2022

The Mechanisms of Peer Support in an Online Support Group for Veterans

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THE MECHANISMS OF PEER SUPPORT IN AN ONLINE SUPPORT GROUP FOR VETERANS

By

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Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at the University of Texas at Arlington

December 2022

Arlington, Texas

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Acknowledgements

I would like to express my gratitude to my supervisor and chair of my committee Dr. Rebecca Mauldin for her invaluable patience, feedback, and competence. I also could not have undertaken this journey without my defense committee, who generously provided knowledge and expertise.

I am also grateful to my cohort members and fellow doctoral students, especially Jessica, for their editing help, feedback sessions, and moral support.

Lastly, I would be remiss in not mentioning my family, especially my parents. Their belief in me has kept my spirits high during this process. I would also like to thank the researchers, professors, programmers, and enthusiasts who took the time to share their knowledge and source code on the internet for the benefit of all.

Table of Contents

Abstract

Military veterans experience a transition process when returning to civilian life that involves reintegration across life domains. Reintegration has been shown to be a significant challenge for a contingent of former servicemembers that can be exacerbated by an erosion of social support networks. Difficulty accessing peers due to wider social trends away from community connectedness and geography have inspired the creation of virtual gathering spaces for a wide range of populations. The emerging evidence for peer-driven online support groups suggests the potential for facilitating development of new supportive interpersonal connections and improved access to tangible resources. The current study seeks to increase knowledge about behaviors driving interactions among veterans in online support groups. To accomplish this, the dissertations' theoretical framework called the Networked Neo-Ecological Framework is developed using foundations from Bioecological Theory, Neo-Ecological Theory, and Networked Ecological Models. This Networked Neo-Ecological Framework is used as a lens for identifying mechanisms contributing to participation, peer support, and negative interactions in an online support group for veterans. Descriptive statistics are used to examine the conversational topics and comment engagement in the support group. Relational event modeling is employed to examine the network structural mechanisms associated with three types of interactions: general participation, peer support, and negative interactions. Findings suggest that peer support is most strongly associated with the mechanism of interactional reciprocity and that volatility may contribute to negative interactions. Implications for social work practice include using online support groups as a potential source of information for determining what topical areas of need may exist for veterans and what factors social workers might consider in implementing online support group interventions.

Research implications are presented detailing how web scraping and social network analyses can be used in conjunction to examine people in their digital environments. Implications for social work policy include recommendations for moderation policies in online support groups and other online service delivery systems. The implications for social work education include incorporating the Neo-Ecological Theory as a supplement to the dated Ecological model to help students understand how development occurs in the context of their digital and physical environments.

Chapter 1: Introduction

Problem Statement and Significance

Since the beginning of the United States lead Global War on Terror in 2001 approximately 4.5 million service members have transitioned from military to civilian life (Department of Labor, 2020). While many veterans transition with relative ease, a considerable minority experience disconnection from their new civilian roles and environments (Mitchell et al., 2020). The transition process involves reintegration across life domains and can be rife with problems as the former servicemember attempts to establish or reestablish new identities, social relationships, access to resources, and vocation. Qualitative studies examining reintegration problems in the veteran population have found common themes such as feelings of alienation, isolation, and identity loss (Orazem et al., 2017; Smith & True, 2014; Tarbet et al., 2021). The inability to adapt quickly can have severe acute and long-term negative effects across life domains. Recent literature suggests that health and social problems may become worse rather than improve from the time of military separation. In a prospective cohort study by Vogt et al. (2022) veterans reported that their perceived health, social wellbeing, anxiety, depression, and PTSD symptoms became worse over the three-year period following military discharge. Findings from Vogt et al. (2022) suggest that early intervention and enhanced prevention is needed, especially in the domain of social interactivity.

The opaque military subculture enforces beliefs and values that often contrast with the values of general American society. An individual's adherence to military culture and identity after discharge can add complex social and psychological barriers to establishing new social ties, making the development of supportive social relationships difficult in the absence of access to others with similar lived experiences (Campbell, 2021; Whiteman et al., 2013). Evidence from veteran peer support group literature suggests that trust is a salient theme, especially when addressing problems arising from military-specific conditioning or experiences, such as aggression or violence (Azevedo et al., 2020). Service experiences vary by individual demographics, combat exposure, military branch, rank class (i.e., enlisted, or commissioned officer), and service era. However, military culture instills a set of values and beliefs centered around collectivism, duty, and responsibility for fellow servicemembers that often persist into civilian life (McCaslin et al., 2021). Absence of trust in group membership can act as a barrier for veteran wellbeing (Campbell et al., 2021; Jain et al., 2014; Wilson et al., 2018) and has been identified as a barrier to treatment and research by the Veterans Administration (VA) (Fischer et al., 2016; Littman et al., 2018).

The bottleneck of access to government health resources and entitlement benefits through the VA adds another unique dynamic to the population in terms of help-seeking as veterans are the only population in the United States entitled to centralized government-provided healthcare (Feinstein, 2015). Peer support programs have been funded and implemented at a growing number of VA centers across the United States, recognizing the utility of including veteran peers in treatment programs (Eisen et al., 2012; Resnik et al., 2017). Evidence-based reasons cited for the development of these peer programs are the improvement of social support and community reintegration (VHA, 2013). Peer-based organizations which work collaboratively with VA centers to improve access to VA services and foster collaboration between veterans and their local communities have also emerged (Franco et al., 2021; Gorman et al., 2018). Despite the apparent usefulness of peer support services, the mechanisms underlying peer interactions among veterans lack empirical study and therefore make formal peer support roles uncertain across clinical settings (Oh & Rufener, 2017). The absence of empirical data to inform protocols for peer support specialists makes formalizing the role difficult and creates ambiguity for its justification from a budgetary standpoint. This is important because expenditures on healthcare by the VA has more than tripled in the past 20 years and the number of unique patients has doubled, making budgetary strain a practical concern for the VA (VA, 2021).

Informal access to peers outside of healthcare settings has traditionally been accomplished through acquaintance or national organizations like Veterans of Foreign Wars in the United States (Leedahl et al., 2011) or Royal British Legion in the United Kingdom (Williams et al., 2018). Veterans in rural areas have less access to face-to-face peer interactions, including through healthcare providers (Garvin et al., 2021). Difficulty accessing peers due to wider social trends away from community connectedness (Borgonovi & Andrieu, 2020; Holt-Lunstad et al., 2017) and geography have inspired the creation of virtual gathering spaces for a wide range of populations.

