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The role of mobile devices in fostering the engagement of stigmatized patients in online health communities

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Abstract

Background Online health communities have emerged to play an important role in delivering support to specific categories of patients. Therefore, the focus of this research is the investigation of satisfaction and engagement intention in online communities of support for patients experiencing a stigmatizing health condition. By integrating Channel Expansion Theory and Expectation-Confirmation Theory, we developed a predictive model to understand the relationships between perceived support, satisfaction, and engagement in online health communities.

Methods Using a snowball sampling method, empirical data from 148 participants of online health communities were collected and analysed through means of structural equation modelling, considering the suitability to the sample size and its wide application in technology continuance intention research.

Results The findings suggest that the relationship between perceived support and satisfaction is mediated by frequency of usage of online communities and individuals' satisfaction has considerable influence on their consequent engagement. Moreover, this study highlights the moderating effect of mobile interaction on the relationship between perceived support and frequency of usage of online health communities such that the strongest association between perceived support and frequency of usage occurs for individuals who report higher usage of mobile devices to access the online community.

Conclusions Important managerial implications were drawn for improving participant satisfaction and maintaining engagement. Drawing on the findings online health communities play are an important source for support for stigmatized patients. Implications for decision-makers highlight the need to make those communities more accessible via mobile devices.

Keywords Online health communities, Channel expansion theory, Expectation-confirmation theory, Perceived support, Satisfaction, Engagement intention

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Introduction

The use of communication technology and social media channels such as Facebook, Twitter, and much more have risen substantially over the last decade. Social media sites can stimulate health and policy dialogues, improve physician-patient communication, and ultimately boost patient engagement by offering individuals an accessible platform to participate in their own health care.

A broad range of research focuses on the positive effects of communication technologies for the patient, such as empowerment [1, 2], relationship improvement [3, 4], improved health outcomes [5–7], improved support [8–10], etc. Yet, extant research finds some contrasting findings of the real benefits to the individual, as is the case of the study of Visser et al. [11] suggesting that patient empowerment may be inhibited by implicit norms of community. Therefore, there is clearly a need to understand the necessary conditions for satisfaction and engagement in online health communities (OHC), as well as address recommendations to improve the benefits. Moreover, few academic programs focus on outreach efforts to increase patient engagement and satisfaction through the use of communication technologies and social media platforms [12].

Stigma remains a significant barrier to mental health help-seeking behaviour and affects individuals' willingness to disclose distress as well as their choice of support channels. Prior research highlights that fear of judgment, discrimination, and stigma often discourages individuals with mental health conditions from seeking face-to-face professional help [13]. Online support communities may therefore provide a safer and more accessible alternative, as they afford greater anonymity, reduce perceived social risks, and foster a sense of shared experience among peers. The mitigating effect of anonymity on anticipated stigma has been found to facilitate self-disclosure, increase perceived social support, and encourage ongoing engagement with mental health resources. By situating our study within this body of literature, we aim to highlight the importance of understanding stigma not only as a barrier to traditional care but also as a key driver of individuals' preferences for digital support environments.

Therefore, this study focuses on a complex social problem and has the potential for positive social impact coming from optimizing satisfaction and engagement for improved support for the stigmatized individual. It is exploratory in nature and aims to investigate how the use of social media, specifically membership in online communities of support for stigmatized patients, may benefit this group of patients. More specifically, we attempt to understand the perceived social support effect on the satisfaction and patients' continuance intention to engage with the online community of interest, to provide insights for a better understanding of the role online communities of support may play in optimizing patient benefits. The research question we address in this investigation is:

RQ What is the role of frequency of usage and mobility in shaping the relationships among perceived support, satisfaction, and engagement in online health communities?

To the best of our knowledge, there are few studies that aim to understand the role of perceived social support in the specific context of online health communities while focusing on specific characteristics of the community [13, 14]. Therefore, the novelty of the study is related to the enrichment of the understanding of perceived social support in online communities and empirical evidence of its effects in the way individuals make use of these communities. Moreover, the current study extends the understanding of satisfaction and continuance intention drawing on Expectation Confirmation Theory (ECT) and adding frequency of usage as a mediator, while it also introduces mobile interaction as a moderator of the relationship between perceived support that in a certain way expresses the perceived usefulness of online health communities, and frequency of usage.

The rest of the paper is structured as follows. Section "Theoretical background and model development" reviews the theoretical background and hypotheses development, while Sect. "Methods" explains the research methodology. Results from the data analysis and discussion are presented respectively in Sect. "Results" and Sect. "Discussion", whereas Sect. "Conclusion" presents the conclusions.

