Effects of Social Support on Toxicity and Mental Well-Being of Older Adult Users in Online Health Communities: An Empirical Study

Abstract

The mental well-being of older adults is a crucial societal concern due to the myriad challenges associated with aging. Addressing these concerns and enhancing the mental well-being of older adults is pivotal to improving their quality of life. Online health communities (OHCs) have emerged as powerful platforms to exchange support among people facing health-related challenges. However, a significant issue within OHCs is toxicity, characterized by harmful or disruptive behaviors that can negatively affect users' well-being and the community's dynamics. Toxicity can create unhealthy and hostile online environments, deterring new users and impeding constructive discourse. Our research thus focuses on the intersection of toxicity and the mental well-being of older adult users within OHCs, emphasizing the role of social support. We aim to bridge this gap by investigating whether social support can mitigate toxicity within OHCs. We use a comprehensive longitudinal dataset spanning 11 years of older adult user interactions in a leading OHC. Our findings reveal that whereas appraisal support has a robust influence on improving the overall mental well-being of older adult users and reducing toxicity, emotional support has a limited influence on these outcomes. The effects of appraisal support are also marginal for users reaching a certain threshold of negativity. Our results also suggest that the timing of social support reception from other users in the OHC plays a crucial role. With these insightful findings, our study holds several implications for advancing our understanding of social support, toxicity, and mental well-being within OHCs.

Keywords: online health communities (OHCs), social support, toxicity, mental health, emotional support, appraisal support, older adult users

1. Introduction

Mental well-being encompasses a person's overall psychological and emotional health (Ryff & Singer, 1996). For older adults, it assumes paramount importance as they confront various challenges associated with aging—including the loss of loved ones, physical health ailments, alterations in living arrangements, and social isolation (Choi et al., 2012; Windle et al., 2010). Compared to those who are young, the mental well-being of older adults exhibits considerable variability and can be influenced by various psychological, social, environmental, and cultural factors. However, by providing appropriate support and resources and addressing their unique needs, it is possible to enhance the mental well-being of older adults, thereby improving their quality of life in their later years (Blazer, 2002; Nyqvist et al., 2013).

Online health communities (OHCs) represent digital platforms explicitly designed to foster connections, offer support, and promote the health and well-being of their users (Hajli, 2014). By leveraging the capabilities of the Internet and technology, OHCs unite people with common health concerns, objectives, or interests. OHCs thus offer a virtual arena where users develop trust to engage in discussions, seek guidance, exchange information, and establish companionship (Fan & Lederman, 2018; Mpinganjira, 2018; Yan et al., 2016). For people grappling with mental illnesses, OHCs facilitate connections and provide emotional support, exchange coping strategies, and offer encouragement rooted in personal experiences (Hodgkin et al., 2018). Overall, OHCs serve as invaluable resources for those searching for support, information, and a sense of belonging concerning their health concerns. They complement conventional healthcare systems and provide additional avenues for nurturing well-being and fostering a sense of community.

Toxicity within online communities denotes the presence of harmful, negative, or disruptive behavior capable of jeopardizing the well-being and experience of community members (Xia et al., 2020). Common manifestations of toxicity within online communities encompass trolling, disrespectful communication, mob mentality, and online shaming (Zhu et al., 2022). Toxicity within online communities, especially within OHCs, has the potential to influence the mental well-being of involved individuals detrimentally. Toxicity can also disrupt the overall dynamics of the community by instilling fear, impeding constructive discourse, and repelling new users (Chipidza, 2021; Zhu et al., 2022), ultimately culminating in an unhealthy or hostile online environment.

Given this background, our research focuses on investigating toxicity and the mental well-being of older adult users within OHCs with a specific focus on the role of *social support*. Research indicates that social support plays a vital role in OHC participation, and exploring outcomes related to social support is pivotal for comprehending the impact of these online platforms (Connolly et al., 2023; James et al., 2022;

Song & Xu, 2023; Wang et al., 2021). Also, as more older adults engage with digital platforms, exploring the impact of online social support on their mental well-being may introduce new theoretical questions about the effectiveness and nature of digital versus face-to-face support in later life (Wang et al., 2021). However, little is known about the influence of OHC social support on the mental well-being of specific groups, such as older adults, who stand to benefit significantly from this form of support.

Moreover, as older adults are more susceptible to emotional distress and mental health issues, exposure to toxic behaviors, such as online bullying or negative comments, can exacerbate feelings of vulnerability and contribute to mental health challenges (as discussed in more detail to follow). However, it remains uncertain whether and to what extent social support can mitigate toxicity in OHCs. We suggest that examining how social support mitigates toxicity in OHCs would hold essential implications in terms of protecting vulnerable users (e.g., older adults) and ensuring that they have access to the support they need.

Finally, as detailed below, our literature review also reveals limited studies addressing the social support concept and its outcomes in the context of OHCs. As elaborated above, social support could be critical in OHC participation regarding supporting vulnerable populations, mitigating negative behavior, and improving health outcomes. These collectively underscore the role of social support in creating inclusive online environments that can significantly benefit older users' mental health in the OHC context. Therefore, in the present study, our objective is to contribute to the Information Systems (IS) literature by answering the following research questions:

RQ1. How does OHC social support influence the mental well-being of older adults?

RQ2. To what extent can OHC social support mitigate the toxicity of older adults in OHCs?

The paper will unfold in the following sequence: we identify the gap by detailing our literature review findings. We then develop the theoretical pieces and hypotheses, followed by a presentation of the data collection and the methodology to analyze the data. Finally, we will delve into our findings' practical and theoretical implications, discussing limitations and opportunities for future research.

2. Literature Review

Given the research questions, our review encompassed two interconnected research domains within the IS literature: (1) social support in OHCs and (2) toxicity in online communities. This examination aimed to pinpoint and clarify the gaps our present study addresses. Regarding social support, our inquiry unveiled a limited number of pertinent studies. Yan and Tan (2014) conducted a study on the exchange of social support within OHCs, evaluating its impact on users' overall health conditions. Their findings demonstrate that users derive significant benefits from active engagement within the community. Actively participating and learning from others enhance their health and empower them to manage their health conditions better.

Conversely, James et al. (2022) approached social support as both an outcome and consequence and explored its dynamics within OHCs. Their investigation revealed that social support can be acquired through both active means (e.g., information sharing) and passive means (e.g., information consumption) within OHCs. Although active engagement directly facilitates the receipt of social support in these communities, the connection between passive participation and social support hinges entirely on the group dynamics within OHCs, including factors like community cohesiveness and altruism. Furthermore, Chen et al. (2020) delved into the origins of social support within OHCs, highlighting the role of affective linguistic signals, such as expressing negative sentiment. Their research demonstrated that such signals elicit the community's informational and emotional support. To encapsulate the studies we examined,

Turning from positive aspects of online communities, toxicity in online communities is gaining traction as a serious concern in IS research and practice. The detrimental impact of toxic behavior by community members is a crucial factor in jeopardizing the long-term viability of online communities. In OHCs, such adverse conduct threatens the essential elements of trust and social support for their effectiveness. Existing

Table 1 provides a comprehensive summary of their key findings and contributions.