Online support groups have gained popularity over the past two decades through informal gatherings of people posting to both public and private message boards (DeAndrea & Anthony, 2013; Jenkins et al., 2021). Much like traditional support groups, people with a common struggle gather to exchange information, emotional support, share experiences, and develop or maintain interpersonal relationships (Ziebland & Wyke, 2012). Evidence suggests that online support groups have similar beneficial outcomes to traditional peer social support groups for people coping with physical illnesses (e.g., cancer, fibromyalgia, etc.) and mental illnesses (Han et al., 2019; Maclachlan et al., 2020; Won et al., 2021). However, online spaces have also demonstrated the capacity for fostering negative interactions (Novin et al., 2018), which can take the form of bullying or harassment and has been associated with increased levels of anxiety, depression, and self-harm (Primack et al., 2017; John et al., 2018). To date, only a few studies exist that examine online support groups for veterans (Yeshua-Katz & Hård af Segerstad, 2020; Yeshua-Katz & Zilberstein, 2021) and just one has examined negative interactions in the online support group context (Stana et al., 2017).

The emerging evidence for peer-driven online support groups is promising because these kinds of groups have potential for facilitating the development of new supportive interpersonal connections and improved access to tangible resources (Drebing et al., 2018; Gorman et al., 2018). Qualities of virtual communication, such as ease of access and the possibility of asynchronous conversations, lend themselves to the potential for a more widespread adoption of virtual support communities. For groups like veterans who may have temporal, geographical, physical, or psychological barriers for participating in face-to-face peer support, virtual spaces have the potential to provide improved access to peers wanting to engage in mutual support.

Provided scant literature examining online peer support and negative interactions for veterans, and the mechanisms underlying peer interactions among veterans, further study is warranted to investigate how both socially supportive and negative interactions occur in those online environments. Examination of behaviors that influence peer interaction, in conjunction with an understanding of the online environment, will lend insight into the mechanisms that impact online support.

The Current Study

The current study seeks to increase knowledge about behaviors driving support group participation and the role that peer support and negative interactions have among veterans in online support groups. The rationale behind this research is that community driven and institutional (i.e., informal and formal) interventions incorporating online peer-based support for veterans will benefit from a better understanding of the mechanisms of peer support within virtual contexts. Findings can inform interventions that leverage the ubiquity of internet connectivity to create and facilitate virtual mediums for peer support during the process of veteran reintegration and beyond. This study aims to expand the existing knowledge of how participation in online support groups leads to social support for veterans. To accomplish this, a networked neo-ecological framework will be used to identify the structural mechanisms contributing to supportive or negative interactions in an online environment. Then relational event modeling, a specialized methodological approach to quantifying evolving social processes, will be employed to examine structural mechanisms leading to the development of peer support.

The study proposes the following research questions (RQs):

RQ.1: What are the characteristics of the content and structure of user participation in the online support group?

RQ2: How do structural network mechanisms and previous interactions that are appraised as either positive, negative, or neutral by the community relate to participation in the online support group?

RQ3: How do structural network mechanisms and previous interactions that are appraised as either positive, negative, or neutral by the community relate to peer support in the online support group?

RQ4: How do structural network mechanisms and previous interactions that are appraised as either positive, negative, or neutral by the community relate to negative interactions in the online support group?

Chapter 2: Theoretical Framework

The basic premise of this dissertation is that online support groups provide convenient access to beneficial peer support for many veterans and organizations serving veterans. However, more knowledge is needed to understand the mechanisms within the social networks of the online support groups that contribute to their success in a virtual context. This dissertation aims to address how positive and negative interactions affect participation in an online discussion board dedicated to veteran news, information, and mutual support. It uses the lens of neo-ecological theory to examine participation and the development of peer support and negative interactions in an online support group.

This chapter outlines the theoretical foundations for the proposed research. First, it presents a brief introduction to Bronfenbrenner's bioecological theory, its shortcomings in a virtual context, and exposition on the neo-ecological theory which establishes a basis to understand the development of peer support in online environments. After the discussion of the bioecological theory and its successor the neo-ecological theory, this chapter presents the theoretical framework for this dissertation which is being named the networked neo-ecological framework (Table 1).

Theoretical Foundations

In this dissertation, neo-ecological theory (Navarro & Tudge, 2022) will be used to provide insight into the development[1] of peer support and negative interaction in the context of virtual space. However, the concept of proximal processes from Bioecological theory will first be introduced (Bronfenbrenner, 2000, 1995) to provide a theoretical history and justification for the use of neo-ecological theory.

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[1] Development is taken to be Bronfenbrenner's minimal definition of development as behavior over time (Bronfenbrenner, 1988).

Bioecological Theory

Bioecological theory posits that understanding human development is best achieved by considering the person in the context of their environment. The *Process–Person–Context–Time (PPCT)* formula[2] (Bronfenbrenner & Evans, 2000; Bronfenbrenner, 1995) hypothesizes key factors influencing development over time. Pride of place is given to proximal processes in the PPCT formula emphasizing its theoretical priority (Merçon-Vargas et al., 2020). Accordingly, proximal processes will be discussed before moving on to the remaining constructs in the neo-ecological theory.

Proximal processes are theorized to be comprised of symbols or objects in the environment that a person has ongoing reciprocal interactions with, which are termed the "engines of development" (Bronfenbrenner, 1995). For example, Farrant and Zubrick (2012) conducted a longitudinal study of children's early vocabulary development while controlling for ecological factors including quality of parenting, number of siblings, household income, community socioeconomic status, as well as individual factors such as child temperament. The hypothesized proximal processes under study were parent-child book reading and joint parental attention, both of which meet Bronfenbrenner's (1995) definition of ongoing reciprocating interactions. Results showed that the proximal processes of parent-child book reading and joint attention mediated environmental and individual characteristics on the developmental outcome of vocabulary development.

A major limitation of applying bioecological theory in a contemporary context is its reliance on face-to-face interactions (Johnson & Puplampu, 2008; Navarro & Tudge, 2022).

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[2] Bronfenbrenner modified Lewin's formula for behavior $B = f(PE)$, where "behavior is a joint function of person and environment" to $D = f(PPCT)$, where D is development. Accordingly, PPCT will be referred to as a formula in this dissertation.

Inception of the bioecological theoretical system occurred prior to widespread adoption of social media technologies. Where social gatherings such as support groups would necessarily occur in physical settings, they are now readily accessible through virtual mediums such as social networking sites and mobile apps. Theoretical problems arise when hypothesizing about how social and cultural forces manifest in the absence of non-traditional spaces and necessitate making significant changes to the original bioecological framework. To deal with this limitation, the neo-ecological theory (Navarro & Tudge, 2022) addresses complicated theoretical hurdles, including the determination of virtual locales and the effects that virtual interfaces and interactions have on developmental processes.