Theoretical background and model development

Emerging online communities

The fast rise of the Internet, continuous technological development, and emerging of mobile services has accelerated the technological diffusion. Nowadays, it is normal to see people conversing on mobiles, and connecting to people living and professionally working miles away in just a click, tracking important information with the help of a personal digital assistant, and being able to connect anytime to a large group of individuals with whom they can share similar interests [15]. The use of technology makes possible all these tasks and facilitates gathering information and gaining support daily to a number of individuals benefiting. Yet, successful use of technology for a range of tasks remains an unmet aim. As the technological options expand, so does the confusion about how technology can be used for the better aim of benefiting the individual, and overall, the society [16, 17]. Obtaining social support has long been recognized as an important factor in achieving life satisfaction [18–20]. The emergence of new communication tools that satisfy such needs have completely transformed the way people

network. Although there are enormous opportunities to network provided by social networking sites, they may be meaningless if fail to provide the social support that recipients demand [21]. Online networking platforms are meant to participate in various supportive activities (for example, sharing information, providing encouragement, etc.,), which may result in diverse outcomes and be associated to different social support dimensions [22]. According to Preece [23] an online community is a group of people interacting over time, that are connected via the Internet and share the same purpose, interest, or need. In the healthcare context, the development of health support communities serves especially to vulnerable populations who can potentially gain from the ability to connect via online social support groups. Online communities, considered an important channel to provide and meet the need for support, can be a useful resource to patients in exchanging information, sharing experiences, and enabling the development of positive interactions between similar others [24]. This is even more relevant when the individual experiences a stigma related to health conditions. Considering the opportunities and benefits achieved from participation in activities in the virtual context, online health communities find an increased use due to the potential to benefit not only the patient, but a set of stakeholders interested in gathering information and improving benefits, such as physicians, providers, policymakers, etc [25, 26].

Channel expansion theory (CET)

In 1999, Carlson and Mud proposed channel expansion theory through a combination of media richness and social influence theories to explain the media use [27]. The central premise of the theory holds that an individual's relevant experiences are central factors that influence perceptions of a channel's richness. Considering the theory, we can assume that media characteristics alone cannot explain users' perception about the media of interest and media richness is an outcome of complex interactions. Instead, as the theory suggests, we should acknowledge that perceptions of media can change over time, and aspects such as experiences with the topic, the communication partner, the organizational context, and the technology available have a significant effect on the individual evaluation of media and the development of consecutive perceptions as either rich or contrary. According to the theory, as individuals acquire relevant experience in each of these domains, they develop associated knowledge bases that may be used to more effectively encode and decode rich messages on a channel. It is proposed that individuals whose experiences build such knowledge bases and who are thus able to participate in increasingly rich communication via the channel will perceive the channel as becoming increasingly rich. Different channel characteristics are considered when adopting a channel by the consumer [28], and the shift from traditional offline to new online channels can be one of the characteristics considered. In tandem with that, the adoption of a mobile channel for information exchange provides insights on the use of an information system in different contexts and it is useful in mapping and understanding behaviors such as engagement [24]. In short, this theory considers that the selection and use of communication media depends on the perception of each medium by the members of an organization, based on their existing knowledge base. Therefore, making use of the theory, great opportunities lie in understanding consumers' perspective focusing closely on the dialogue generated between communication partners across a media device to determine channel expansion. The theory finds extensive use in investigations of new media such as online discussion forums [29–31], mobile mediated communications [32], etc.

Expectation confirmation theory (ECT)

Expectation–Confirmation Theory (ECT), also known as Expectation–Disconfirmation Theory (EDT), is believed to provide an explanation on consumer's repurchase intention as it assumes that post adoption satisfaction is a function of expectations and perceived performance by the consumer, as well as a possible disconfirmation of beliefs. Bhattacherjee [33] discovered that consumers' continued use of information technologies and services may be explained by causal links and the original decision to accept technologies and services. Confirmation is described as «the users' level of appropriateness between their actual performance and expectations of the usage of information systems and services» [34]. Confirmation, as one of the key factors in ECT, is important in influencing users' perceived satisfaction with information systems and services and is related to their intention to use the systems and services. Furthermore, because satisfaction is mostly described as "the users' post-evaluation on their overall experience with a specific information system or service" [33], several studies investigate users' perceived satisfaction as a core determinant of their intention to continue usage. Therefore, according to ECT, users' continued intention is predicted by (a) user satisfaction, (b) the level of user confirmation, and (c) post-adoption expectation, mostly expressed by perceived usefulness. Summarizing, consumers will form an expectation about a specific product or service which is based on actual knowledge and prior experience. Next, after purchasing the product/service and using it, they will form perceptions about the performance. Through a comparison with their initial expectation, the consumer will assess the level to which their expectations are confirmed and, on that basis, remain satisfied if the product/

service performs as expected, or dissatisfied if it performs below expectations. The last decision is if they will develop a repurchase intention or not. Some of the satisfied consumers may decide to repurchase, while others may consider searching for substitutes. This approach is distinct in that it focuses on post-adoption expectations rather than pre-purchase expectations. The theory finds wide application in exploring and predicting continuance intention in information systems research [33, 35, 36]. Moreover, ECT finds application in marketing research, with a focus particularly on consumer behavior, to study consumer satisfaction and post-purchase intention [37, 38] and to explain continuance intention for different technology contexts [39–42].

Expectation-Confirmation Theory (ECT) provides a useful lens for understanding not only post-purchase behavior but also user experiences in online communities. In this context, satisfaction emerges when perceived benefits and support meet or exceed prior expectations, which subsequently drives continuance and engagement [33]. In online health communities, perceived social support refers to the emotional, informational, and instrumental resources that individuals believe they receive from other members, shaping their expectations and evaluations of community participation. When these expectations are confirmed, satisfaction and sustained engagement are more likely.