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Table 1. Social Support in Online Health Communities

Study	**Method**	**Main Findings**	**Focus**
Chen et al. (2019b)	Quantitative analysis using dynamic panel models	Structural social capital is a precursor to the exchange of social support within OHCs. Social support provisioning has a more pronounced influence on enhancing health literacy and fostering positive health attitudes than receiving social support.	Antecedents and outcomes of social support in OHCs
Chen et al. (2020)	Quantitative analysis using text analysis and machine learning	Affective linguistic signals, such as conveying negative emotions, elicit informational and emotional support in OHCs.	Antecedents of social support in OHCs
Goh et al. (2016)	Quantitative analysis using network analysis	For a rare disease, OHC, urban users are net suppliers, and rural users are net recipients of online social support.	Exchange of social support in OHCs
Guo et al. (2017)	Quantitative analysis using multilinear regression	Doctors benefit from participating in OHCs by developing professional capital from the exchange of social support in OHCs.	Social support and outcomes in OHCs
Huang and Fan (2023)	Quantitative analysis using individual survey	Structured health information positively affects users' acquisition of health knowledge within OHCs. This impact is mediated by users' perceptions of information completeness and ease of understanding.	Informational support and outcomes in OHCs
James et al. (2022)	Quantitative analysis using online individual survey	Active engagement directly fosters the receipt of social support within OHCs. In contrast, the connection between passive involvement and social support relies entirely on the group dynamics within OHCs, including factors like OHC cohesiveness and altruism.	Antecedents of social support in OHCs
Leimeister et al. (2005)	Quantitative analysis using online individual survey	The designed and implemented technology artifacts effectively built trust through components that conveyed the competence and goodwill of the operators.	Social support and outcomes in OHCs
Li et al. (2022a)	Quantitative analysis using online individual survey	Users' perceived social support affects their perception of the usefulness of an OHC for smoking cessation. Also, perceived usefulness positively influences users' intention to share knowledge and continue using the OHC.	Social support and outcomes in OHCs
Liu et al. (2016)	Quantitative analysis using instrumental variable regressions	For the social support of diabetes and depression in OHCs, physicians' participation significantly increases patients' involvement.	Social support and outcomes in OHCs
Park et al. (2018)	Quantitative analysis using text mining and visualization	The sharing of positive emotions, expressions of appreciation for receiving emotional support, discussions related to sleep, and issues related to work are four common themes that emerged in OHCs.	Emotional support in OHCs
Wang et al. (2021)	Quantitative analysis using machine learning and logistic regression	The quantity and alignment of received informational and emotional support serve as positive and significant predictors of the sustained engagement of new users in OHCs.	Social support and outcomes in OHCs
Yan and Tan (2014)	Quantitative analysis using Hidden Markov Model	Users derive substantial benefits from learning and actively engaging within the OHCs. Interacting with others improves their health and bolsters their capacity to manage their illness effectively.	Social support and outcomes in OHCs
Yan and Tan (2017)	Quantitative analysis using linear latent and mixed models	The consensus of users about treatments in OHCs has a positive impact on users' perception of treatment effectiveness.	Social support and outcomes in OHCs

research in online communities has explored various manifestations of online toxicity, including cyber harassment (Lowry et al., 2019), cyberbullying (Chan et al., 2023; Chan et al., 2019; Lowry et al., 2017), disinformation (French et al., 2024; Villacis Calderon et al., 2023), fear of missing out (FOMO), and addiction to their use (James et al., 2017), the spread of fake news (George et al., 2021; Horner et al., 2021; Moravec et al., 2020), toxic polarization, and negative emotions (Horner et al., 2021), trolling activities (Li et al., 2022b), fostering extremism and radicalization (Risius et al., 2024), and discrimination, racism, sexism, homophobia, and other prejudiced behaviors (Kearns et al., 2023). All these toxic behaviors can be inadvertently fostered in OHCs.

Further, our review in the context of online communities indicates that research predominantly focuses on identifying and understanding the causes and effects of toxic behavior. For instance, Li et al. (2022b) investigated how technical aspects like self-anonymity and anonymity of others in online communities affect intentions to engage in collective trolling, examining the interplay between these technical factors and individual social elements such as perceived online disinhibition and social identity. Similarly, Zhu et al. (2022) studied the precursors of toxic behavior in online gaming communities, uncovering how players' interdependence and power dynamics indirectly drive prosocial and toxic behaviors through their passion for gaming.

Additionally, Chipidza (2021) examined the impact of toxicity on the formation of news networks within political subcommunities on Reddit. This study reveals that news sources associated with higher toxicity levels gain prominent positions in these networks, suggesting a reward system that fosters political polarization by disparaging opposing views. In another vein, Xia et al. (2020) investigate the origins and implications of toxicity in online discussions, finding that factors like the propensity of the author and the context of the debate significantly affect language toxicity, which, in turn, influences user engagement and the volume of discussion. There is also a body of research dedicated to the classification (e.g., Fortuna et al., 2021) and dissemination (e.g., Obadimu et al., 2021) of toxic content within online communities, reflecting the breadth and depth of scholarly interest in toxicity within online communities.

In closing, our research distinguishes itself from prior literature by its specific focus on toxicity and the mental well-being of older adult users within OHCs. Leveraging a longitudinal dataset spanning over 11 years, our primary objective is to investigate a causal relationship between social support and the mental well-being of older adults. We also recognize that the issue of user toxicity holds relevance within the context of OHCs, given their inherent purpose and objectives—namely, providing a platform for individuals seeking information, resources, and encouragement related to their health and well-being. Consequently, our research extends its scope to examine an additional relationship between social support and toxicity. We aim to comprehensively elucidate the multifaceted role of social support within OHCs, ultimately contributing to a more holistic understanding of its influence on these online health communities.

3. Theory and Hypotheses

OHCs provide a valuable source of social support for older adult users dealing with challenges related to aging. Existing research has established a connection between social support in the physical world and improved mental well-being in older adults, addressing issues like depression and loneliness (Chen et al., 2019a; Liu et al., 2016). This study examines the relationship between the social support that older adult users receive in OHCs and their mental well-being. We propose that social support in OHCs has a similar impact on the mental well-being of older adult users akin to its effects in the physical world. Additionally, our theoretical framework examines whether OHC social support can mitigate toxic communications from sharing frustrations and ailments associated with aging. Our proposed theoretical model is shown in **Figure 1**.

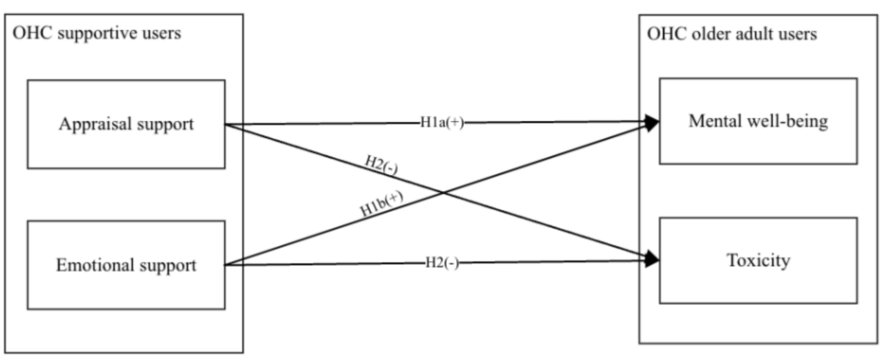

Figure 1. Theoretical Model

3.1. Social Support and Mental Well-Being in OHCs

Social support is defined as the presence or availability of individuals who can receive care, love, and value

(Taylor, 2011). It is pivotal in an individual's overall well-being (Taylor, 2011). Social support encompasses four dimensions, with our study focusing on *emotional* and *appraisal* support, which are particularly protective against mental illnesses like depression and loneliness in older adults (Chen et al., 2019a; Liu et al., 2016).

Appraisal support entails providing feedback, validation, affirmation, and constructive criticism to individuals, allowing them to understand their situation better, evaluate their choices, and feel validated in their thoughts and actions (Langford et al., 1997; Sarason et al., 1990). This form of support contributes to an individual's sense of self-worth and confidence (Haley et al., 1987; Maton, 1988). In the context of OHCs, appraisal support may involve offering positive feedback, validation, and constructive suggestions or alternative viewpoints to individuals who share their health management progress or achievements.