Neo-Ecological Theory

Like the physical world, the virtual world has symbolic features that invite or inhibit engagement. Unlike the physical world, these features can adapt rapidly based on highly specialized algorithms aimed at enticing or dissuading individuals from interacting with them (Min & Kim, 2015). The neo-ecological theory (Navarro & Tudge, 2022) adapts the constructs of the bioecological theory to a technologized world to address dynamic environments.

Key definitions for virtual phenomena within this theory include platforms, content, and context. *Platforms* are the technological vehicles ranging from text messaging apps to social media websites (McFarland & Polyhart, 2015; Navarro & Tudge, 2022). Platforms facilitate the sharing of *content*, which is comprised of modes of communication like text, video, images, and audio. Platforms contain content and are subject to additional contextual factors, or context. *Context* in neo-ecological theory is understood using McFarland and Polyhart's (2015) omnibus context continuum, which helps explain the role that context has on virtual interactions and their relationship to the physical world. One end of the continuum is tangible and comprised of

Table 1

Comparison of Ecological Models and Dissertation's Framework

Theory Name	Brief Description	Proximal Process	Person	Context	
Bioecological Theory (Bronfenbrenner, 1995)	Development is best understood by considering the social process, person in the context of their environment, and time.	Proximal processes are comprised of symbols or objects in the physical environment that drive development through frequent and increasingly complex reciprocal interactions. The effect of positive versus negative interactions in the is largely unaddressed.	Person in face-to-face interaction.	Single physical microsystem with at least one proximal process.	Micro, meso, macro.
Neo-Ecological Theory (Navarro & Tudge, 2022)	Development is best understood by considering the social process, person in the context of their virtual and physical environments, and time.	Relational proximal processes occur between persons in the virtual and physical microsystems. Complex proximal processes have both persons and objects or symbols in virtual microsystems. Peer support is a positive proximal process.	Person's directed attention (opening and closing microsystems).	Multiple microsystems spanning physical and virtual spaces.	Micro, meso, macro.
Networked Ecological Model (Neal & Neal, 2013)	Relationship types form the basis for organizing ecological systems. Multiple microsystems exist contributing to the understanding of development.	Proximal processes are absent in this model.	Person's association with other people in face-to-face interactions represented by a network tie.	Multiple microsystems intersecting at shared mesosystem boundaries.	Micro, meso, macro.
Networked Neo-Ecological Framework (Developed by and presented in this dissertation research)	Valued relational events occurring in a social process contribute to understanding development in conjunction with the person, virtual and/or physical context, and time.	Proximal processes are represented by a sequence of dyadic network ties indicative of interactions over time. Incorporates the concept of paralinguistic digital affordances (PDAs) to distinguish between positive and negative proximal processes.	Person's directed attention represented by a network dyad.	Multiple microsystems spanning physical and virtual spaces.	Continuous or aggregate.

immediately physical communication contexts (e.g., face-to-face conversation), while the opposite end is purely virtual and intangible (e.g., social media posting). The taxonomy of system levels in traditional bioecological models (i.e., micro, meso, exo, macro) are addressed by Navarro and Tudge (2022), with key modifications occurring at the microsystem and macrosystem levels. In this dissertation research, only the microsystem and macrosystem will be addressed in detail because (1) they contain the ecological system levels of interest regarding social context relative to the individual (i.e., the support group), and (2) the neo-ecological theory is permissive of piecewise system emphasis due to the ontological separation of virtual and physical space (Navarro & Tudge, 2022).

Microsystem in Neo-ecological Theory. The virtual microsystem is described as a context that is co-constructed by its constituents (Navarro & Tudge, 2022) with the caveat that the virtual platform is meant to be interacted with (e.g., social media or video games). Three modifications to the microsystem are proposed by Navarro and Tudge (2022) that differentiate it from the microsystem in bioecological theory. First, the microsystem is divided into the virtual and physical domains. This proposition preserves the traditional bioecological definition of a microsystem (Bronfenbrenner, 1995) as being comprised of patterns of activities, social roles, and interpersonal relationships while also allowing a new domain of microsystem to exist. Persons in the virtual microsystem are influenced by symbolic features that either invite or inhibit engagement with proximal processes (Navarro & Tudge, 2022); for example, a smart phone application designed for instant messaging invites interaction in a virtual microsystem where the proximal process may be friendship maintenance or spousal appeasement. Spatial constraints implied in the nested bioecological theory (Bronfenbrenner, 1977) are overcome by Navarro and Tudge (2022) through emphasizing activities and social roles in the virtual microsystem. Having established that a virtual microsystem can exist in addition to the traditional face-to-face microsystem, the physical ontological component of face-to-face microsystems is preserved.

The second modification to the concept of microsystem posited by the neo-ecological theory is permitting developing individuals to exist in multiple microsystems simultaneously. Navarro and Tudge (2022) liken this to multitasking, in that a person can open and close microsystems where context is both produced and maintained. For example, a teenager playing an online videogame can leave the videogame microsystem to talk to a sibling in the physical microsystem, then reenter the virtual gaming microsystem upon the completion of sibling conversation. This example leads to the final theoretical modification of the neo-ecological microsystem – that the ‘opening’ and ‘closing’ of microsystems is defined by the interactions and/or activities that the individual engages in on the specific platform. Reusing the previous example, features in the videogame microsystem can be different than the features in a social environment. A detailed but non-exhaustive list of platform-dependent variables to describe the microsystem in an online context are provided by Navarro and Tudge (2022), but only variables considered relevant for this study are addressed below: anonymity, synchronicity, publicness, and cue absence.

Anonymity affords users the ability to only be identified by self-disclosed characteristics. For example, a person’s identity on Reddit, a content aggregation and sharing website, is anonymous and the person is only recognizable by username and whatever characteristics about themselves they chose to disclose through text-based discussion. On the other end of the spectrum, the social networking platform Facebook lends itself to less anonymity because identity association is a key feature of the platform.

Synchronicity is a term referring to communications happening in real time (e.g., face-to-face conversation). Asynchronistic communication occurs with temporal lag between sending and receiving communication (McFarland & Ployhart, 2015). Asynchronicity lends itself to convenient communications like message boards or emails where immediate responses are not necessarily expected.

Publicness of a platform has implications for the size of the audience, where publicness invites more viewings or interactions (Navarro & Tudge, 2022). An implication for public platforms is the capacity for a large number of people to communicate with little control over who sees what. For example, Yeshua-Katz and Hård af Segerstad (2020) noted that a benefit of public online support groups is that they are easier to find through search engine queries, but negative aspects on publicness include a higher incidence of bad actors, or unwanted members, that threaten the integrity of the space.