Model development

We draw on two theories, namely the channel expansion theory (CET) and the expectation-confirmation theory (ECT), to develop the investigation of perceived support, satisfaction, and engagement in online health communities. From this perspective, participants create expectations for their participation in the OHC. When their expectations are confirmed, they will remain satisfied. Otherwise, a possible non-confirmation of the expected support within the community will leave them dissatisfied and possibly impact their future engagement. Therefore, the actual study aims through the consideration of CET and ECT, by making use of user-oriented theories, to better understand users' perceptions and their consequent behavior in the context of online health communities.

Perceived social support. Perceived social support represents an expectation that support will be accessible when it is needed [43]. Anyway, the concept is more complex than just that and a set of important elements can contribute to the perceived support. Social support reflects "an individuals' experiences of being cared for, being responded to, and being helped by people" in a specific social group [44]. An important element is related to the usefulness of support generated in online communities, and this comes from an alignment of the need of the individual with what gets from the community [45]. Incongruities in social support can be perceived as negative considering support may not be desirable or effective if the support received does not match the recipient's needs [46]. In a study by Hogan et al. [47] focused in investigating if social support interventions work, the authors suggest that it is important to understand the usefulness of online support considering that extant research is scarce. Moreover, they suggest that support received is equivalent to support perceived. Therefore, if there is an alignment between the request for support and the support received, this will affect the perception of online community as useful to the individual joining. According to extant research, social support should satisfy individual psychological needs and provide a network of relationships involving the provision of the type and amount of support that is required in a specific situation and serves the needs of a specific individual [48].

A study by Melrose, Brown and Wood [49] measures perceived support as both satisfaction with and availability of support. Extant research on online health communities confirms that patients report to receive much more understanding from participating in these communities than from their offline social network including family members, friends, and coworkers [50]. Social support in an online health community can lead to perceived support considering members' experience. Drawing on self-determination theory, people engaging with the environment aim to meet their basic needs, and when the fundamental needs are met and social contexts create possibilities for positive interpersonal interactions, it may lead to higher satisfaction [51]. Individuals perceiving positive interactions within the online community and perceiving that they received the support they asked for, will consequently report higher satisfaction. Moreover, considering from the perceived usefulness perspective, individuals experiencing higher perceived support from online communities, are expected to use the OHC more frequently than those who do not perceive it as useful in terms of support perceived. Thus, we expect that perceived support positively affects frequency of usage.

H1 Perceived support from online communities positively affects frequency of usage.

Frequency of usage mediation effect. In our model, frequency of usage will be studied as a mediating factor. Usage has been investigated in literature as an antecedent of satisfaction [52]. The broad usage of mobile devices, and the frequency of usage driving from the fact that extant research finds that more than half of the day is spent on social media platforms [53], may have an effect on the level of satisfaction of users in the OHC of interest. In extant research the frequency of usage is one of the most studied variables for social networking sites

(SNS) [54, 55]. The amount of use, which is usually defined by the frequency with which one goes online, is expected to influence satisfaction and repeated use of online platforms. The idea that consumers who utilize a service frequently may be more satisfied over time due to their frequent exposure to beneficial service experience supports the assumption of a positive relationship [56]. Thus, we expect that frequency of usage mediates the relationship between perceived support and satisfaction and exerts a positive relationship with satisfaction.

H2 Frequency of usage of online communities positively affects satisfaction.

Satisfaction of need. Extant research states satisfaction is the "consumer's fulfillment response" and in the development of a satisfaction judgement is involved an outcome and a comparison element [57]. Most conceptualizations of consumer satisfaction refer it as either an emotional or cognitive response [58]. Considering that satisfaction is a post-usage phenomenon, based on an experiential outcome, this study focuses on users' feelings considering their experience with the online community. Satisfaction results from positive cognitive and affective evaluations of consumption outcomes [59]. Drawing on the ECT this study investigates satisfaction as the confirmation of the expectations. Several studies find satisfaction as a determinant of engagement and continuance intention. Psychological needs satisfaction specifies the necessary conditions for psychological growth, integrity, and well-being [60] and moreover, satisfied consumers exhibit an enthusiasm and enjoyment that is indicative of strong consumer engagement, especially in social media environments [61, 62]. Thus, we expect that satisfaction positively affects customer engagement.

H3 Satisfaction of need from online communities positively affects engagement.

Mobility moderation effect. In our model, the level of mobile interaction will be studied as a moderating factor. Mobile devices enable users to reach out to and interact with friends and similar others from anywhere and at any time. Smartphones have become one of the most frequently used devices to access the Internet. Studies suggest that effects differ when users receive information via a mobile device or a computer device [63]. These devices differ from desktop computers in their mobility, thus allowing an easy and fast access to the content of information acquired or generated on the Internet. According to the Digital 2023 Global Overview Report, the number of mobile users has reached 5.44 billion in 2023, representing 68% of the worldwide population that makes use of a device to go online [64]. Extant research suggests smartphones are used about three times as often as tablet devices [65, 66] and suggest the need for greater attention on content adaptation on mobile devices [67]. Studies focusing on mobile usage characteristics confirm that the level of mobility, in terms of mobile interaction, influences the frequency of usage.

H4 Mobility moderates the relationship between perceived support and frequency of usage.