Conversely, emotional support encompasses empathy, understanding, and comfort (Langford et al., 1997; Sarason et al., 1990). It provides a safe environment for people to express themselves, receive compassion, and share their experiences— fostering a sense of connection by addressing emotional needs (Uchida et al., 2008). In OHCs, emotional support may involve responding with empathetic messages to those sharing their health struggles or offering encouragement. Emotional support primarily focuses on well-being by providing empathy and understanding, whereas appraisal support concentrates on evaluating and providing positive feedback to enhance self-assessment and confidence. Both forms of support are invaluable as they contribute to an individual's overall support network and well-being.

In the context of OHCs, we hypothesize that appraisal support positively affects the mental well-being of older adult users. First, appraisal support offers validation and recognition for older adult users' experiences, efforts, and achievements, countering feelings of invisibility or marginalization often experienced by this demographic (D'Cruz & Banerjee, 2020). Feeling valued and acknowledged bolsters self-esteem, ultimately leading to improved mental well-being. Second, positive feedback and constructive peer criticism can reinforce confidence and belief in one's capabilities, fostering a sense of competence. This competence may enhance control and empowerment, reducing helplessness and promoting mental well-being (Feral, 1998; Thompson, 2021). Moreover, we propose that receiving appraisal support cultivates a sense of belonging and connectedness within the OHC. When older adult users receive positive feedback and encouragement, they feel part of a supportive network that understands their unique challenges. This sense of community can act as a social support system, combating isolation and loneliness and fostering positive mental well-being (Girmay & Singh, 2019; Leavell et al., 2019; Son et al., 2021). In summary, we propose the following hypothesis:

H1a. Appraisal support positively affects the mental well-being of older adults in OHCs.

We also anticipate a favorable impact of emotional support on older adult users' mental well-being within OHCs. This expectation is grounded in several key considerations. First, as previously discussed, older adults often grapple with social isolation or loneliness due to many factors. The provision of emotional support within OHCs has the potential to instill a sense of belonging and connection among them. Knowing that their peers empathize with their experiences and emotions can alleviate loneliness, bolstering their mental well-being. Second, older adults are particularly susceptible to heightened emotional distress, often stemming from health-related issues or significant life transitions (Jerusalem & Mittag, 1995; Sun et al., 2011). Having a supportive network within OHCs that actively listens, offers empathy, and provides comforting words can significantly aid in coping with emotional distress. By doing so, it reduces the negative impact of emotional distress on mental well-being.

Furthermore, older adult users may encounter distinct challenges associated with aging or specific health conditions. Emotional support from peers who comprehend their circumstances can validate their experiences and offer a sense of being heard and understood. This validation enhances their mental well-being by affirming their emotions and diminishing self-doubt (Chang & Arkin, 2002; Veage et al., 2014). Lastly, the reception of emotional support within OHCs can bolster the emotional resilience of older adult users (Kamalpour et al., 2021). Older adults can develop the strength and confidence to confront challenges, adapt to changes, and rebound from setbacks through encouragement, empathy, and emotional reassurance. This augmented emotional resilience equips them to better manage their health and mental well-being. Therefore,

H1b. Emotional support positively affects the mental well-being of older adults in OHCs.

3.2. Social Support and Toxicity in OHCs

Toxicity in online communities is characterized by user behaviors and attitudes that engender a detrimental or antagonistic environment, impeding fruitful engagement and amicable interactions. Aside from the several adverse outcomes we reviewed on online toxicity (e.g., cyberharassment, disinformation, FOMO), this toxicity can take various forms and can engender discrimination, racism, sexism, homophobia, and other prejudiced actions (Kearns et al., 2023). These contribute to hostility and marginalization based on individual identities or backgrounds. The adverse impacts of toxicity on online communities are multifaceted: it fosters an unwelcoming environment (Elsayed & Hollingshead, 2022), deters the participation of constructive contributors (Xia et al., 2020), erodes trust and undermines the credibility of the community (Salminen et al., 2021), hampers effective learning and collaboration (Chipidza, 2021), and, most critically, inflicts profound emotional and psychological harm on individuals targeted by such behavior (Zhu et al., 2022).

In the context of OHCs, we argue that if toxicity prevails, it poses a significant threat to the mental well-being of community users. OHC users have distinct characteristics, including a specific focus on health and well-being, a need for trust, support, empathy, and considerations for privacy and confidentiality. These factors shape the unique dynamics of OHCs. Therefore, addressing toxicity within OHCs is of paramount importance. By actively investigating toxicity, we can provide valuable insights to help OHCs fulfill their mission of delivering health-related support, information, and resources to needy individuals.

We hypothesize that receiving social support, whether in the form of appraisal or emotional support, within OHCs will positively reduce toxicity among older adult users. First, when people receive social support and feel understood and validated, it can mitigate feelings of frustration and negativity that may contribute to toxic behavior. Enhanced emotional well-being through social support may reduce the likelihood of engaging in toxic interactions. Second, social support fosters a sense of belonging and connection within the communities, potentially reducing the isolation or alienation experienced by older adult users. This, in turn, can enhance positive interactions and reduce the inclination to engage in toxic behavior. Third, social support helps reinforce positive community norms and values (Chiu et al., 2015).

Community users collectively cultivate a culture of respect, empathy, and kindness through empathetic responses, validation, and encouragement. This positive reinforcement can reduce toxicity and promote healthier interactions within the community. In summary, we propose the following hypothesis:

H2. Social support, whether appraisal or emotional, reduces the toxicity of older adults in OHCs.

4. Methodology

In this study, we utilized a text-mining approach to measure the social support provided to older adults and its relation to their mental well-being within OHCs. To identify the features and affordances that older adults rely on to satisfy their need for support, we draw from the Need-Affordances-Features framework (Karahanna et al., 2018). Similar to previous research (e.g., Chen et al., 2019b, 2020), we gauge the social support older adult users receive due to posting in OHCs. Posts and comments are the main features in OHCs that provide older adults the ability (i.e., affordance) to receive support. To analyze the mental well-being of older adult users, we identify journals in OHCs as the feature that allows older adults to reflect on their problems without the need for intervention from other users (i.e., egocentric affordance). Accordingly, we measure older adults' well-being and toxicity longitudinally over the text of their OHC journals, similar to research that analyzed text to examine mental health features in other contexts (e.g., Amanat et al., 2022; Kawasaki et al., 2020; Trotzek et al., 2020). Next, we examined the causal relationships between social support, toxicity, and well-being among older adult users in OHCs. Given the focal point of our research, we conducted a comprehensive analysis spanning 11 years of data to elucidate the interplay over time between OHC social support and the outcomes of mental well-being and toxicity among older adult users. We place special attention to the identification of causal relationships within the framework of our theoretical model. The following sections describe our data, measures, and analyses.

4.1. Data

To validate our theoretical model, we procured data from DailyStrength, an OHC primarily dedicated to facilitating support groups, fostering connections, and extending support by exchanging experiences and challenges among its users. This community encompasses a diverse array of support groups catering to various medical conditions and life-related obstacles, including but not limited to depression, divorce, and parenting. Given our research questions, our primary focus was on users participating in the *Depression* and *Loneliness* groups, which constitute the largest part of the Mental Health sub-community. Users in these groups can maintain personal journals for self-reflection on their mental health, pose queries, initiate discussions through the platform's discussion boards, and engage with other users by commenting on posts.

Our dataset in its raw form encompasses a longitudinal collection of information, explicitly targeting users aged 50 and above, amounting to 853 individuals who registered on the platform between 2006 and 2016. The rationale behind considering individuals aged 50 and above as "older adult users" is grounded in recognizing that the definition of "older adult" can vary across different contexts and cultures. However, considering several factors associated with aging, health, and life transitions, the age threshold of 50 and above is a reasonable demarcation point (Santini et al., 2020).