Cue absence refers to social cues used in face-to-face communications such as facial expressions and tonality that can be easily lost in the virtual realm (Nguyen & Fussell, 2014). Platforms in which text-based communication is most prominent have a high degree of cue absence, whereas platforms with technologies that incorporate synchronous audio or video have lower cue absence.

Macrosystem in Neo-ecological Theory. The neo-ecological framework emphasizes culture as the driving force at the macrosystem level (Navarro & Tudge, 2022). A synthesis of Bronfenbrenner's conceptualization of culture and cultural-ecological theory (Tudge, 2008) is used to recast culture as a phenomenon arising from "a group of people who share a set of values, beliefs, and practices; who have access to the same institutions, resources, and technologies; who have a sense of identity of themselves as constituting a group; and who attempt to communicate those values, beliefs, and practices to the following generation" (pp. 3-4). By this definition, cultural forces are bound to a group identity.

Groups of individuals provide context and socializations informing the person of their expected role (Stryker, 1986; Tajfel, 2010). In the virtual context, platforms, groups, and group situation (e.g., playing a video game or participating in a support group) dictate peer expectations and set the symbolic indicators for performance. For example, platforms like Reddit, Stack Exchange, and Quora use several symbol indications of group appraisal which include upvotes, downvotes, and awards. Through symbols of group approval provided by platform mechanisms, the individual can obtain a sense of how their role is being evaluated by others, which may influence how they evaluate themselves (Navarro & Tudge, 2022).

Proximal Processes in Neo-ecological Theory. A more expansive definition of proximal processes is used in neo-ecological theory (Navarro & Tudge, 2022) than in its predecessor (Bronfenbrenner, 1995). Foundationally, proximal processes remain the interactive features in an environment that drive development through competence (i.e., adaptive behavior) or dysfunction (i.e., maladaptive behavior) over time (Bronfenbrenner, 1995; Bronfenbrenner & Morris, 2000). Like in bioecological theory, a proximal process is reciprocal and takes place over time in a microsystem.

The effect of positive versus negative interactions in the *PPCT* formula remains largely unaddressed theoretically in bioecological theory. Bronfenbrenner and Morris (2000) viewed proximal processes as a beneficent force for competence, where the absence or diminishment of exposure to proximal processes were thought to be the driver of dysfunction in the developmental process. Neo-ecological theory uses the proposition by Merçon-Vargas et al., (2020) – that the development of poor outcomes can mirror that of the development of desirable outcomes. For example, abusive relationships can be thought to grow increasingly more complex over time, with regular exposure, in the same way that healthy relationships do, but with inverse outcomes. By the same reasoning, dysfunction is thought to become adaptively worse in the presence of a harmful social process rather than becoming worse by the mere absence of a beneficent processes (Merçon-Vargas et al., 2020).

The neo-ecological theory proposes a similar idea by defining dysfunction as the detrimental conceptual inverse of a proximal process. This conceptualization results in a bidirectional model. Positive proximal processes suggest adaptive behavior toward wellbeing and negative proximal processes are adaptive toward detriment. Outcome measures for proximal processes are not considered to be universal in neo-ecological theory, instead they vary by culture and subcultural group (Navarro and Tudge, 2022).

An implicit premise of neo-ecology theory is its utility in facilitating peer support through positive proximal processes and multiple citations are made by Navarro and Tudge (2022) referencing the beneficial and potentially harmful aspects of having access to similar peers through virtual microsystems. The constructs of group identification and group expectations are refenced by Navarro and Tudge (2022), which align with Identity Theory (Stryker, 1968; Howard, 2000).

Identity theory posits that an individual has a set of perceived role expectations determined by their contextual heuristics and that subsequent behavior is influenced by the invocation of one identity over another (Stryker, 1968; Howard, 2000). The depth of shared identity does not necessarily imply beneficent peer relationships. Rather, role expectations and perceived performance resulting from identity can be thought to determine the positivity or negativity in situational context. To understand how perceived performance (e.g., as a contributor to peer support or negative interactions) might affect an individual in the context of an online support group, a functional definition for what peer support and negative experiences might entail are required.

This dissertation posits that a functional definition for the mechanisms of peer support be based on previous research into peer support in public health, consisting of group cohesiveness, interactional reciprocity, and information/experience sharing (Fisher et al., 2015; Lindgreen et al., 2021). These concepts in the peer support literature have been thematically associated with lived experience and identity, consistent with identity theory (Watson, 2019). Indeed, Oh and Rufener (2017) suggest that similarities in shared military experiences and prominence of an individual's veteran identity are key mechanisms for effective peer support services at the VA. On the other hand, negative experiences would be phenomena reducing the efficacy of the mechanisms of peer support. Disengagement from the social process is the most plausible outcome from negative online experiences based on the relevant literature (Kang, 2022).

The mechanisms for peer support (i.e., group cohesiveness, reciprocity, and information sharing) can be thought manifest in ways that are objectively measurable and have conceptual analogues through social network analysis (Pinheiro et al., 2014; Wang et al., 2021). To incorporate these structural network factors into a theoretical framework for its inquiry, this dissertation creates a networked neo-ecological framework. The networked neo-ecological framework employs functional measures for peer support and negative interactions and will be discussed after first presenting the networked ecological model.

The Networked Ecological Model

Conceived by Neal and Neal (2013), the networked ecological model redefines ecosystem levels by patterns of social interactions relative to the individual. Multiple microsystems can be present in the ecological systems model and vary by interaction context. The modification of the networked ecological model to the ecological model (Bronfenbrenner, 1977) is subtle but substantial in that it emphasizes with whom and where individuals interact rather than constraining influential social forces to a nested ecological system.

An illustrative example provided by Neal and Neal (2013) places a child as the person at the center of a model represented by a network node. Two microsystems are present in the example – the family microsystem and the school microsystem. Supposing the mother and teacher have regular parent-teacher meetings, the two microsystems are joined by a mesosystemic tie. The teacher may have regular interaction with the superintendent who is a member of the policy exosystem. All the child's systems exist within a broader cultural macrosystem intertwined with temporal trends. Neal and Neal (2013) also make the case that macrosystemic changes can be accounted for by changes in individual attributes and behaviors. For example, desegregation of schools undoubtedly changed the demographics in school networks and network measures, like those for homophily.

