefits regarding a wide range of health conditions and illnesses. For
322 instance, involved health community members seek informational support regarding medical
323 experiences, treatment history and suggestions, disease diagnosis and prevention, health risk
324 assessment advice from doctors (Gibbons et al., 2011; Oh, 2012; Xiao et al., 2014). Also, community
325 members can provide emotional support, increasing community members' ability to fight stress,
326 depression, loneliness, emotional hardships, bad moods, and continue treatment regimens
327 (Lieberman and Goldstein, 2005; Menon et al., 2014; van Uden-Kraan et al., 2008). In other virtual
328 community contexts, Cao et al. (2021) showed that engagement intention positively influences
329 content creation, contribution, and consumption behaviour. Also, Molinillo et al. (2020) identified
330 that engaged customers are likely to co-construct unique experiences by exchanging information and
331 knowledge (i.e., willingness to co-create) on social commerce websites. Furthermore, Ray et al.
332 (2014) showed that the exchange of information is driven by the greater sense of engagement that
333 inspires community members to help others in a meaningful way. Besides, in a qualitative study,
334 Azer et al. (2021) capture that engaged social community platform users to manifest informational,

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

338 ***H3_a**: Community Engagement has a positive effect on users' emotional support.*

339 ***H3_b**: Community Engagement has a positive effect on users' informational support.*

340 **2.4 Social support and intention to participate**

341 Social support is a critical element of human interaction (Rozzell et al., 2014) and significant
342 indicator that leads to experiencing social benefit (Vicary and Fraley, 2010). According to Vaux
343 (1988), it is a process of seeking, offering, and evaluating supportive behaviours, regularly projected
344 through the exchange of verbal and nonverbal messages. Online social support helps users with their
345 intangible needs, such as emotional and informational support (Coulson, 2005; Madjar, 2008).
346 Especially, people need emotional and informational support because of their health-related issues
347 (Schaffer et al., 2008) and such support may attract individuals to be more active and participative in
348 online community platforms (Liang et al., 2011). According to Hsu et al. (2012) dependable and
349 responsive exchange of information will lead to better community involvement. Besides, Li et al.
350 (2018) show that people get benefits from informational and emotional support that ultimately
351 increase their intention to share health information in the online social network communities.
352 Therefore, social support has a significant effect on the individual's psychological state (Hajli et al.,
353 2015), which may affect an individual's willingness to participate/act on the support received in
354 OHCs. So, we propose that:

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

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

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

Insert Figure 1 here

360 **3.0 Research Method**

361 **3.1 Data Collection**

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

Insert Table 1 here

370 **3.2 Measurements**

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

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

Insert Table 2 here

386 **4.0 Data Analysis and Results**

387 Structural equation modelling (SEM) is a distinct technique that implies a confirmatory approach to
388 assess multiple relationships for developing a model (Hair et al., 2013; Tabachnick and Fidell, 2013).
389 As a result, to assess the conceptual model and its related hypotheses, structural equation modelling
390 (SEM) has been used as an analytical technique, and the data have been analysed with IBM AMOS
391 26.0 software. First, we have carried out some preliminary assessments to determine the plausible
392 context of the distribution and understand the data's appropriateness for multivariate analysis.
393 Second, we have assessed the measurement model to determine the reliability and validity of
394 theoretical constructs. Third, we examine the common method variance (CMV). Fourth, we have
395 measured the structural model by estimating the significance of the causal relationships among the
396 constructs. Results from each analysis are presented in the following.

397 **4.1 Preliminary Analysis**

398 Prior to structural equation modelling, we have carried out various analyses to establish a logical
399 context of the distribution and identify the data's appropriateness for multivariate analysis. At first,
400 we have calculated the normality assessment of distributions of variables using a z-score by dividing
401 the skewness and kurtosis values by their standard errors. At a conservative statistical significance
402 level of 0.01, the z-score values show that not all variable falls between the threshold values of \pm
403 2.58. Further analyses using Shapiro-Wilk and Kolmogorov-Smirnov tests ($p < .05$) also illustrate
404 that the distributions of variables violate the normality assumption. Besides, we have also assessed
405 the multivariate normality by using Mardia's coefficient of multivariate kurtosis, which indicated that

406 the dataset was multivariate non-normal.