Figure 2 shows a typical scenario of social support exchange in OHCs. This exchange typically unfolds over various time frames, beginning when an older adult member posts a support request. Subsequently, other members respond with supportive comments, often leading the original poster to document their self-reflections in a journal entry. We collected all journals, posts, and comments associated with these older adult users to analyze this process. This was accomplished using a specialized web data extraction tool developed by one of our team members. This method compiled a comprehensive dataset comprising 14,250 journals initiated by these users, 2,268 original posts, and 22,762 comments received in response.

4.2. Variables and Measures

This study examined three primary variables: social support (appraisal and emotional), toxicity, and mental well-being. We employed a text-mining approach to assess these variables, analyzing user-generated content, including posts, comments, and journals. This textual approach has gained prominence in IS and

Figure 2. Social Support Exchange Scenario

healthcare research, leveraging machine learning techniques to measure online social support, mental health, and online community toxicity across various contexts (e.g., Chen et al., 2019b, 2020; Chipidza, 2021; Fortuna et al., 2021; Zhang et al., 2022).

In contrast to previous research, our text-mining approach is based on the innovative SenticNet API (https://sentic.net/api/). SenticNet represents a cutting-edge neurosymbolic AI framework that integrates natural language processing techniques, such as parsing, symbolic encoding, and knowledge maps, with machine learning methods, including deep learning, to identify affective states and salient emotions within texts (Cambria et al., 2020; Cambria et al., 2022). Unlike conventional lexicon-based models like AFINN and SentiWordNet, SenticNet incorporates the symbolic meanings of words in texts, enhancing its capacity to detect sentiment and meaning within textual content. This novel approach has demonstrated superiority over lexicon-based models in sentiment analysis (e.g., Rastogi et al., 2022). Furthermore, the latest version of the SenticNet API offers the ability to derive stress-related metrics, such as depression and well-being scores, from texts. These metrics are computed using language encoders/decoders (e.g., Roberta and XLNet) in conjunction with SenticNet neuro-symbolic structures, as illustrated by (Kumar et al., 2022).

Our study focuses on two dependent variables: the mental well-being and toxicity of older adult users. To measure mental well-being, we harnessed the well-being assessment functionality provided by the API. This function evaluates subjective mental well-being, encompassing various aspects of mental health, including cognitive and emotional assessments of life satisfaction and happiness (SenticNet, 2023). The

API accepts text input, whether a sentence or a paragraph, and produces a well-being score ranging from -1 (indicating high stress) to 1 (meaning high well-being).

As discussed earlier, we selected user journal entries as the input texts for analysis. These journal entries (exemplified in **Table A.5**) often contain specific language and semantic structures that offer valuable insights into users' mental health. Consequently, we analyzed well-being assessment scores derived from user journals over time to track changes in the mental health of older adult users as conveyed through their journaling within the community.

To assess user toxicity, we employed the API's toxicity spotting functionality. Detecting toxicity is a significant challenge in online communities and social networking platforms (Fortuna et al., 2021; Obadimu et al., 2021). However, the API utilizes a sophisticated approach for toxicity measurement in a multilabel environment, employing a multichannel convolutional bidirectional gated recurrent unit, as detailed in SenticNet (2023). Toxicity scores range from 0 (indicating minimal toxicity) to 1 (representing high toxicity). We analyzed toxicity spotting scores derived from user journals over time to track changes in toxicity reported by older adult users through their journal entries.

Our independent variables comprise two dimensions of social support: appraisal and emotional support. We employed the Valence Aware Dictionary and sEntiment Reasoner (VADER) semantic rule model developed by Hutto and Gilbert (2014) to measure appraisal support. VADER was explicitly designed and trained on text content like that found in OHCs (Hutto & Gilbert, 2014) and has been commonly used in prior research within online health settings (e.g., Gui et al., 2021; Valdez et al., 2020). We quantified appraisal support using the positivity scores generated by VADER based on comments made by other users on the focal user's posts. These scores assess the degree of affirmation and validation expressed by other users (i.e., appraisal support) and range from 0 (low) to 1 (high).

We derived emotional scores from user comments on the focal user's posts to measure the emotional dimension. The API generated the raw scores used for calculating emotional scores, capturing four emotional aspects: introspection, temper, attitude, and sensitivity (SenticNet, 2023), as conveyed to older adult users through the comments they received. We then averaged these raw scores across the four emotional dimensions to compute an overall emotional score for each more senior adult user, ranging from -100 (low) to 100 (high). For illustrative examples of user posts, comments, and journals analyzed using the API, refer to **Table A.6**, **Table A.7**, and **Table A.8**. Additionally,

summarizes all the variables.

Table 2. Variable Description and Measures

Variable	**Description**	**Measure**
Social support: appraisal (Langford et al., 1997; Sarason et al., 1990)	The degree of feedback, validation, and affirmation provided to users.	The positivity score of user comments generated by the VADER semantic rule model.
Social support: emotional (Langford et al., 1997; Sarason et al., 1990)	The degree of empathy, understanding, and emotional comfort provided to users.	The average raw scores of the four emotional degrees (introspection, temper, attitude, and sensitivity) were generated by the SenticNet API.
Mental well-being	The absence of stress expresses the overall psychological and emotional well-being.	The well-being assessment score is based on user journals generated by the SenticNet API over time.
Toxicity (Xia et al., 2020)	The degree of users' harmful, negative, or/and disruptive behavior.	The toxicity spotting score is based on user journals generated by the SenticNet API over time.
Depression (Blazer, 2002)	The degree of continual hopelessness, sadness, and lack of pleasure or interest in daily activities.	The depression spotting score is based on user journals generated by the SenticNet API over time.
Personality	The aggregation of unique patterns of thoughts, emotions, and behaviors that set an individual apart from others.	The MBTI (Myers-Briggs Type Indicator) categories/types are based on user journals generated by the SenticNet API over time.
Age	A user's age.	Users' community profile data.
Gender	A user's gender.	Users' community profile data.
Friends	The number of connected friends of a user in the community.	Users' community profile data.
Posts	The number of posts by a user.	Users' community profile data.
Length	The length of the original post.	The number of characters in a post.
Time	The difference in time between a user writing a journal and receiving a comment.	The unit for the time difference is in milliseconds.
Likes	The total count of "likes" received on a post.	Users' community interaction data.
Comments	The total count of comments received on a post.	Users' community interaction data.
Positivity (post)	The mental positivity level of a user is reflected by the user's original posts.	The mental positivity score is based on user posts from the SenticNet API.

4.3. Estimation Approaches and Models

Our study adopted an OLS model framework to examine the causal impact of social support from other users in OHCs on an elderly user's mental well-being. Importantly, taking advantage of the panel structure of the dataset, we gauge social support (the main explanatory variable) based on information, i.e., other people's comments, before the well-being (the outcomes) measures. Specifically, we derive the level of social support based on other OHC users' comments on an earlier post written by an individual. Then, the outcomes are measured utilizing a new journal written by that individual after other users' comments are made on their previous posts. This procedure guarantees that there would be no reverse causality in our regression model. We discuss this point further later in the paper. Additionally, we endeavored to address other potential endogeneity issues and arguably provide a causal estimate of the effect of social support on the outcomes of interests. We discuss this in detail later in the section.

We set two restrictions on the data. First, we designated one week for comments on an individual's post based on the understanding that feedback received after an extended interval is often perceived as less relevant. Nonetheless, this seven-day timeframe was chosen to ensure a sufficiently large sample size for our analysis, balancing the need for temporal relevance with the availability of ample data for robust statistical evaluation. Second, we limited the time gap between receiving a comment and writing a new journal entry. Specifically, we excluded journal-comment pairs if a journal is written two days or less after receiving a comment on the individual's original post. As elaborated later in the paper, we have observed that longer time gaps result in more minor effects of social support.