Engagement. According to extant research engagement is "the intensity of an individual's participation and connection with the organization's offerings and activities which either the customer or the organization initiate" [68]. Engagement is investigated as outcome variable in our model. Consumers' engagement is found to be driven by satisfaction, positive emotions, and trust. Therefore, satisfaction is a strong predictor of consumer engagement [12]. When consumers experience emotionally bonding relationships, they participate in activities such as online consumption and recommendations [69, 70] and satisfaction can exert an influence on engagement intention [71]. According to ECT, the users' continuance intention in using a product/service is positively affected by the overall satisfaction in using the respective product/service [71]. As regards online health communities, the relationship between satisfaction and engagement, here investigated as continuance intention within the OHC, should be addressed.

The hypothesized model is visually represented in Fig. 1.

Methodology

Measurement instrument

We carefully checked and reviewed previously used scales in the literature, to adapt the scales in our model and develop the measuring instrument in line with the literature. The measurement instrument consists of three main sections: 1- the first collects information on general filtering questions in terms of usage of online communities of support and stigmatized status, as well as information on the moderating variables, where frequency of usage is measured on a five-point rating scale (including the categories of few times per day, few times per week, every two weeks, every month and every few months) and mobile interaction is measured on a five-point rating scale as a combination of devices used to access the OHC (including a set of desktop and mobile devices); 2- the second collects specific information to measure respondents' perceived support, satisfaction and engagement; and 3- the third collects socio-economic and demographic profile information (age, gender, marital status, living status, education and employment). For the specific information section, with the aim to measure the constructs of perceived support, satisfaction, and engagement, we used a 5-point Likert scale (ranging 1 = strongly disagree, 2 = disagree, 3 = neither agree, nor

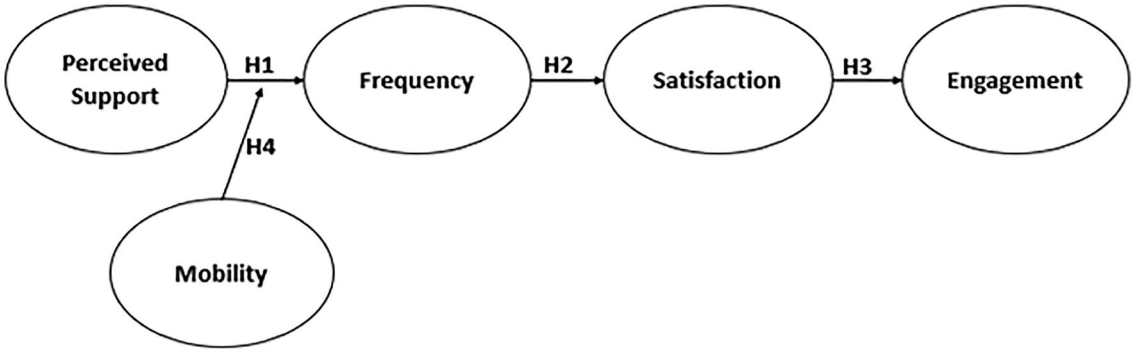


Fig. 1 Hypothesized model

Table 1 Questionnaire scales

Construct (No. of items)	Source	Adapted item
Perceived support (3)	Peng et al. (2020) Feeney and Collins (2015)	**PS1.** The online community is useful in providing the emotional help and support I joined for.
		PS2. I can count on the community when things go wrong with my health condition.
		PS3. I feel the community very supportive.
Satisfaction (3)	Ribbink et al. (2002) Taylor, Shiau and Luo (2012)	**SAT1.** I am very satisfied with the support provided at the community.
		SAT2. My expectations were met in the community.
		SAT3. The overall quality of support I received from this community was excellent.
Engagement (3)	Mirzaei and Esmaeilzadeh (2021) Bhattacherjee (2001)	**ENG1**. I felt engaged to stories shared in the community.
		ENG2. I am very willing to return to the community in future than use any alternative means (e.g., traditional communities).
		ENG3. I intend of quitting my use of the community.

disagree, 4 = agree, 5 = strongly agree). Perceived support items (PS1–PS3) assess participants' ongoing sense that support is available and accessible in the community (e.g., "I can count on the community when things go wrong"), whereas satisfaction items (SAT1–SAT3) capture a retrospective, evaluative judgment about whether the community met their expectations and provided high-quality experiences. This conceptual separation aligns with prior literature [72, 73], where perceived support reflects received/anticipated resources, while satisfaction reflects overall appraisal of those resources. Engagement (ENG1–ENG3) captures members' active involvement and intention to remain connected with the community. These items assess both behavioural engagement (e.g., paying attention to stories shared) and future-oriented commitment (e.g., willingness to continue using the community versus alternatives, or intention to discontinue). Engagement thus reflects the degree to which participants are psychologically invested in, and motivated to sustain, their participation in the community. At the end of the questionnaire the respondents had to consent the usage of the information shared and for all the data we got we considered the approved consent to proceed with the data analysis. Information on the adapted scales is included in Table 1.