All the components of the ecological system are present in the networked ecological model with the added benefit of being able to measure interactions using social network methodologies. However, limitations exist in Neal and Neal's conceptualization. Most notably, they draw from the original ecological theory to posit the networked model. The development of ecological theory into bioecological theory was accompanied by important theoretical updates, most important of which was the concept of proximal processes. This dissertation draws from Neal and Neal’s networked ecological model and applies the crucial concept reformulated by neo-ecological theory (Navarro & Tudge, 2022).

The Dissertation's Theoretical Framework: Networked Neo-Ecological Framework

This dissertation proposes extending neo-ecological theory to the *networked neo-ecological framework*, incorporating proximal processes and concepts from the social network analysis paradigm. This new framework is necessary to support empirical examinations of relational interactions using neo-ecological constructs in virtual environments. This theoretical modification takes a pragmatic approach in linking theory to method, with the purpose of furthering social work research and intervention (Hothersall, 2019).

Social Network Paradigm

The social network paradigm draws from structuralist perspectives of behavior in sociology (Borgatti et al., 2009; Durkheim, 1951), which perceives the individual as an element that both comprises a social system and exists within it (e.g., a military veteran in a support group). The field of social network analysis has established theoretical systems and methods for analyzing relationships between individuals and structural configurations in social processes (Borgatti et al., 2009). Configurations of social interaction patterns have the capability to model structural mechanisms (i.e., mechanisms within the structure of a broader social network in which individuals are embedded) of human behavior. Examples of structural mechanisms in social network analyses include mutuality (i.e., reciprocity) in friendships (An, 2022), a person's popularity (i.e., indegree) in receiving votes for political appointments (Davis et al., 2022), and a person's perceived number of friends (i.e., outdegree) by initiating conversations with others (Graupensperger et al., 2020).

In an egocentric social network paradigm, individual persons (egos) are the base unit in the social structure and other individuals with whom they interact or have relationships with are called their alters. The most basic structure in a social network is a dyad (Figure 1), which is composed of a single ego and alter, joined by a network tie representative of the theorized interaction or relationship between them (Borgatti et al., 2009). For example, a student (ego) and teacher (alter) could be considered to have a learning type of interaction represented by a network tie classified as "learning." More complex patterns of relationships could unfold over time that may lend insight into learning outcomes based on the observed structural patterns within an entire classroom (e.g., students perform better when there are more reciprocated interactions between the students and the teacher). The basic principles of a face-to-face networks are applicable to virtual spaces (Pfeil & Zaphiris, 2009; Zhao et al., 2016) and are used here to extend the neo-ecological theory to a network-based model called the networked neo-ecological framework.

This dissertation's networked neo-ecological framework applies concepts from the social network paradigm to neo-ecological theory. A similar approach for a physical, face-to-face context has been taken by Neal and Neal (2013) in their networked ecological model, redefining traditional ecological system levels (Bronfenbrenner, 1977) using clusters of social interactions relative to the individual. Their approach made the nested structural component of ecological theory secondary to the relational component, allowing for multiple microsystems. Neo-ecological theory calls on patterns of activities and social roles to transcend the physical domain (Navarro & Tudge, 2022). Both theories reach the same functional outcome of overcoming physical system boundaries through the mechanism of relational interactions, but the networked neo-ecological model incorporates the concept of proximal processes, which is absent in the networked ecological model by Neal and Neal (2013). Including the construct of proximal process in the networked neo-ecological model lends explanatory power in examining social processes in virtual contexts.

Updating the Networked Ecological Model

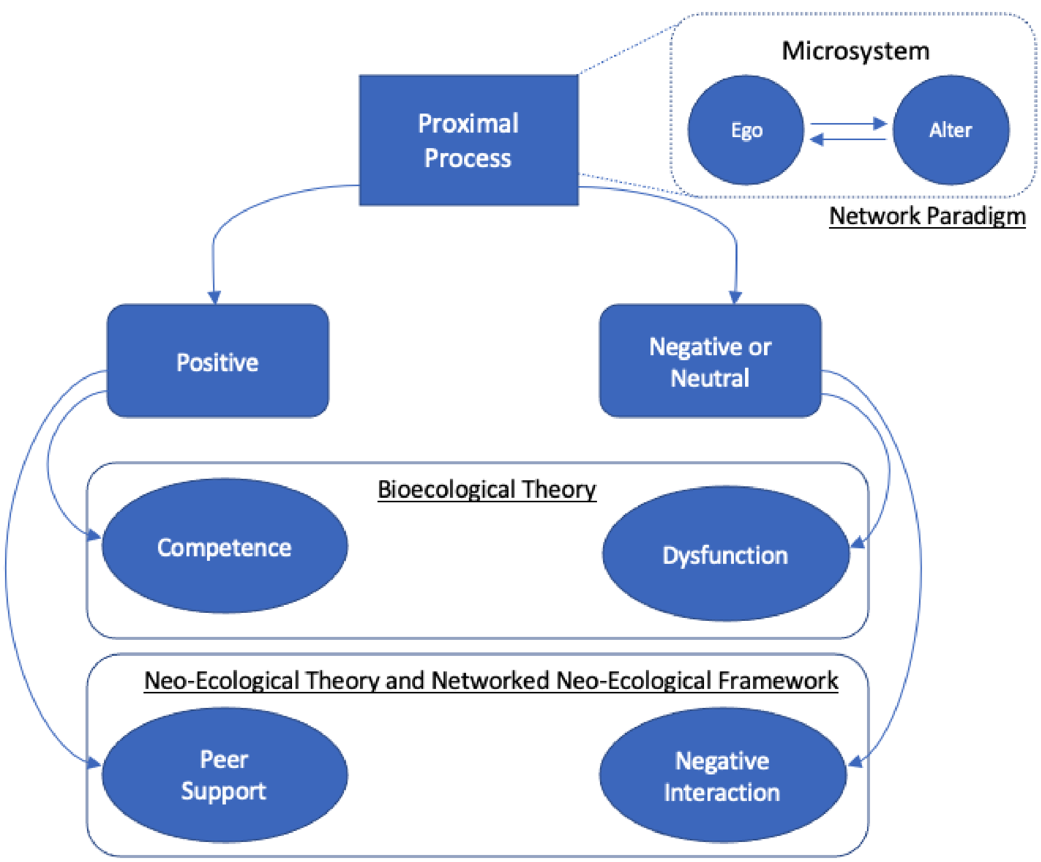
Social and cultural forces comprise the macrosystem in ecological theory (Bronfenbrenner, 1977) and provide the common theoretical grounds for neo-ecology and Neal and Neal's (2013) networked ecological model. The networked neo-ecological framework therefore capitalizes on the extant theoretical similarities and extends a networked approach to neo-ecological theory with minor modifications proposed to account for proximal processes such as the presence of positive and negative processes, which are non-existent in the original networked ecological theory (Neal & Neal, 2013).