To formally investigate the impact of social support on the mental well-being and toxicity of older adult users, we formulate the following model:

$$Y_{ij} = \alpha_0 + \alpha_1 Social\ Support_{ij} + X_{ij}\Omega_2 + \lambda_k + \gamma_m + \upsilon_{ij} \tag{1}$$

In equation (1), Y_{ij} denotes the dependent variables that measure the mental well-being and toxicity of individual i, reflected by journal j. Our primary explanatory variable is denoted by $Social\ Support_{ij}$. We employ two variables to capture two dimensions of social support: appraisal and emotional support. As discussed, these two measures are obtained from quantifying comments written by peer users on individual i's posts. X_{ij} stands for a set of pre-determined covariates controlled in our baseline specification, including individual i's demographic information (i.e., age and gender), number of friends and posts in the community, and the length of the original post on which other users commented. λ_k and γ_m denote year and month fixed effects, respectively, accounting for potential differences in the outcomes across years and months. υ_{ij} is the error term. In this study, we analyze the two dependent variables separately. Robust standard errors are employed in all analyses.

The coefficient of main interest is α_1, which captures the effects of social support on the outcomes. We examine appraisal and emotional support separately. Also, because of our social support measures, i.e., obtained from comments independently written by other users online, they are arguably exogenous. Therefore, α_1 represents a causal link between social support and the dependent variables.

4.4. Addressing Endogeneity Concerns about Potential Threats to Identification

Several potential threats to our model identification warrant consideration. First, one might express concerns regarding the possibility of reverse causality, which could arise if there was a question of whether other users' comments are provided after reading an individual's journal, potentially leading to reverse causation. However, this concern does not apply to our study for two crucial reasons. First, comments from other users are directed toward posts, not journals, establishing a clear separation between the two. Moreover, our approach intentionally measures dependent variables based on fresh journal content created by an individual *after* receiving comments on their previous post. This deliberate sequencing eliminates any possibility of reverse causation.

Second, our dependent variables are constructed by quantifying the content of journals authored by different individuals, reflecting their mental well-being to some extent. To mitigate potential endogeneity concerns arising from unobserved user characteristics, we adopt a strategy akin to previous studies (Chen et al., 2019b; Kuang et al., 2019) by incorporating personality-fixed effects in an extended specification. This adjustment allows us to account for the mean differences across groups of individuals composed of varying personality traits. Notably, controlling personality, when orthogonal to other users' comments, enhances the precision of our estimations without affecting the coefficients. Conversely, the personality of the journal's author becomes an omitted variable if it is correlated with the outcome and explanatory variable (the social support measure derived from other users' comments) simultaneously. If this is the case, although arguably very unlikely to happen, we must include the personality of the journal's author as a covariate. Our detailed results, which follow in the subsequent sections, provide compelling evidence that this is not a concern in our study because including personality does not influence the estimates.

Third, although an individual journal author has no control over other users' comments, there is a potential source of an omitted variable issue. Other users' comments could be influenced by the tone and content of the individual's original post on which these comments are made. For instance, if an individual's original post conveys positivity and optimism, it might inspire other users to feel joy and provide positive comments. Consequently, if the individual continues to exhibit positivity by writing a positive journal later and thus appears to have high mental well-being in our data, we might observe a positive correlation between social support (appraisal or emotional) and mental well-being. However, this correlation merely reflects an individual's cheerful disposition during that time rather than the positive effect of social support on mental well-being. To address this concern, we control the original post's positivity measure and individual personality. Our later findings demonstrate that including this control variable does not alter the results.

Furthermore, in an alternate specification, we introduce controls for the treatment intensity of social support. This allows us to disentangle any effects of treatment intensity from the two dimensions of social support under investigation. In this study, our primary focus is to examine how the "level" of social support influences individuals' well-being. However, we also recognize the potential impact of the "intensity" (for how long and how many times) of the treatment on the outcomes of interest, independent of its importance. Therefore, we need to disentangle the effects of both the level and intensity of the treatment. We gauge treatment intensity using three variables: the time elapsed between an individual receiving a comment and writing a journal, the total count of "likes," and the total count of comments received on the corresponding post. Our results indicate that accounting for the effect of treatment intensity has no bearing on our primary conclusions.

Lastly, one might raise concerns that the random content of journals could influence our results. However, this concern does not threaten our identification for several reasons. First, supportive comments are more likely to coincide with journals that reflect higher levels of mental health. This can be viewed as a mechanism through which social support contributes to improved mental well-being, propelling individuals toward more positive future journal content. Second, if journal content is genuinely random, with no inherent influence of social support, it remains orthogonal to other users' comments on previous posts. In this scenario, comments and journals are uncorrelated. Third, conversely, if individuals with better mental health, who produce positive posts and journals, coincidentally receive a higher level of social support from other users, our identification strategy, encompassing individual personality and the positivity of the original posts, mitigates such concerns, as discussed earlier. Finally, our mental health measures do not rely on the narrative content of the journals in the first place. Therefore, the randomness of journal content does not influence our results.

5. Results

Table 3 summarizes the descriptive statistics (see **Table A.5** for correlations). **Table 4** presents the main results from estimating Equation (1) above. In all the models, we also include *depression* as an additional analysis to examine whether social support affects specific mental illnesses. The three dependent variables that gauge people's overall mental well-being, depression, and toxicity are analyzed in panels A, B, and C, respectively. All regressions contain a set of predetermined individual covariates, month fixed-effects, and year fixed-effects. **Table 4** also details the causal effects of appraisal support on these three outcomes using four different specifications and reports the results from the least to the most conservative specification.

In column 1, the results indicate that receiving higher appraisal support significantly and positively enhances overall mental well-being. The coefficient signifies that a 10% increase in appraisal support from other users provides a 0.03 standard deviation increase in overall mental well-being, equivalent to a 9% rise when considering the average score of 0.229. This effect is statistically significant at the 1% level. In

Table 3. Summary Statistics

Variables	**Mean**	**SD**	***n***
Outcomes			
Overall Well-being	0.229	0.655	1,704
Depression	0.228	0.370	1,704
Toxicity	0.166	0.294	1,704
Social Support			

Appraisal support	0.205	0.191	1,704
Emotional support	27.70	47.20	1,388
Covariates			
Age	66.30	19.56	1,704
Female	0.587	0.493	1,704
Number of friends	2.95	1.12	1,704
Number of posts	146.67	135.97	1,704
Length of the original post	490.06	426.79	1,704
Number of likes	0.036	0.291	1,704
Number of comments on the original post	2.58	0.985	1,704
Time gap from comment received to journal writing	17.58	1.44	1,704
Positivity of the original post	0.102	0.087	1,704

Notes. The time gap from comments received to journal writing is log-transformed; SD = standard deviation.

Table 4. The Effects of Appraisal Support on Toxicity and Mental Well-Being

	Dependent Variables			
	(1)	**(2)**	**(3)**	**(4)**
Panel A:	*Overall Mental Well-Being*			
Appraisal support	0.208***	0.206***	0.205***	0.186**
	(0.080)	(0.078)	(0.077)	(0.078)
Mean of DV	0.229	0.229	0.229	0.229
Panel B:	*Depression*			
Appraisal support	-0.020	-0.045	-0.046	-0.047
	(0.050)	(0.045)	(0.045)	(0.045)
Mean of DV	0.228	0.228	0.228	0.228
Panel C:	*Toxicity*			
Appraisal support	-0.088**	-0.091***	-0.091***	-0.089***
	(0.038)	(0.033)	(0.033)	(0.034)
Mean of DV	0.166	0.166	0.166	0.166
Predetermined individual controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes
Personality fixed effects	no	yes	yes	yes
Intensity of social support	no	no	yes	yes
Positivity of the original post	no	no	no	yes
Observations	1,704	1,704	1,704	1,704

Notes. Standard errors in parentheses; *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$.

column 2, we introduce personality fixed effects to address concerns about potential correlations between an individual's personality and the appraisal support provided by others. This also helps capture average differences across groups of individuals with similar personalities. Notably, the estimate remains consistent. Moving to column 3, we incorporate multiple variables to measure treatment intensity stemming from appraisal support. This step aims to disentangle the effect of appraisal support from the impact of treatment intensity. We precisely control the total number of "likes" and comments on the corresponding post and the time difference between an individual's journal entry and receiving a comment on the original post. The coefficient remains unaffected after accounting for these treatment intensity measures.