Data collection procedure

A questionnaire was developed and shared on online health communities offering support to patients that have experienced a mental health condition, as a health condition related to high social stigma. Before sharing the questionnaire with the target respondents, a pilot testing was carried with a convenience sample of 6 individuals to check for the readability and the level of understanding of the questionnaire, as well as reduce the possibility of misleading questions. The comments gathered from the pilot testing of the questionnaire were used to improve it before proceeding with the data collection process. The study received ethical approval as of 27 January 2023 through an evaluation process on the honesty, rigour, transparency, and protection of participants. After the ethical approval was granted, the data collection process started. The first contact was established with users of social networking sites and online platforms and groups available on different networking sites such as Facebook, Instagram, etc. In the next phase we included medical doctors dealing with patients that present any mental health condition, and they established a contact and shared the questionnaire with potential respondents through electronic means. The combination of these means to reach potential respondents aimed to reduce the non-response bias. We developed a snowball sampling procedure that fits the specificity of this topic and

Table 2 Demographic and socio-economic characteristics

Attributes	Distribution	Frequency	%
Gender	Female	86	58.1%
	Male	61	41.2%
	Other	1	0.7%
Age	18–24	20	13.5%
	25–34	30	20.3%
	35–44	46	31.1%
	45–54	27	18.2%
	55–64	15	10.1%
	65+	10	6.8%
Education level	High school or lower	53	35.8%
	Bachelor student	10	6.8%
	Bachelor graduate	48	32.4%
	Master or PhD student	7	4.7%
	Master or PhD graduate	29	19.6%
	Not stated	1	0.7%
Employment status	Employed full-time	63	42.6%
	Employed part-time	18	12.2%
	Seeking opportunitites	9	6%
	Retired	14	9.5%
	Not working	44	29.7%

is useful in hard-to-reach populations aiming to reach a broader sample of respondents. The questionnaire was self-administered, and the data collection process took place from 28th of January to 11th of June. Respondents were ensured that the purpose of the data collection was purely academic, and confidentiality was guaranteed. Moreover, with the completion of the questionnaire they were asked to consent the usage of the information shared with the researchers. By the end of this process, a total of 231 responses were returned. Yet, of the 231 respondents not all were users of online health communities, as according to the results of the filtering question in Sect. 1 of our questionnaire. Therefore, the effective sample size is of 148 respondents, which are considered sufficient for the analysis [74].

The demographic and socio-economic characteristics of the sample are presented in Table 2. According to the results, 58.1% of our sample consists of females and 31.1% are between 35 and 44 years old. Approximately 35.8% of the respondents have an educational level of high school or lower, and most respondents in our sample report to be full-time employed, about 42.6%.

Although these distributions offer valuable information on the composition of our sample, they cannot represent the broader population. This is probably due to the relatively small sample size and the specificity of our sample, which consists of people with a mental health diagnosis who participate in online health support groups. Therefore, to evaluate how sociodemographic traits relate to those of the greater population of online health community users, this limitation shall be considered for future studies which would benefit from using bigger and diverse samples.

Table 3 Factor structure results

Factor	Indicator	Estimate	SE	z	*p*
Perceived Support	PS1	0.566	0.0561	10.09	< 0.001
	PS2	0.677	0.1005	6.74	< 0.001
	PS3	0.761	0.0816	9.33	< 0.001
Satisfaction	SAT1	0.845	0.0605	13.98	< 0.001
	SAT2	0.888	0.0704	12.62	< 0.001
	SAT3	0.903	0.0645	13.99	< 0.001
Engagement	ENG1	0.617	0.0694	8.89	< 0.001
	ENG2	0.757	0.0699	10.83	< 0.001
	ENG3	0.666	0.0820	8.13	< 0.001
Frequency	FREQ	1.349	0.0784	17.20	< 0.001
Mobility	MOB	1.902	0.1105	17.20	< 0.001

Results

The data obtained through the questionnaire were statistically analyzed. We used structural equation modelling to test the overall fit of our hypothesized model. We initially performed a confirmatory factor analysis and afterwards the structural model was assessed.

Confirmatory factor analysis

The confirmatory factor analysis was used to examine the factor structure for the observed variables. The results for the factor structure are presented in Table 3. In our analysis, the loadings of each indicator are greater than 0.50, which indicates an appropriate contribution of each of the items to their corresponding factors [75].

Next, we assessed the goodness of fit indices for total scales obtained from the CFA. The model fit measures the variance between observed and model-implied data. It helps conclude if the model is a good fit for the data observed. Initially, we considered absolute fit indices to determine how well the model fits the sample data, as suggested in literature [76]. We accordingly used the Chi-Square value to assess the overall model fit. Next, considering that the chi-square is sensitive to sample size, the relative chi-square was considered ($\chi 2/df$) [77]. According to literature, a value of < 3 indicates a good fit between the hypothesized model and the sample data [78]. This considered, we can assume that our model is a good fit for our sample data. We considered multiple fit measures such as the comparative fit index (CFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA). According to literature, Comparative Fit Index (CFI) where values equal to 1 show a perfect fit, values ≥ 0.95 are considered excellent fit and values ≥ 0.90 are considered an acceptable fit [79, 80]. For the Standardized Root Mean Square Residual (SRMR) values of ≤ 0.05 are considered acceptable fit [81]. For the Root Mean Square Error of

Approximation (RMSEA) values higher than 0.1 are considered poor, values between 0.08 and 0.1 are considered borderline, values ranging from 0.05 to 0.08 are considered acceptable, and values ≤ 0.05 are considered excellent [82]. The RMSEA is reported together with the lower and upper values of a 90% confidence interval (CI). Lower boundary of a 90% CI < 0.05 and upper boundary of a 90% confidence interval > 0.10 are the thresholds for the model fit. According to the results achieved from our analysis (χ^2/df = 1.9, CFI = 0.962, SRMR = 0.0422, RMSEA = 0.0779, RMSEA 90% CI [0.0491, 0.106]) the model provides a sufficient fit for the data.