Paralinguistic Digital Affordances. This dissertation's networked neo-ecological framework distinguishes between positive and negative processes by incorporating the concept of paralinguistic digital affordances (PDAs) (Hayes et al., 2016). Online platforms often present users with lightweight forms of communication that are not permissive of nuance that can be found where cue absence is less present. For example, Facebook incorporates the "like" button allowing users to convey sentiment with a single click whereas communicating with an audio/video platform like Zoom is permissive of vocal tonality and facial expression. Similar linguistic devices have been studied across major social media platforms (Hayes et al., 2018; Wohn et al., 2016) and suggest a high degree of contextual complexity involved in the perception of PDAs. However, positive sentiment (e.g., likes or upvotes) has been consistently associated with perceived social support (Wohn et al., 2016; Zell & Moeller, 2018), congruent with the neo-ecological conceptualization of peer support (Navarro & Tudge, 2022). Platforms differ in their capacity to relay negative PDAs. For example, social media websites such as Facebook do not include a counter-sentiment option to the “like” button (i.e., dislike), but discussion board platforms including Reddit and Stack Exchange permit direct negative appraisal through downvotes. In the case of platforms that use directional appraisals (e.g., both up and downvotes), negative appraisals correspond with negative emotional valence (Davis & Graham, 2021). In some cases, a post or contribution will receive no appraisal from other users on the platform. The networked neo-ecological framework considers these cases to have a *neutral* appraisal from the community. However, in the absence of appraisal, this lack of PDA can lead to feelings of ostracism and negative emotionality (Hayes et al., 2018; Reich et al., 2018). Through the lens of neo-ecological theory (Navarro & Tudge, 2022), absence of appraisal (i.e., neutrality) lends itself to the inability to socially integrate and can therefore be considered functionally negative.

Proximal processes in the networked neo-ecological framework are modeled after those in neo-ecological theory, which have the potential to be reciprocal, occur over time, and necessarily exist where microsystems exist (Navarro & Tudge, 2022). In the networked neo-ecological framework, proximal processes that occur at the dyadic level can be identified as positive or negative based on whether they promote context-relative competence or dysfunction. Context-relative judgments of competence or dysfunction can be reflected by the appraisals within the platform itself. The distinction between positive and negative dyadic proximal processes can be operationalized as an attribute associated with the tie between a dyad. Figure 1 provides an illustration for the proximal process of a virtual peer interaction and how positive and negative community appraisals correspond to their outcomes in the original bioecological theory (i.e., positive proximal processes imply competence and negative proximal processes imply dysfunction) and outcomes according to neo-ecological theory and the networked neo-ecological framework (i.e., positive proximal processes imply peer support and negative proximal processes imply negative interactions). Virtual peer interactions are depicted as a series of dyadic events with valued ties in the network paradigm, contributing to network structure over time. A depiction of how a dyadic event in a proximal process occurs is also provided in Figure 1 where a dyadic exchange constitutes a proximal process in the networked neo-ecological framework.

Figure 1

Concept Map of the Proximal Process of Virtual Peer Interaction with Ecological Theory Constructs



In bioecological and neo-ecological theories (Bronfenbrenner, 1995; Navarro & Tudge, 2022) time is represented at the micro, meso, and macro level, each acting as boundaries for understanding sets of events in context. Time in the networked neo-ecological model can be considered as continuous (i.e., non-simultaneous) or aggregate (i.e., a static network cross section). Defining time as a continuous or aggregate construct serves the purpose of simplifying complexities in the rapid “opening and closing of virtual microsystems” (Navarro & Tudge, 2022, p. 4) through the ego’s directed attention. The continuous approach to time is proposed to offer a route for granular insight into relational dynamics such as turn-taking in conversation (Gibson, 2005) or accounting for recency of someone's last interaction relative to future interactions (Butts, 2008). The aggregate approach is proposed to analyze the structural makeup of networks as a whole retrospectively. By considering time as either continuous or aggregate, the networked neo-ecological framework of this dissertation lends itself to social network analysis, which has a broad family of theories and methodologies capable of modeling either approach (Butts, 2008; Wasserman & Faust, 2005).

A strength of the dissertation’s networked neo-ecological framework is its ability to model interactions such as social support and its development in virtual spaces. The ability to incorporate community appraisal as a means for determining contextual directionality in social interactions through paralinguistic digital affordances has implications for improving the chances for positive group interactions leading to continued community participation and support network building. The networked neo-ecological framework introduces the capacity for quantitative examination of virtual interactions through methods of social network analysis. Using the networked neo-ecological framework, this dissertation hypothesizes that the structural mechanisms of peer support (group cohesiveness, reciprocity, and information sharing) in a veterans online support group will predict the evolving processes of group participation, peer support, and negative interactions.

Chapter 3: Literature Review

This chapter outlines the literature for veteran peer support, online support groups, network mechanisms involved in the process of building peer support, and how community feedback affects individuals participating in online environments. First, literature for veteran peer support is presented to provide a foundation for understanding how veteran peers have been used in health services geared toward the veteran population. Then extant literature for the contemporary use of online platforms by veterans and veteran organizations is outlined. Next, literature for online peer support with non-veteran populations is explored to inform the theoretical network mechanisms underlying peer support. After, the literature for paralinguistic digital affordances are presented. Finally, gaps in the literature are summarized and the dissertation's research questions and hypotheses are presented.

Veteran Peer Support

Research investigating veteran-to-veteran support has received growing attention in recent years from researchers (Azevedo et al., 2020; Blonigen et al., 2021; Possemato et al., 2022). The premise of peer support is that others who have experienced the same condition or process can provide beneficial interactions in the form of informational or emotional supportive interactions (Myrick & del Vecchio, 2016). Peer support programs have been formally implemented by the VA to supplement existing treatment programs to improve program efficacy and to enhance collaboration and self-efficacy among patients (Azevedo et al., 2020; Gorman et al., 2018; Oh & Rufener, 2017). Relatively few studies investigate how peer support is perceived among veterans, but the existing evidence suggests that peer support is perceived as a favorable component in healthcare and social interventions.