To address the potential influences of the original post on other users' comments, we control the positivity measure of the original post in the final column (column 4). Although the coefficient experiences a slight decrease from 0.205 to 0.186, it retains both statistical significance and substantive magnitude. Consequently, in our most conservative specification, as presented in column 4, the results indicate that a 10% increase in appraisal support leads to an 8% increase in overall mental well-being. Our estimates exhibit remarkable consistency across all specifications, underscoring a substantial and positive causal effect of appraisal support on individuals' overall mental well-being.

Panel C, akin to the mental well-being estimation process, presents the estimated effects of appraisal support on individuals' toxicity levels. The findings reveal that appraisal support strongly and negatively influences toxicity, implying that people exhibit lower toxicity levels when receiving more positive support from other community users. To be precise, a 10% increase in appraisal support corresponds to a reduction of approximately 5.4% in toxicity levels. These results include a comprehensive set of covariates and fixed effects in alternative specifications. As an additional analysis, we investigate the impact of appraisal support on individuals' depression levels and report the results in panel B. Although the results suggest a negative effect of appraisal support on depression levels, all coefficients lack statistical significance.

Applying a similar empirical approach, we explore the effects of emotional support on individuals' toxicity and mental health in **Table 5**. Two key observations emerge. First, unlike appraisal support, emotional support does not influence the dependent variables. The coefficients remain modest in magnitude and statistically insignificant. Second, the consistency of estimates across specifications reinforces these findings' robustness and causal nature.

Table 5. The Effects of Emotional Support on Toxicity and Mental Well-Being

	Dependent Variables			
	(1)	**(2)**	**(3)**	**(4)**
Panel A:	*Overall Mental Well-Being*			
Emotional support	0.006	0.004	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Mean of DV	0.159	0.159	0.159	0.159
Panel B:	*Depression*			
Emotional support	-0.005*	-0.003	-0.003	-0.003

	(0.003)	(0.002)	(0.002)	(0.002)
Mean of DV	0.252	0.252	0.252	0.252
Panel C:	*Toxicity*			
Emotional support	-0.002	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Mean of DV	0.184	0.184	0.184	0.184
Predetermined individual controls	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes
Personality fixed effects	no	yes	yes	yes
Intensity of social support	no	no	yes	yes
Positivity of the original post	no	no	no	yes
Observations	1,388	1,388	1,388	1,388

Notes. Standard errors in parentheses; *** = $p < 0.01$; ** = $p < 0.05$; * = $p < 0.1$.

5.1. Additional Analyses

In addition to considering depression as an outcome, we conducted several supplementary analyses. First, in our primary analysis, we restricted the time gap between a person's creation of a new journal entry and receiving a comment, limiting it to two days or less. This allowed for a relatively brief time window within which social support could potentially be sufficiently relevant to influence mental health. Intuitively, one would anticipate that as the time gap lengthens, the relevance of these comments diminishes, leading to a weaker effect of social support. We re-estimated equation (1) to test this hypothesis while gradually extending the time window to three and four days. Detailed results are presented in **Appendix A**, **Table A.1**, **Table A.2, Table A.3**, and **Table A.4.**

Several noteworthy findings emerged. First, as a general trend, we observed that the estimates decrease in magnitude as the time window expands. When individuals promptly receive peer social support, the effect is more pronounced. Conversely, when other users' comments on an individual's post are delayed, their impact becomes less significant, and the beneficial effect of social support diminishes.

Second, in contrast to the baseline results in **Table 5**, where we found no significant effect of emotional support, we did identify statistically significant effects on the three outcomes in some of the specifications. This is attributed to the inclusion of more data observations in the working sample as we increased the time gap, resulting in more precise estimates and improved statistical significance. However, the magnitude of the coefficients is smaller in these cases, as explained earlier.

Third, the estimated effects of appraisal support consistently maintain statistical significance within all

2 to 4-day time windows, highlighting the substantial influence of appraisal support on improving individuals' mental well-being.

Fourth, we explored the possibility that the effects of social support may exhibit heterogeneity. We thus examined potential variations in treatment effects based on individuals' gender and the pre-determined degree of positivity evident in their original posts, on which other users commented. We conducted separate analyses for appraisal and emotional support, and the results are presented in **Table 6** and **Table 7**, respectively.

In Panel A of **Table 6**, we investigated the potential heterogeneous effects of appraisal support on the three outcomes based on gender. The coefficient of the interaction term between appraisal support and the female indicator, which captures any differences in treatment effects between females and males, is particularly interesting. All three estimates were statistically indistinguishable from zero across columns (1) to (3). These results suggest that the effects of appraisal support on individuals' overall mental well-being and toxicity levels do not differ significantly based on gender.

Panel B analyzes the outcomes based on the degree of positivity in individuals' original posts, a pre-determined and exogenous factor. We categorized the sample into three groups: the "very positive," the "very negative," and the remaining 40% serving as the benchmark (omitted) group for reference. Specifically, the "very positive" group includes individuals whose posts ranked among the top 30% in positivity, whereas the "very negative" group comprises the bottom 30% in post positivity. Our regression analyses focus on the coefficients of the interaction terms. In summary, our findings suggest that compared to individuals who composed relatively neutral posts, the impact of appraisal support on the "very positive"

Table 6. Heterogeneous Effects of Appraisal Support

	(1)	**(2)**	**(3)**
	Wellbeing	**Depression**	**Toxicity**
Panel A:	*by Gender*		
Appraisal support	0.296**	-0.071	-0.129**
	(0.124)	(0.071)	(0.052)
Female	0.176***	-0.016	-0.065**
	(0.057)	(0.033)	(0.026)
Appraisal support × Female	-0.217	0.048	0.078
	(0.154)	(0.089)	(0.066)
Panel B:	*by Original Post's Positivity*		

Appraisal support	0.371**	-0.153	-0.162**
	(0.158)	(0.097)	(0.071)
Very Negative (bottom 30%)	0.201***	-0.149***	-0.132***
	(0.052)	(0.028)	(0.022)
Very Positive (top 30%)	0.077	-0.020	-0.021
	(0.058)	(0.036)	(0.026)
Appraisal support × Very Negative	-0.429**	0.293**	0.209**
	(0.201)	(0.118)	(0.087)
Appraisal support × Very Positive	-0.096	0.032	0.014
	(0.203)	(0.127)	(0.087)
Predetermined individual controls	yes	yes	yes
Year fixed effects	yes	yes	yes
Month fixed effects	yes	yes	yes
Personality fixed effects	yes	yes	yes
Intensity of social support	yes	yes	yes
Positivity of the original post	yes	yes	yes
Observations	1,704	1,704	1,704

Notes. All regressions include the complete set of covariates and fixed effects, as shown in Table 5, with one adjustment: the positivity of original posts is now divided into two separate indicators in Panel B. These two indicators represent the groups of individuals with the top 30% and bottom 30% positive posts.

group is not statistically distinguishable. All the coefficients in this group exhibit relatively small magnitudes and lack statistical significance. Conversely, the results indicate that the effects of appraisal support on enhancing overall mental well-being and reducing toxicity are notably reduced in magnitude for the "very negative" group compared to the benchmark group. This implies that when people reach a certain level of negativity in their posts, the potency of appraisal support in improving their mental health substantially weakens. Subsequently, we explore potential variations in the effects of emotional support using a similar approach. The results are presented in **Table 7.** In Panel A, we examine the impact of emotional support by gender and find no evidence of heterogeneous effects on any of the outcomes.