The results of the fit indices are presented in Table 4.

Table 4 Goodness of fit indices

Fit indices	Accepted value	Model value
χ^2 (Chi-square)	-	68.4
df (Degrees of Freedom)	-	36
χ^2/**df** (Relative Chi-square)	< 3	1.9
CFI (Comparative Fit Index)	≥ 0.90	0.962
SRMR (Standardized Root Mean Square Residual)	≤ 0.05	0.0422
RMSEA (Root Mean Square Error of Approximation)	< 0.10	0.0779
RMSEA 90% CI Lower bound	< 0.05	0.0491
RMSEA 90% CI Upper bound	> 0.10	0.106

Table 5 Evaluation of reliability and convergent validity

Constructs	Cronbach's Alpha	McDonald's Omega (ω_1)	McDonald's Omega (ω_2)	McDonald's Omega (ω_3)	AVE
Perceived support	0.685	0.703	0.703	0.705	0.452
Satisfaction	0.912	0.913	0.913	0.915	0.779
Engagement	0.749	0.750	0.750	0.748	0.501

Model assessment

We used structural equation modeling (SEM), which has been proven suitable for testing theories and verifying models in marketing, information systems and social sciences research [83, 84], to examine the relationships among constructs. We considered "maximum likelihood estimation with robust (Huber-White) standard errors" (robust ML) drawing on literature suggestions to use "robust ML, if the sample size is not large and there is appreciable nonnormality." [85].

The measurement model was assessed in terms of validity and measures' reliability for the full sample (N = 148). The consistency of the constructs was assessed by analyzing the level of construct reliability and convergent validity, taking into consideration Cronbach's alpha (α), McDonald's omega coefficient (ω) and Average variance extracted (AVE). Considering that internal consistency reliability cannot be computed for single-item scale, we computed the reliability and validity indices only for the perceived support, satisfaction, and engagement. Construct reliability and validity values for our study are shown in Table 5. According to literature, Cronbach's alpha (α) values higher than 0.7 are considered acceptable to suggest internal consistency of the construct [86, 87], Omega values (ω) higher than 0.7 are considered acceptable and suggest good internal consistency and reliability of measures [88], and Average variance extracted (AVE) values higher than 0.5 are considered acceptable and indicate that a substantial portion of the variance is attributed to the construct [89]. In our study, all our results are accepted considering the suggested thresholds. Accordingly, only for the perceived support variable our values of Cronbach alpha (α) and Average variance extracted (AVE) are in the borderline of the accepted thresholds. This can be because our sample size is not big enough considering the sensitivity of the topic we are dealing with and the difficulty of reaching a broader sample of participants.

As a measure of how well the model fits the data, we used the Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI). According to literature, the GFI measures variances and covariances jointly accounted for by the model, while AGFI corrects the GFI based upon degrees of freedom [90]. For both indices, values range from 0 to 1, and a threshold of 0.90 is recommended, even though studies suggest that for small sample sizes the threshold should rise at 0.95 [91]. For our model, the GFI is 0.983, and the AGFI is 0.969, which suggests a good fit of the specified model as compared to no model at all.

Next, we developed a path analysis for the testing of the hypotheses of our study. Below are shown the standardized effects of our model (Table 6). There are four specific relationships in our model, respectively: perceived support and frequency, frequency and satisfaction, satisfaction and engagement and the moderation of mobility

Table 6 Results of structural model

Effect	Estimate	SE	95% Confidence Intervals Lower	Upper	β	Z	*p*-value
H1: PS ->FREQ	0.857	0.3466	0.1773	1.536	0.309	2.47	0.013
H2: FREQ ->SAT	0.174	0.0556	0.0654	0.283	0.281	3.14	0.002
H3: SAT ->ENG	0.665	0.0921	0.4845	0.846	0.906	7.22	< 0.001
H4: MOB x PS ->FREQ	0.231	0.0525	0.1278	0.334	0.325	4.39	< 0.001

on perceived support and frequency. The first hypothesis postulates an association between perceived support and frequency of usage of online communities. Based on the results, the relationship between perceived support and frequency (β = 0.309, 95% CI [0.1773, 1.536], $p = 0.013$) is positive and significant. Thus, H1 is supported. The second hypothesis in our study postulates an association between frequency of usage of online communities and satisfaction. Based on the results, the relationship between frequency and satisfaction (β = 0.281, 95% CI [0.0654, 0.283], $p = 0.002$) is positive and significant. Thus, H2 is supported. The third hypothesis postulates an association between satisfaction and engagement. Based on the results, the relationship between satisfaction and engagement (β = 0.906, 95% CI [0.4845, 0.846], < 0.001) is positive and significant. Thus, H3 is supported. The fourth hypothesis of our study postulates a moderation effect of mobility on the relationship between perceived support and frequency of usage of online communities. Based on the results, the moderation effect of mobility on the relationship between perceived support and frequency (β = 0.325, 95% CI [0.1278, 0.334], $p < 0.001$) is positive and significant. Thus, our last hypothesis H4 is also supported.