A study by Jain et al. (2016) exploring the efficacy of a peer-only “Big Brother” program in a PTSD residential rehabilitation program at a VA hospital implemented a survey study to measure perceived social support that patients received from their assigned Big Brother and from other veterans in treatment. The sample consisted of 32 male veterans where the Big Brother program was offered alongside standard clinical treatment. Results showed that, on a Likert-type scale of 1-5, measurement of perceived support from other veterans was larger (M = 4.04, SD = .78) than family and friends (M = 3.51, SD = 1.04) and metal health staff (M = 3.62, SD = .96), with mixed results (M = 3.31, SD = 1.10) for the Big Brother. In addition, receiving support from other veterans was also associated with a reduction of PTSD symptom severity. These findings suggest that while the efficacy of the Big Brother program implemented is inconclusive, the availability of veteran peers was the strongest source of social support in the study.

Azevedo et al. (2020) conducted an ethnographic study of peer support in a sample of rural veterans (n = 29) seeking treatment at a VA outpatient clinic hosting support groups for violent traumatic experiences. Four themes emerged from the analysis, with two centering around veteran peer support and peer trust. Relevant themes included peer support, which focused on the fostering of trust to speak freely, and multidimensional relationships that certified peer specialists had in treatment. The “trust to speak freely” theme entailed a sentiment of shared experience serving as the foundation for understanding how emotions, such as anger and frustration, can arise without dismissal or fear of stigma from veteran peers. The “multidimensional nature of peer support specialist relationships” theme conveyed that participants felt the support specialist were more akin to a friend, or an understanding equal, than a member of a treatment team. Findings suggest that veteran peers and veterans who occupy a clinically adjacent role are perceived as trustworthy and non-judgmental sources of support.

Hundt et al. (2015) conducted a one-time qualitative interview on a sample of 23 veterans who had undergone treatment at the VA for PTSD to assess the participant's attitudes towards the prospect of veteran peer support. Purposive sampling was used to achieve diverse demographics, resulting in 17 male and 6 female participants, with the majority being non-Hispanic white (n = 8) or African American (n =10). Results of the interviews showed that participants who have and who have not had experience with peer support previously were in favor of the prospect of using veteran peers in treatment. Qualitative coding revealed that *social support and understanding* was the most prominent theme in interviews. The most cited reason for being in favor of peer support was “like-mindedness” among veteran peers about military related problems.

Veteran peer services have extended beyond the realm of clinical mental health and addressed social issues, such as homelessness, disproportionately affecting the veteran population. A mixed-methods study (Resnik et al. 2020) of 23 homeless veterans with a mean age of 55 (SD = 8.8) investigated the efficacy of veteran peer support and found that perceived support was largely dependent on the homeless veteran’s perception of their peer’s knowledge of services. Some homeless veterans reported that they could not relate to their peers because they did not perceive them as their equal in the sense of being homelessness. This finding suggests that the identity role of a veteran may be secondary to more functional purposes of the situational context. The importance of contextual identity salience found by Resnik et al. (2020) has also been observed by Ahlin and Douds (2020) who noted that veterans in special treatment courts wrestled with their identity as a veteran and as a criminal offender. Conflict in identity salience suggests that some peer intervention programs may be limited in their efficacy depending on identities in social context.

A recent study supports the notion that veterans tend to prefer support from other veterans. A social network study by Harris (2021) sampled 1,338 U.S. veterans and found that veterans are more likely to see benefit in seeking support from fellow veterans than non-veteran peers, including professional counselors. This result is notable because peer networks (other veterans) consisted of an average of 3 people (*SD* = 2.23) and non-peer (non-veteran) support networks averaged 11 (*SD* = 7.39), indicating that there is a need to find effective ways of expanding the peer network of veterans. This finding is consistent with previous literature suggesting veterans tend to find benefit in support from other veterans (Azevedo et al., 2020, Jain et al., 2016; Hundt et al., 2015). Further, the study highlights that veterans tend to have fewer connections to other veterans compared to civilians which has been observed in previous literature (Campbell et al., 2021).

Much of the extant research suggests that veteran-to-veteran support is beneficial in health interventions and social interventions. The role of trust in willingness to share experiences, especially regarding stigmatized topics like PTSD, is a recurring theme and is reflective of a larger body of literature identifying stigma as a barrier for veteran help-seeking (Stata et al., 2017; Yeshua-Katz & Hård af Segerstad, 2020). However, social context and competing identities are factors to consider when attempting to apply peer support as a tenable intervention. One of the most notable limitations of the current literature is the prominence of samples using face-to-face interventions (e.g., Azevedo et al., 2020; Gorman et al., 2018; Resnik et al. 2020). In an increasingly technologized world, studies using online peer support group samples with veterans are underrepresented. Considering that many online platforms allow for the individual to promote a salient identity, while simulations building and maintaining a social network, further investigation into the role of veteran peer support online is needed.

Online Support Groups for Veterans

The knowledge about veterans' peer support and support groups in face-to-face contexts may not apply to online support groups. The current state of literature investigating online peer support for veterans fluctuates in levels of detail regarding which platforms are being used, the size and scope of the online support group, and the amount of time the groups have existed. Gray literature mentioning online discussion boards or forums for veterans also tends to omit detail about the structure, content, or scope of the groups (Ridenour, 2021; Stevens, 2013). Some insight regarding past and current platforms used by veterans for the purpose of peer support can be achieved by synthesis of the available information.

Online veteran peer support groups may be difficult to locate outside of major social media networks like Facebook. The difficulty in finding large or more popular communities for veteran peer support might be explained by the concept of digital affordances as described by Yeshua-Katz and Hård af Segerstad (2020) who noted the public availability of a platform, along with the group population and topic, can act as a barrier to locating online peer support groups. Groups like veterans often gather to exchange support on topics like PTSD and substance abuse that can be perceived as stigmatizing and therefore may be intentionally difficult to find through search engines or have strict gatekeeping procedures that limit access even if successfully found (Yeshua-Katz & Hård af Segerstad, 2020).

To date, only a small body of literature addresses the processes or outcomes of online peer support among military veterans. Findings suggest beneficial outcomes akin to other types of online peer support groups where positive outcomes are thought to be derived from being able to communicate with similar others (Trail et al., 2020; Flannery et al. 2022). A cross-sectional survey analysis (*n* = 113) of Israeli veteran Facebook users (Yeshua-Katz and Zilberstein, 2020) measured PTSD symptoms, depression, self-reported happiness, self-reported health. In the cross-sectional survey, a comparison between Facebook users in a veterans support group and those not in the support group showed that support group participation was positively associated with happiness and negatively associated with depression symptoms. In another study by Yeshua-Katz and Hård af Segerstad (2020), a qualitative approach (*n* = 14) was used to examine social media affordances including a PTSD peer support group for Israeli veterans on the WhatsApp platform. Though outcomes were not the primary topic of the research, interviews suggested that there was a relief for veterans in finding others with similar lived experiences.