In Panel B, we consider the effects of emotional support based on the degree of post-positivity. The results indicate that, when assessing the impact of emotional support on depression, the "least positive"

Table 7. Heterogeneous Effects of Emotional Support

	(1) Wellbeing	**(2) Depression**	**(3) Toxicity**
Panel A:	*by Gender*		
Emotional support	0.006	-0.003	-0.003
	(0.006)	(0.004)	(0.003)
Female	0.216***	-0.022	-0.082***
	(0.058)	(0.034)	(0.027)
Emotional support × Female	-0.006	0.000	0.003
	(0.008)	(0.005)	(0.004)
Panel B:	*by Original Post's Positivity*		

Emotional support	0.007	-0.006	-0.002
	(0.006)	(0.004)	(0.003)
Very Negative (bottom 30%)	0.197***	-0.127***	-0.142***
	(0.053)	(0.028)	(0.023)
Very Positive (top 30%)	0.139***	-0.028	-0.054**
	(0.047)	(0.031)	(0.021)
Emotional support × Very Negative	-0.007	0.010*	0.004
	(0.010)	(0.005)	(0.004)
Emotional support × Very Positive	-0.004	0.000	0.000
	(0.010)	(0.006)	(0.005)
Predetermined individual controls	yes	yes	yes
Year fixed effects	yes	yes	yes
Month fixed effects	yes	yes	yes
Personality fixed effects	yes	yes	yes
Intensity of social support	yes	yes	yes
Positivity of the original post	yes	yes	yes
Observations	1,388	1,388	1,388

Notes. All regressions include the complete set of covariates and fixed effects, as in **Table 4**, with one adjustment: the positivity of original posts is now divided into two separate indicators in Panel B. These two indicators represent the groups of individuals with the top 30% and bottom 30% positive posts.

group experiences a somewhat more pronounced effect compared to the omitted group of people who composed relatively neutral posts. However, this difference only reaches marginal significance. We find no evidence of a stronger or weaker effect on the "post-positive" group compared to the omitted group.

6. Discussion

OHCs serve as invaluable resources for people who need support, information, and a sense of belonging concerning their health concerns. They complement conventional healthcare systems and offer additional avenues for nurturing well-being and fostering a sense of community. OHCs are particularly helpful for mental well-being, involving a person's overall psychological and emotional health. Notably, the mental well-being of older adults exhibits significant variability and can be influenced by many factors. By providing tailored support and valuable resources and addressing their unique needs, OHCs have the potential to enhance their mental well-being and improve their quality of life. However, OHCs have the potential to harm users' well-being if they develop toxicity. Toxicity can instill fear, impede constructive discourse, and repel new users, creating an unhealthy or hostile online environment. It remains uncertain whether and to what extent social support can mitigate toxicity within OHCs.

Against this backdrop, our research delves into the intersection of toxicity and the mental well-being of older adult users within OHCs, with a specific focus on the role of social support. Using a comprehensive longitudinal dataset spanning 11 years of more senior adult user interactions in a leading OHC, our study delves into the effects of social support on older adult users' mental wellness and toxicity. Our findings reveal that although appraisal support has a robust influence on improving the overall mental well-being of older adult users and reducing toxicity, emotional support has a limited influence on these outcomes. Additionally, we examine the potential heterogeneous effects of appraisal support based on the mental positivity level reflected in older adults' original posts. The impact of appraisal support is marginal for users reaching a certain level of negativity, referred to as the "very negative group." Moreover, our results suggest that the timing of social support reception from other users in the OHC plays a crucial role. With these insightful findings, our study holds several implications for advancing our understanding of social support, toxicity, and mental well-being within online health communities.

6.1. Contributions to Research, Theory, and Practice

Our original research makes several noteworthy contributions to research and theory related to the mental well-being of older adult users of OHCs. These contributions shed light on essential aspects of these phenomena and have practical implications for practitioners and future research.

Appraisal Support's Causal Effect: One of the primary contributions of our study is the finding of a causal effect of appraisal support on the mental well-being and toxicity of older adult users in OHCs. Unlike previous research that primarily focused on emotional and informational dimensions of social support (recall **Table 1**

Turning from positive aspects of online communities, toxicity in online communities is gaining traction as a serious concern in IS research and practice. The detrimental impact of toxic behavior by community members is a crucial factor in jeopardizing the long-term viability of online communities. In OHCs, such adverse conduct threatens the essential elements of trust and social support for their effectiveness. Existing

Table 1), we emphasize the significance of appraisal support. Appraisal support involves validation, self-esteem reinforcement, coping with loneliness, and promoting a sense of purpose (Taylor, 2011). These elements play a vital role in enhancing the mental well-being of older adult individuals.

On the one hand, our findings offer actionable insights for practitioners and healthcare providers by establishing a causal link between appraisal support and improved mental well-being. This evidence suggests that fostering a culture of appraisal support within OHCs can yield multiple benefits. It enhances senior members' well-being and contributes to the community's health and information dissemination. Practitioners dedicated to improving the mental health of older adults, primarily through digital platforms like OHCs, can use this knowledge to design interventions and support strategies that prioritize appraisal support (Sarason et al., 1990).

On the other hand, we suggest that elderly users' toxic behavior may be more likely to lead to the dissemination of harmful and misleading information within the community because of factors like perceived authority, trust in seniors, and cultural respect. As such, the finding of a causal effect of appraisal support on the toxicity of older adult users indicates that fostering a culture of appraisal support would enhance senior members' well-being and better support others in their health journeys.

Unique Insights on Emotional Support: Our research stands out by providing unique insights into the role of emotional support in OHCs, particularly for older adult users. In contrast to previous studies that have shown a positive effect of emotional support on mental health in OHCs (Park et al., 2018; Yan & Tan, 2014), our findings do not support this relationship. This deviation can be attributed to several key differences in our study design.

First, we focused exclusively on older adult users, whereas prior research did not differentiate users by age. This distinction acknowledges that the impact of emotional support may vary across different demographic groups, and our study emphasizes the importance of considering these nuances when examining the effects of social support.

Second, our investigation spans an extensive 11-year period, offering a longitudinal perspective on the impact of emotional support. In contrast, previous results were based on datasets covering shorter timeframes, ranging from several weeks to years, and this extended observation period allowed us to capture long-term trends and changes in mental well-being, offering a more comprehensive understanding of the relationship between emotional support and mental health.

Furthermore, our study employed textual analysis using users' journals and introduced a novel approach, the SenticNet API, to measure mental health metrics. This methodology allowed us to measure mental health more precisely by capturing users' self-reflection and changes over time. This detailed analysis provides a nuanced view of the effects of emotional support on mental well-being in OHCs (Liu et al., 2020).

Given these considerations, our findings are consistent with the importance of emotional support but underscore the need for future studies to explore different methodologies and contexts to corroborate or complement our results. Understanding how emotional support operates in specific demographic groups and over extended periods can provide a more nuanced perspective on its role in promoting mental well-being in OHCs (Chen et al., 2020; Park et al., 2018; Yan & Tan, 2014).

Heterogeneous Effects of Social Support: Our research delves deeper into the heterogeneous effects of social support, revealing a condition where the impact of appraisal support hinges on the degree of positivity in a user's original post. This finding is crucial as it suggests that the effect of appraisal support may be marginal for users with severe mental issues. Although receiving social support benefits mental health, this insight emphasizes its limitations.

This finding aligns with existing research, which demonstrates that in OHCs addressing diabetes and depression, the active involvement of physicians markedly amplifies the effects of social support (Liu et al., 2020). This emphasizes that although cultivating a culture of social support is beneficial, it represents just one facet of the multifaceted formula for the sustained success of OHCs. Collaboration with healthcare professionals and experts who can offer precise information and insights is essential. Such partnerships are critical not only for the well-being of a diverse user base but also for bolstering the community's credibility and trustworthiness (Liu et al., 2020).