We further tested the effects socioeconomic status (proxied through education level and occupation status). However, our results did not reveal statistically significant differences across these variables in relation to the structural equation model outcomes. We recognize that this may be partly due to the modest sample size and the specificity of our study population, which consisted solely of individuals with a mental health diagnosis.

Discussion

This study examines the effects of perceived support (with its items of *usefulness*, *responsiveness*, and *amount of support*), on satisfaction, mediated by the frequency of usage and the consequent relation to online engagement in the OHC of interest. It further introduces mobility as a moderator and examines its effects in enhancing the relationship between perceived support and frequency of usage. Considering that the proposed hypotheses were empirically supported, the results reveal a set of interesting findings.

This study confirms that satisfaction of need is a strong driver of engagement, which is in line with extant research [61, 62, 71]. Moreover, *perceived support* measured by its three items of *usefulness*, *responsiveness*, and *amount of support*, has a strong impact on frequency of usage of the OHC. The variance in engagement can be partially explained by these factors, which represent various determinants important when considering a need fulfilled by using the OHC of interest. Together, these dimensions have all significantly impacted and provided a notable amount of explanatory power on satisfaction and engagement in online communities. An important finding relates also to the mediation effect of frequency of usage, confirming that higher frequency of usage is related with stronger positive association between perceived support and satisfaction.

The findings of this study make important contributions to both literature and practice, as well as can serve to inform policymakers decisions. Its contributions account to the three distinctions this study presents from extant research: (1) the context of the study which considers OHC for a particular category of patients such as the stigmatized, (2) the extension of ECT model with the introduction of frequency of usage variable as a mediator, and (3) the integration of mobility variable drawing on CET insights as a moderator to the model of investigation.

To begin, while satisfaction and engagement in online communities is broadly researched also in the healthcare context through the ECT model, this study extends from existing research by considering the importance of perceived support online for a specific category of patients such as the ones subject to a stigmatizing health condition. Drawing on this context, the perceived support from the online community gains increased relevance when considering that it has an important effect on the well-being and quality of life of these individuals [7]. Delving deeper into the context of online communities in general and health communities particularly, our findings add to the few studies that suggest that important determinants of participation in online communities can contribute to a great extent in the satisfaction and engagement of the user and calling for studies that pay more attention "to the quality of activity in terms of its relevance for the community" [92]. Moreover, it suggests a shift of the focus to investigations which are mainly related to how the support is offered, rather than merely if it is offered and what type of support is offered as mostly researched and already evidenced in literature.

Next, it suggests the importance of frequency of usage as a mediator of the relationship between perceived support from online interaction and satisfaction with the online community. The findings of this study confirmed that frequency of usage plays a strong positive effect on satisfaction, thus addressing that actions to increase the frequency of usage of members of an online community contribute to an increase in satisfaction. This is in line with extant research that suggests that the higher the frequency of usage, the higher the satisfaction of individuals in both online and offline environments [56].

To add to that, the introduction of mobility from the CET and the empirical evidence of the influence it exerts on the relationship between perceived usefulness of online communities, here investigated as perceived

support, and frequency of usage, adds to the literature on online channels and social media strategies [28]. This line of investigation sounds promising in bringing a solution to problems of low satisfaction and engagement in communities of support.

Therefore, the findings of this study provide insights useful to practitioners that can guide OHC design and management. First, OHC users' satisfaction (and consequently their engagement intention) can be driven by the level of perceived social support. In general, since many OHCs are designed to fulfil different user needs, such as informational support need, network support need, emotional support need or instrumental support need [93], it is especially important for OHC developers to leverage usefulness benefits to increase user satisfaction with the OHC and consequently their engagement. To increase the perceived usefulness, the OHC developer could design features that enrich users' experiences and align with the requested support. In tandem, OHC mangers may think of strategies to increase the responsiveness and improve the amount of support delivered to its members, as other important elements of social support [48]. Therefore, it would be important to improve usefulness, responsiveness, and amount of support by including different interaction features when designing an OHC, which can now be made possible through the rapid advancement in technology. Platform interoperability with other resources of support both in the online and offline context may in this case provide a solution to the need to improve usefulness, responsiveness, and amount of support in OHCs. Drawing on the CET, these features can include different output for the user such as voice output, real-world simulation, and interactive interfaces that support enriched experiences in virtual spaces and will enable the OHC to achieve its goals [94]. The findings of this study may guide the development of engagement strategies. To achieve high satisfaction and engagement of users, it may be a good strategy for OHC developers to put relatively more weights on social features and focus more on promoting the development of social networks and interpersonal interaction that encompass a sense of affiliation and make participants feel belonging to a group, which according to extant research are important determinants of successful virtual communities [95]. Designing interactive interfaces, organizing online in-group activities, such as different thematic activities, creating and sharing valuable content through live chat and real-time support, may be only some of the strategies to increase satisfaction [96]. On the other hand, the above-mentioned strategies may be useful in increasing frequency of usage of online health communities and thus mediate the relationship between perceived support and satisfaction, as a finding of the current research. While our hypothesized model treats frequency as primarily driven by perceived support and moderated by mobility, future research should examine the possibility of feedback looks, particularly with satisfaction and engagement, using larger samples. This would enable a stronger test of potential cyclical processes in online community participation. Next, it is important to acknowledge that engagement strategies may differ according to the group they target. Therefore, considering that different groups may exhibit differences in perceptions of social support received and how much it may affect their satisfaction and future engagement within the OHC when considering the mediation of the relationship from frequency of usage, it is important to suggest diverse strategies to increase user satisfaction within different usage groups. To add to that, studying other characteristics including the severity of the illness and cultural background are likely to affect how people feel supported, satisfied and involved in online health communities. Therefore, future studies may benefit from richer clinical and contextual data, that was not available for the current study and further advance the understanding of the mechanisms here involved in the usage of online health communities by this group of individuals. Although this study is focused on a specific group of patients facing stigmatization, the underlying mechanisms, such as the role of perceived support in fostering satisfaction and engagement through increased usage, are likely to be relevant across different OHC contexts. Thus, while practical strategies may require tailoring to the needs of particular user groups, the conceptual model and its implications can be extended to broader populations, including users of wellness, chronic illness, or lifestyle-cantered online communities. In line with other studies, there is a need to develop policies that stimulate online platform providers in developing secure online communities where participants feel they can share personal sensitive information and engaging strategies to sustain a thriving online health community that benefits its participants [97]. Again from a policymakers perspective, considering that social sharing of emotions can contribute to destigmatization and empowerment of individuals [98], the design and development of such communities should be a collaborative effort and integrate different stakeholders that can help alleviate the burden of stigmatization and ensure social inclusion.