407 Given that the data are multivariate non-normal, to fix this problem, a Bollen–Stine bootstrap
408 (n=2000 at 95% bias-corrected confidence interval) has been performed to achieve stronger accuracy
409 in confidence intervals (Nevitt and Hancock, 2001; Schumacker et al., 2015). Moreover, the
410 detrimental effects of nonnormality and underestimating variance disappear with sample sizes over
411 200 (Tabachnick and Fidell, 2013; Waternaux, 1976). Therefore, with a sample size of $N=202$, non-
412 normal distributions of variables do not impose any constraints derived from the normality
413 assumption.

414 To identify potential outliers in the dataset, the Mahalanobis distance method (Mahalanobis
415 D^2) has been used. The results illustrate that all observation values of D^2/df ($df=5$) are less than the
416 threshold value of 4.0, exhibiting no characteristics of outliers in the dataset (Hair et al., 2013).
417 Levene's test of equality of variance also shows that homogeneity of variances is present. Besides,
418 Variance Inflation Factor (VIF) analysis indicates no evidence of multicollinearity issue, as VIF
419 values are between 1.001 to 1.260, well below the cut-off point of 4.0, and tolerances are more than
420 0.10 ranging from 0.79 to 0.99 (Pallant, 2016). Finally, potential non-response bias has also been
421 assessed by comparing the early and late respondents (Armstrong and Overton, 1977). We have split
422 the data based on the response order of the survey before and after the first seven days as a dividing
423 point. The results show no statistically significant difference between these two groups at a 95%
424 confidence level, supporting that non-response bias does not appear to be an issue in this study.

425 ***4.2 Measurement Model Analysis***

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

432 index (CFI) = 0.974, Tucker–Lewis index (TLI) = 0.969, incremental fit indices (IFI) = 0.975, have
433 met the requirements of recommended values (Bagozzi and Yi, 1988; Bentler and Bonett,
434 1980; Brown, 2006), thus exhibiting a good fit to the collected data.

435 Also, convergent validity has been used to determine the construct validity by assessing
436 Cronbach's alpha (α), standardised factor loading estimates (FL), average variance extracted (AVE),
437 and composite reliability (CR) values (Fornell and Larcker, 1981; Hair et al., 2013). Cronbach alpha
438 is commonly used to assess internal consistency as it involves correlating inter-item responses to
439 determine whether principal items are measuring the same domain (Ratray and Jones,
440 2007; Tabachnick and Fidell, 2013). The results in **Table 2** illustrate that for each variable, the alpha
441 values are above 0.70, ensuring high reliability (ranging from 0.722 to 0.970) (Bollen and Lennox,
442 1991; Sarantakos, 2013). Standardised factor loading estimates for all variables are statistically
443 significant at $p < 0.001$ and range from 0.765 to 0.848, which exceeds the minimum criterion of 0.50.
444 Besides, composite reliability values range from 0.744 to 0.970, which are greater than the
445 commonly accepted cut-off value of 0.70 and ensure construct reliability. Finally, the average
446 variance extracted (AVE) for each variable exceeded the recommended benchmark of 0.50 (See
447 **Table 3**). These results confirm that the research has sufficient reliability and convergent validity.

448 Next, the following techniques have measured the discriminant validity of the scales. First, the
449 results show that the square root of AVE for each construct (bold letter on the diagonal in **Table 3**) is
450 higher than the correlation between any pair of distinct constructs (Fornell and Larcker, 1981).
451 Second, none of the correlation coefficients exceeds the threshold value of 0.70 (Sepasgozar et al.,
452 2019; Yukl et al., 2008). Finally, all maximum-shared squared variances (MSV) for the factors are
453 smaller than the AVE. These results presented in **Table 3** show that all latent variables differ
454 sufficiently from each other and thus provide evidence of discriminant validity (Urbach and
455 Ahlemann, 2010).