Understanding the conditions under which different forms of social support are most effective can inform targeted interventions and support strategies within OHCs. For example, users with severe mental issues may require additional interventions beyond social support, such as access to mental health professionals (Sarason et al., 1990).

Timing of Social Support: Our study also reveals the importance of the timing of social support within OHCs. Specifically, we found that when other users comment on an elderly user's post with longer delays, the positive influence of appraisal support diminishes. This observation aligns with studies in online communities showing that users tend to pay more attention to earlier replies than later ones (Hamilton et al., 2017; Idowu & McCalla, 2018).

OHCs can consider implementing content sorting algorithms that arrange replies/comments by relevance instead of time to address this issue. This approach ensures that users receive the most appropriate content and support when they need it most. Additionally, using tags or labels and providing timely notifications can enhance the user experience and engagement within these communities (Hamilton et al., 2017; Idowu & McCalla, 2018).

6.2. Implications for Management, Practice, Society, and Policy

Given our findings, we provide two actual cases that further illustrate the implications of our research on management, practice, society, and policy. They show how research findings such as ours can inform management decisions, influence practice, drive societal changes, and even shape policies to create more supportive and healthier online environments for users.

6.2.1. Case 1: PatientsLikeMe, A Platform for Patients with Chronic Conditions

PatientsLikeMe (https://www.patientslikeme.com/) is an online platform that allows patients with various chronic conditions to connect, share their experiences, and support each other. The platform embodies the principles of social support and fosters a sense of community among users. Research findings on social and appraisal support's positive effects have influenced the platform's management.

PatientsLikeMe has implemented features that encourage users to provide and receive emotional and appraisal support. Users can share their health experiences, track progress, and receive peer feedback. The platform also provides resources and information on various conditions. By prioritizing these forms of support, PatientsLikeMe has created a valuable resource for individuals facing chronic illnesses.

The success of PatientsLikeMe has drawn attention from policymakers and healthcare providers. It demonstrates the potential of online communities in improving the mental well-being and quality of life of patients with chronic conditions. Policymakers may consider supporting initiatives that encourage the development of similar platforms and ensure that patient data privacy and ethical considerations are addressed. Additionally, healthcare providers may integrate OHCs like PatientsLikeMe into their care plans to enhance patient support and engagement.

6.2.2. Case 2: Reddit's r/AskDocs, A Subreddit for Medical Advice

Reddit hosts online communities called subreddits, where users can discuss assorted topics. One such subreddit is r/AskDocs, where individuals seek medical advice from healthcare professionals and share their health concerns. This platform exemplifies seeking emotional and informational support in an OHC.

In this case, Reddit's management recognized the importance of fostering a culture of empathy, understanding, and constructive engagement. They have implemented a system where verified medical professionals respond to users' health-related queries. Users can also share their experiences and receive support from others who may have faced similar health issues. This approach ensures that users receive reliable medical advice while benefiting from emotional support.

The existence and success of platforms like r/AskDocs highlight the potential of harnessing online communities for health-related purposes. Healthcare policymakers may consider guidelines and regulations that encourage transparency in online healthcare discussions and ensure the qualifications of professionals offering advice. Additionally, healthcare providers may leverage platforms like r/AskDocs to supplement traditional healthcare services, especially in cases where patients seek initial guidance or second opinions. The collaboration between healthcare professionals and online communities can improve patient outcomes and satisfaction.

6.3. Limitations and Future Research Opportunities

Although our research has illuminated crucial facets of social support, mental well-being, and toxicity within OHCs tailored for elderly users, it is incumbent upon us to acknowledge its constraints. These limitations serve as signposts pointing the way toward several compelling research opportunities. Addressing these limitations and venturing into further unanswered questions will propel understanding of these intricate phenomena and pave the path toward cultivating more supportive and healthier OHCs.

Generalizability: Our study predominantly hinges on a specific OHC dataset spanning 11 years, a snapshot of the diverse OHC landscape. Recognizing that social support and toxicity dynamics may ebb and flow across various platforms and communities, future research endeavors should encompass multiple datasets and platforms. For example, researchers can conduct comparative studies that traverse the diverse contexts of community dynamics, support structures, and toxicity levels. These comparisons can serve as further evidence that can be used to illuminate best practices and inform the development of guidelines aimed at fostering healthier OHCs. This approach is essential to ensure the effective generalization of our findings and to paint a more comprehensive picture.

Age Focus: Our research's exclusive spotlight on elderly users within OHCs, although pivotal, beckons for exploration beyond age confines. Future investigations should delve into the intricate interplay of social support, toxicity, and mental well-being across user groups of diverse ages. Moreover, there are many opportunities to examine the influence of demographic factors. By dissecting how variables like age, gender, and cultural backgrounds intersect with social support, toxicity, and mental well-being in OHCs, researchers can unearth valuable insights. This insight will pave the way for tailoring support strategies catering to the diversity of user populations.

Measurement Precision: Employing advanced tools such as textual analysis and the SenticNet API to gauge mental health metrics has undoubtedly bolstered our research. Nonetheless, it is vital to acknowledge that these tools harbor their own set of limitations. Thus, prospective research should refine measurement methods to elevate precision and bolster the reliability of results.

For example, a more profound understanding can likely be gleaned using these techniques by diving into the content and context of user interactions within OHCs. Future research should analyze the content's nature, the topics that dominate discourse, and the context against which support is offered. This in-depth exploration should help unravel the intricate mechanisms at play. Such an innovative study could be used to develop and validate a more comprehensive measurement tool for assessing mental well-being within OHCs, considering linguistic nuances and cultural factors.

Causality Considerations: Although our study has successfully unveiled a causal link between appraisal support, improved mental well-being, and reduced toxicity, other potential causal relationships remained unexplored. To paint a more nuanced portrait of these causal pathways, future studies should extend their purview to consider the mediating and moderating variables that further inform the underlying relationships. For example, research could explore the role of personality traits in moderating the influence of appraisal support on mental well-being, providing insights into the interplay of individual differences and social support.

A more compelling opportunity to do this is through the development and evaluation of interventions within OHCs to combat toxicity and elevate mental well-being. Implementing and testing diverse support strategies, moderation techniques, and user engagement initiatives can usher in more effective community management and new research insights.

Ethical Considerations: Given the potential for toxicity and harm to people, ethical considerations for managing OHCs require substantial research. Future research endeavors should thus delve into the ethical dilemmas entwined with user privacy, data sharing, and content moderation. This ethical scrutiny is vital to ensure these platforms' responsible and ethical utilization. Findings that can help resolve some of the ethical tensions can also be used to inform policy development for the greater societal good.

6.4. Conclusion

In conclusion, our research illuminates the pivotal role of OHCs in enhancing the mental well-being of elderly users while addressing toxicity challenges within these platforms. We emphasize the significance of appraisal support, showcasing its causal effect in improving mental well-being and reducing toxicity. This finding underscores the importance of fostering a culture of validation, self-esteem reinforcement, and coping assistance within OHCs, offering actionable insights for practitioners and healthcare providers. Additionally, our study provides unique insights into the role of emotional support, indicating the need for further exploration in different contexts and demographic groups.

Our research delves into the heterogeneous effects of social support, revealing that the impact of appraisal support varies based on users' initial positivity levels of posts. This insight highlights the importance of tailoring support strategies to user needs and collaborating with healthcare professionals. Moreover, we emphasize the timing of social support within OHCs, suggesting the implementation of content-sorting algorithms to ensure timely responses. As real-world cases illustrate, these findings have substantial implications for OHC management, practice, society, and policy. Although our research makes significant contributions, we acknowledge its limitations, pointing to future research opportunities, such as generalizability across platforms, exploration of diverse age groups, measurement precision improvement, causality considerations, and ethical dilemmas surrounding OHCs. This comprehensive understanding paves the way for more supportive and healthier online health communities.

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