Conclusions

A conceptual model was constructed based on existing research, using data and information acquired via a questionnaire encompassing the main elements of satisfaction and engagement in virtual communities. The postulated correlations between the variables were empirically validated using structural equation modeling. The findings of this study suggest that the relationships between

perceived support and frequency, frequency and satisfaction, between satisfaction and engagement are all significantly positive, thus supporting H1, H2, and H3. Moreover, the results suggest a moderating role of mobility on the relationship between perceived support and frequency, thus supporting H4. Based on these considerations all the study hypotheses were supported. Given the exploratory nature of our study, the findings assist us in better understanding the role that online health communities play in providing support for stigmatized patients, as well as developing recommendations to drive action in optimizing the benefits of satisfaction and engagement for this category of patients.

Yet, this study is not without limitations and its findings should be interpreted with caution. Considering the usage of a snowball sample, our study does not represent the entire population of patients that make use of online health communities, as the participants are not chosen by chance. Therefore, it might not be representative of the population. Moreover, there is a high risk for bias, considering that participants recruit other participants based on their judgement that can give information on the set of questions addressed in the questionnaire. Also, the difficulty to maintain anonymity when using a snowball sample, since participants are required to recruit each other and this may contribute to missing potential respondents due to the possible fear of anonymity, is another limitation. We must also acknowledge that an important limitation of this study is related to its' sample size, considering the difficulty to reach a broader sample size due to the sensitivity of the topic. This is a common trait of research dealing with sensitive topics. Even though we tried to optimize the data collection efforts by making use of social networking sites to disseminate the questionnaire, the sample size remains limited. This may restrict the generalization of the results achieved in this study.

This said, in the domain of consumer behavior research the use of social network sites proves useful in studying hard-to-reach populations, as it expands its geographical scope and facilitates the identification of potential individuals. We believe future research may benefit from replicating the same study in different virtual contexts or empirically testing its findings with larger samples. To add to that, future research may benefit from further investigating the frequency of usage, aiming to quantify it and explore patterns of satisfaction for different usage frequencies. This will enable the development of strategies to improve satisfaction, according to the frequency of usage patterns. Last, the research model in this study does not consider age and gender-specific variations, which may influence the relationships between perceived support, frequency, satisfaction, and engagement in online communities. A comparison of satisfaction and engagement across gender and age groups is expected to provide community and platform providers with useful insights into methods for targeting the needs of various age and gender groups. Therefore, future research may benefit from assessing age and gender effects in the model and investigating the patterns of the relationship between the variables with the aim to improve the explanatory power of this research model. Again, future research may try to include other demographic variables such as country, employment status, education level and marital status. In all cases, for future research there is a need to identify strategies for increasing the response rate to the questionnaire, as this can help to further validate the current findings and expand the model. The practical implementation of such investigations has relevant potential in bringing benefits to platform providers, managers and individuals making use of online communities.

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Author contributions
Johana Hajdini: Conceptualization; Methodology; Investigation; Data curation; Validation; Writing - original draft; Writing - review & editing. Stefano Za: Conceptualization; Methodology; Formal Analysis; Validation; Writing - original draft; Writing - review & editing. Taşkın Dirsehan: Conceptualization; Methodology; Resources; Writing - original draft; Writing - review & editing. Lea Iaia: Conceptualization; Supervision; Writing - original draft; Writing - review & editing.

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Data availability
Participants' shared data are not publicly available to preserve individuals' privacy under the European General Data Protection Regulation.

Declarations

Ethics approval and consent to participate
This study was conducted in accordance with the Declaration of Helsinki (2013). Additional ethics approval was waived by Marmara University Ethical Committee.

Consent for publication
Not applicable.

Human ethics and consent to participate declarations
Study participants provide informed consent to participate and approve the usage of their data for the aims of this specific research when filling the questionnaire under the specific section 'Consent Approval' of the questionnaire.

Competing interests
The authors declare no competing interests.

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