Insert Table 3 here

456 **4.3 Common Method Variance**

457 While researchers report different post-hoc statistical tests for CMV bias, disagreement remains
458 regarding the application of the most appropriate approach (Malhotra et al., 2017; Simmering et al.,
459 2015). Thus, we have used three different statistical analyses to assess the severity of CMV in the
460 study. First, Harman's single factor test extracted six factors explaining 79.29% of the variance and
461 un-rotated factor solution shows that the first factor explains only 17.38% of the variance, which is
462 below the threshold of 50%, showing the potential bias for common method variance is low
463 (Harman, 1976; Podsakoff et al., 2003). Second, a partial correlation technique using a marker
464 variable has been used to assess the influence of common method variance. The results show that
465 adjusted correlations were only slightly deviated from the unadjusted correlations with unchanged
466 significance levels, thus showing that common method variance is very unlikely to contaminate the
467 results (Lindell and Whitney, 2001).

468 Third, a confirmatory factor analysis (CFA) marker technique recommended by Williams et al.
469 (2010) has been used to identify potential CMV impact on the study results. The results presented in
470 **Table 4** show that the test for Method-C Model (constrained model) resulted in a significant chi-
471 square difference of $\Delta\chi^2=34.557$ at $\Delta df=6$, which indicates that there is shared CMV between the
472 latent marker variable and substantive variable indicators. Next, a model comparison between
473 Method-U (unconstrained model) and the Method-C model shows a significant chi-square difference
474 of $\Delta\chi^2=53.472$ at $\Delta df=20$, showing CMV is not affecting all substantive constructs related
475 correlations equally (Malhotra et al., 2017). Finally, to assess whether the correlations are
476 significantly biased by marker variable method effects, a comparison of the Method-U and Method-R
477 has been performed. The chi-square difference test resulted in a non-significant difference of
478 $\Delta\chi^2=2.619$ at $\Delta df=15$, which shows that the presence of CMV does not spuriously inflate or skew the
479 relationships between the substantive variables (Shuck et al., 2017; Williams et al., 2010). Thus, the
480 above three different analyses indicate CMV does not pose any concerns for the results.

Insert Table 4 here

481 **4.4 Structural Model Analysis**

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

490 **4.5 Hypothesis Testing**

491 The H_{1a} predicts the relationship between perceived control of information and emotional support
492 ($\beta_{H1a} = 0.522$, t-value = 8.814, $p < 0.001$), which was significant. However, in terms of H_{1b} , we did
493 not find any significant relationship between perceived control of information and informational
494 support ($\beta_{H1b} = -0.004$, t-value = -0.073, $p = 0.942$). Thus, *Hypothesis 1a* has been supported, but
495 *Hypothesis 1b* has been rejected. Moreover, the surprising result shows that the relationship between
496 perceived control of information and intention to participate ($\beta_{H1c} = .000$, t-value = 0.006, $p = 0.996$)
497 is non-significant, rejecting *Hypothesis 1c*. With regard to research hypotheses H_{2a} and H_{2b} , results
498 show the relationships between perceived privacy risks, emotional support, and informational
499 support. Perceived privacy risk shows no significant relationship with emotional support ($\beta_{H2a} = -$
500 0.079 , t-value = -1.291, $p = 0.197$), indicating *Hypothesis H2a* is rejected. While the result suggests
501 that the perceived privacy risk has a significant positive influence on providing informational support
502 ($\beta_{H2b} = 0.428$, t-value = 6.730, $p < 0.001$), this study hypothesised the relationship inversely. Hence,
503 *Hypothesis H2b* is also rejected. In hypotheses H_{3a} and H_{3b} , results again show that community
504 engagement has no relationship with emotional support ($\beta_{H3a} = -0.103$, t-value = -1.675, $p = 0.094$),

505 while informational support has a significant relationship with it ($\beta_{H3b} = 0.157$, t-value = 2.460, p =
506 0.014), indicating the acceptance of *Hypothesis 3_b* and rejection of *Hypothesis 3_a*. The relationships
507 between emotional support, informational support, and intention to participate variables are
508 supported in the path analyses. The results show that emotional support ($\beta_{H4} = 0.332$, t-value =
509 4.273, p < 0.001) and informational support ($\beta_{H5} = 0.147$, t-value = 2.227, p = 0.026) influence
510 intention to participate, confirming both the *Hypotheses 4* and *Hypotheses 5*. **Figure 2** and **Table 5**
511 show regression coefficients, squared multiple correlations (R^2), t-values and related p-values for
512 each path hypothesised.

Insert Figure 2 here

Insert Table 5 here

513 **4.6 Multi-group Analysis**

514 After evaluating the structural model, the study performs a multi-group analysis to identify the
515 difference in the model between two different groups. A chi-square difference test shows the results
516 of gender-based subgroup analysis ($\chi^2/df = 13.783$, $df = 9$, $p = 0.130$) and indicates no significant
517 difference between the groups. However, scholars (e.g., Yuan and Bentler, 2004; Yuan and Chan,
518 2016) argue that the chi-square difference test can be problematic and unable to control Type I or
519 Type II errors. Besides, the chi-square difference test is directly affected by sample size (Hair et al.,
520 2013) and for large samples, even inconsequential differences may become significant. Hence, even
521 a chi-square test shows an insignificant difference; the base model can still be substantially different
522 between the groups. So, a comparison between the paths for each group has been performed. Results
523 in **Table 6** shows that out of 9 different paths, only three paths have a significant difference between
524 the groups. Analysis confirms that community engagement has a greater negative effect on male
525 respondents toward emotional support than female respondents. Whereas the result shows that
526 community engagement has a greater positive effect on male respondents toward informational

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

Insert Table 6 here

533 **5.0 Discussion**

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

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

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

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

590 This finding also shed light on how people's wellbeing may be better understood when they
591 become more willing to explore information in OHCs. The term wellbeing first appeared in 1948
592 through the World Health Organization's (WHO) definition of health, which is "a state of complete
593 physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO,
594 1948, p.1). Statham and Chase (2010) suggest the emergence of this definition was to give a de-
595 medicalized view of health and to encourage the government to understand the various factors that
596 link to poor health rather than disease and infirmity, such as the physical, mental and social
597 wellbeing of individuals. However, the worldwide knowledge and development of wellbeing has
598 resulted in confusion and complications to its meaning, with Forgeard et al. (2011, p.81) suggesting
599 this "has given rise to blurred and overly broad definitions of wellbeing". To add to this, its
600 development has created objective and subjective views of wellbeing, with objective wellbeing
601 measured by hard facts (e.g., income, educational achievement, housing, life expectancy) and
602 subjective wellbeing relating to an individual's personal perspective of life (e.g. happiness, quality of
603 life, satisfaction) (Statham and Chase, 2010). As community engagement and privacy concerns can

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

607 Furthermore, the different online platform has distinctive features, which provide users with
608 various gratifications. For instance, Zhang and Jung (2019) did not find emotional support to be a
609 motivational factor for WeChat health community engagement because such a platform may be
610 desirable for providing informational support, rather than emotional support. Additionally, as
611 community engagement may require users to constantly co-create information with their peers, the
612 additional strain might limit their emotional and social resource sharing behaviour (Bowman,
613 2016; Shensa et al., 2016). Besides, variation in characteristics such as disease severity and time
614 since treatment received can vary the urge for emotional support (Coughlin, 2008; Crossley, 2003).
615 However, such investigation lived out of the scope of our study and thus warrant further
616 investigation.

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

630 with the effects of the contradictions between individuals' privacy concerns and behaviours (Jang
631 and Sung, 2021; Jozani et al., 2020). While OHC users can be capable of acting in their own
632 interests, their perception of privacy risk and control of information influence their ethical
633 perceptions, which in turn affects their subsequent behaviours (Wang et al., 2020). Moreover, ethical
634 issues related to privacy concern will prevail as long as the information is shared (Hajli and Lin,
635 2016), but providing a mechanism of privacy protection to enhance the sense of assurance and new
636 security policies can help to reduce users' perceived privacy related ethical concerns (Shirazi et al.,
637 2021). Hence, ethical companies should collaborate with OHC users to increase their control over
638 shared information and privacy to build a trustworthy environment (Wang et al., 2020). This could
639 be an important factor in the continuous and sustainable use of OHC platforms. Overall, the results
640 also contribute to online ethics related issues by showing how we can build an ethical digital
641 environment for triggering users' social support and OHC participation behaviour.

642 Our result also shows that community engagement leads to informational support for
643 community members. This finding is aligned with previous studies examining the links between
644 community engagement and social support exchange behaviour. People show their interest to go to
645 OHCs and share their experiences and information about health-related issues, which can be a
646 valuable source of knowledge for others, leading individuals to act on the information provided
647 within the health community (Lin and Kishore, 2021). For instance, Shao (2009, p.10) stated that
648 information seeking "is driven by people's desire to increase awareness and knowledge of one's self,
649 others, and the world". In addition, Johnston et al. (2013) state that the more involved the individual
650 is with the community, the more likely they are to gain information by having access to new
651 information and hearing redundant experiences that reinforce the credibility of the information. This
652 may suggest that information provided through community engagement can lead to more
653 information seeking behaviour, providing personal benefits to individual participants (Nambisan,
654 2011). Besides, Azer et al. (2021) found that community engagement leads users to engage in
655 informative behaviour, such as individuals who want to support others, raise awareness, and/or keep

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

661 Another key finding of our research is that social support encourages more people to
662 participate in OHCs. This finding is in line with the social support literature (e.g., Chiu et al., 2006;
663 Wang, et al., 2017; Zhang et al., 2018) inferring that expected social supports are powerful predictors
664 of an individual's intention to take part in OHC platform. For instance, Mirzaei and Esmailzadeh,
665 (2021) show that informational and emotional support plays essential roles in enhancing an
666 individual's intention to participate in OHC platform. When people seek or receive informational
667 support and emotional support, they are likely to act on the support received on the OHC platform.
668 Wang et al. (2021) found that users' experience in seeking and receiving social support predicts their
669 successive OHC participation. It makes them feel they belong to a network of communication with a
670 shared purpose and such sense encourages them to offer the same supports for others. According to
671 Shumaker and Brownell (1984), receiving social supports from others in the community can provide
672 a sense of fulfilment and mutual obligation, which can motivate them to provide similar support to
673 other community members. Thus, high emotional and informational support levels can result in a
674 better chance of engagement with people in OHCs to share or find valuable information, experience,
675 and emotions. With respect to our third research question, our analyses find the evidence that the
676 quantity and the quality of support in the form of informational and emotional support has a
677 significant influence on individual's health-related online community participation intention.

678 Finally, this paper also tries to identify the difference between gender regarding the importance
679 they place on perceived control and privacy risks in their decisions about information seeking and
680 online community participation intentions. While there is no such difference between men and
681 women overall, the study found that men place significantly greater importance than women on

682 informational support in terms of community engagement and intention to take part in OHCs. The
683 finding is supported by a study conducted by Lin et al. (2016). Our study also shed light on the
684 argument (e.g., Kristiansen et al., 2010) that variation in characteristics such as sex can alter the type
685 of social support required.

686 **6.0 Theoretical and practical implications**

687 ***6.1 Theoretical contributions***

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

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

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

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

729 ***6.2 Practical contributions***

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

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

748 **7.0 Limitations and future research direction**

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

759 pandemic situations influence the patients' information sharing and seeking behaviour. Third, we
760 note that relatively little research has examined how cultural/normative influences shape patient's
761 online community participation behaviour. On online platforms, their virtual community norms
762 mainly affect user's participation (Chiu et al., 2006; Zhou, 2011) or country cultures (Li et al.,
763 2018; Wang and Liu, 2019). Hence, given that cultures/norms can affect user participation
764 behaviour, future research should examine how factors interact with social support issues to
765 influence users' online participation intention. Fourth, the current study focuses on the degree of
766 social support, while examining the contents of the social support issues in OHCs could be an
767 interesting avenue for future research. Besides, examining the role of government can also be a new
768 idea for future research. This is critical in the era of pandemic and epidemics, when governments are
769 asking people to manage the health issues by staying home and getting basic health supports through
770 online platforms.

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Figure 1: Research Framework

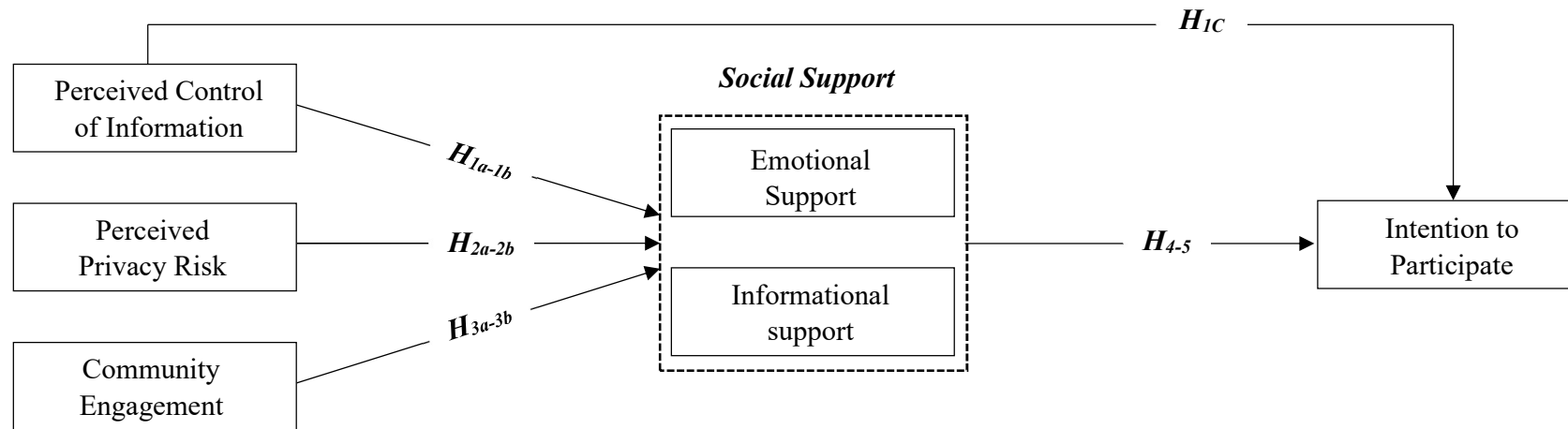


Figure 2: Estimation Results for the Structural Model

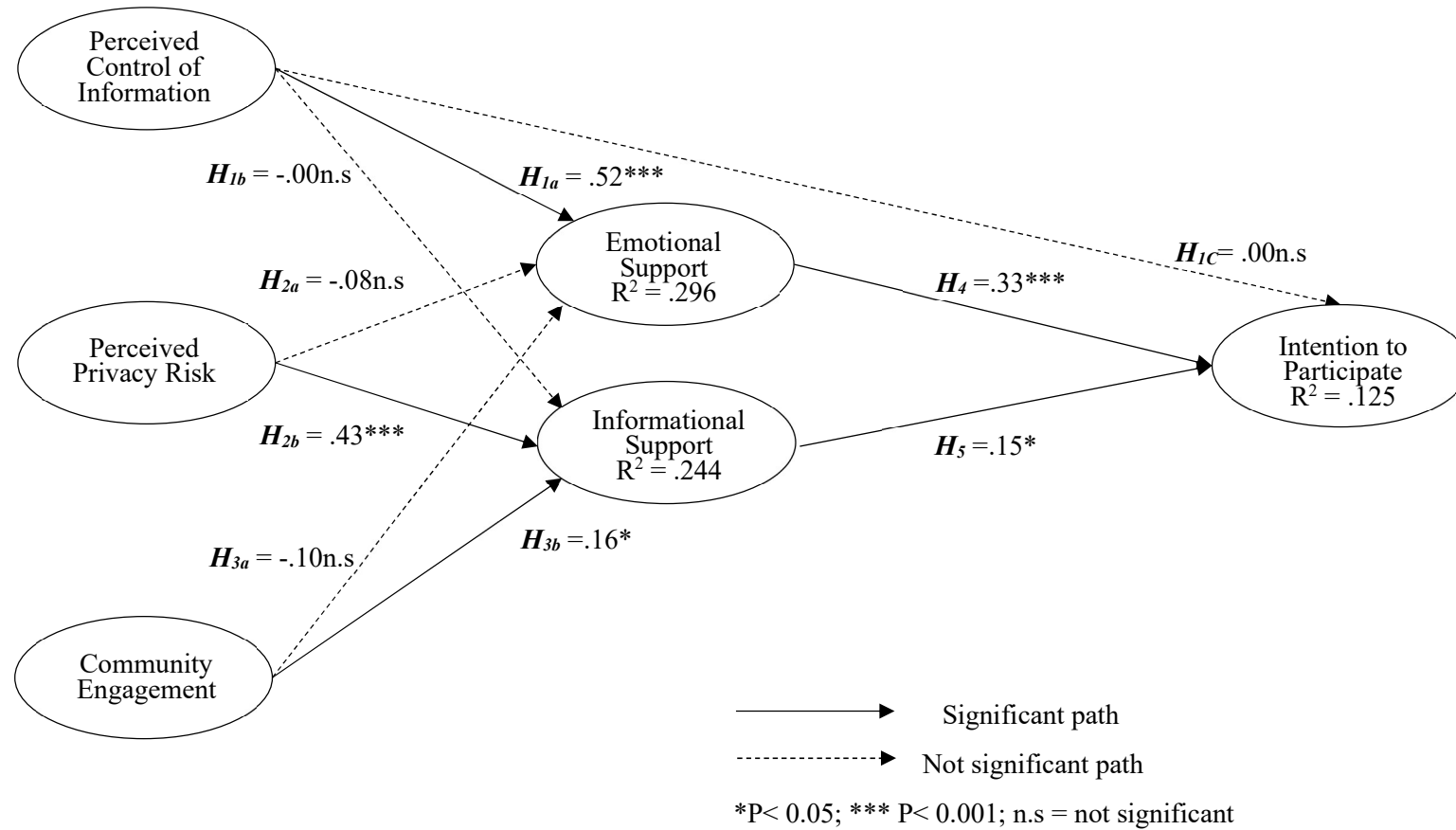


Table 1: Demographic Background (N=202)

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)

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)						
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	$\chi^2(df)$	CFI	RMSEA (90% CI)	LR of $\Delta\chi^2$	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

<i>H_s</i>	Path Directions	Std. β	Std. error	t-value	p-value	Results
<i>H_{1a}</i>	→ Emotional Support	0.522	0.068	8.814	***	Supported
<i>H_{1b}</i>	Perceived Control of Information → Informational Support	-0.004	0.123	-0.073	0.942	Rejected
<i>H_{1c}</i>	→ Intention to Participate	0.000	0.086	0.006	0.996	Rejected
<i>H_{2a}</i>	Perceived Privacy Risk → Emotional Support	-0.079	0.040	-1.291	0.197	Rejected
<i>H_{2b}</i>	→ Informational Support	0.428	0.071	6.730	***	Rejected
<i>H_{3a}</i>	Community Engagement → Emotional Support	-0.103	0.068	-1.675	0.094	Rejected
<i>H_{3b}</i>	→ Informational Support	0.157	0.122	2.460	0.014	Supported
<i>H₄</i>	Emotional Support → Intention to Participate	0.332	0.074	4.273	***	Supported
<i>H₅</i>	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)		x ² /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