A thematic analysis of an online PTSD message board for veterans from English speaking countries including the United States, United Kingdom, and Australia by Stata et al. (2017) provides the most comprehensive look into the contents of online peer support groups for veterans. The findings from a sample of 63 users across 12 discussion threads indicated that the majority of communication was supportive and most of the support exchanged was informational in nature. A noted abundance of network support suggests that maintaining social networks may be an important component of the efficacy of online peer support beyond more obvious types of social support (e.g., informational, and emotional).

The Overwatch program is a non-profit mental health crisis intervention service for veterans that has been in operation since 2015 (Colder Carras et al., 2021). The Discord platform is used to provide a place for veterans to come together and communicate through voice, text, or a combination of both, about online video gaming. Peer volunteers are recruited and trained to help identify veterans exhibiting signs of mental health crisis and responding to user requests for support. The structure of Discord as a platform operates as a synchronous and/or asynchronous mode of communication through text or voice chat. The server operated Overwatch tends to have more than 500 users in the “#general” channel, which contains veterans chatting or playing online games with other veterans and non-veterans. Outcomes indicating the efficacy of the Overwatch program have not yet been published but descriptions for the program are premised on the utility of using existing hobbies and online platforms to promote mental health services and interventions (Colder Carras et al., 2021).

The current body of literature for veteran online support groups suggests that veterans tend to find benefit in online peer support groups, which is in alignment with the general findings of face-to-face peer support group literature. However, little information is provided about the social processes involved in establishing peer support or what promotes continued interaction with the online group. Also missing from the current body of literature is an indication of how larger popular social networking platforms outside of Facebook affect veteran group participation. Having the knowledge of how social ties are created and maintained can inform future interventions, and future research, aimed at veteran outreach and integration.

Online Peer Support and Social Networks

Much of the current literature for online peer support investigates the outcomes of participation and involves samples other than military veterans. The existing research for online peer support indicates that the intended purpose of online support is akin to traditional face-to-face support – reducing feelings of isolation, bolstering supportive social networks, and providing social support (Trail et al., 2020; Flannery et al. 2022; Bacon et al., 2000). For example, a systematic review of peer-to-peer online support groups for persons with musculoskeletal conditions (*n* = 10) reported beneficial outcomes (Maclachlan et al., 2020). Specific outcomes included development of social support, self-efficacy, and health literacy. Similarly, a systematic review for online peer support for caregivers of people with cognitive impairments found beneficial outcomes in measures of health and wellbeing (Wallace et al., 2021). Studies reporting outcomes of online peer support (*n* = 11) included improved caregiver knowledge, reduced measures of stress, depression, burden, and increased self-efficacy and perceived support.

Initial and sustained interactions in online groups is essential to maintenance of an online peer support network (Urbanoski et al., 2017). Structural network-based mechanisms (e.g., popularity or indegree, network activity or outdegree) and mechanisms derived from content (e.g., paralinguistic digital affordances) contribute to an individual's propensity to participate in online support groups. Evidence for structural and contextual phenomena are found in a structural equation analysis of peer support and online support group participation by Zhu and Stephens (2019), in which participants (*n* = 371) in online breast cancer support groups were measured on three factors: (1) information seeking, which could be operationalized as indegree or the total count of incoming messages, (2) information giving, which could be operationalized as outdegree or the total count of messages being sent, and (3) relationship building, which could be operationalized as reciprocity or the reciprocation of messages between users. Each factor contributed significantly to the latent construct of group participation with information seeking having the strongest association, followed by relationship building and information giving. Results also showed that personal identification with the group and developing interpersonal bonds with the group were positively associated with a measure of perceived social support. The bonding process was posited to create stronger social ties out of extant weak ties, thereby increasing the users' ability to cope with stressors (Zhu & Stephens, 2019).

Approaching interactions in an online support group from a social network analysis perspective has permitted more expansive investigations of the evolution of interactional ties over time. A social network analysis of a support group for parents of children diagnosed with attention-deficit hyperactivity disorder (Chewning & Montemurro, 2016) found that a smaller subset of core users acted as a persistent driving force for generating forum content over a 13-month period. Less well-connected and less frequent users of the group were still able to access support despite not being among the core active userbase. Results indicate that online support groups can form a readily accessible infrastructure that does not require active participation from most users over time (Chewning & Montemurro, 2016). Network-level insight into participation begs the question as to which network mechanisms, other than those associated with a network's core density, are involved in establishing and maintaining peer support.

According to the networked neo-ecological model, social network indicators for information/experience sharing, interactional reciprocity, and group cohesiveness will provide deeper insight into mechanisms of peer support for veterans in an online context. Presently, no study has examined how these social network constructs contribute to online support groups for the veteran population. Elucidation on the role they play in peer support can help fill gaps in the knowledgebase about the mechanisms underpinning veteran peer support (Oh & Rufener, 2017).

Information/Experience Sharing

The distribution of sending and receiving messages (i.e., degree) are important structural properties of online social networks that can describe and predict the spread of behavior (Centola, 2010). In directed networks, degree is distinguished by the incoming or outgoing status of social ties. In the context of online support groups, indegree may be thought of as the number of times an individual receives a message. On the other hand, outdegree corresponds to a total count of an individual sending messages to somebody else in the network.

Indegree and outdegree were studied in an online support group for smoking cessation by Zhao et al. (2016), where indegree was defined as the total count of incoming messages for an individual and outdegree was the count of outgoing messages. The sample consisted of interactions on message boards and private messages on a web-based community designed to help people overcome tobacco use and dependence (n = 1,337). Findings showed variation among average indegree and outdegree between publicly viewable message boards and private messages between users. Message boards showed a higher positive correlation in receiving messages for users of different message boards, suggesting that message boards permit greater opportunity for others to influence a single user. Private messages had a flatter distribution and were reflective of less activity in receiving messages over time. Overall, there was a tendency for users to have more incoming connections than outgoing connections when examining aggregate power law distributions. There was a higher rate of low-participating users who preferred to be recipients of interaction rather than providers of it. Findings from this study were inconclusive regarding association of degree on abstinence behavior but suggest that platform design plays an important role in accessibility of peers in support groups and that indegree may be expected to have a larger effect size in public online group communication when compared to outdegree.

A study by Yang et al. (2018) sampled 90,965 user submission to and online support group for persons with inflammatory bowel disease (n = 9,369) over the span of 5 years and found that receiving support (indegree) was positively associated with providing others with peer support (outdegree) in the short-term (1 year), while providing peer support was predictive of continued provision of peer support for up to 2 years. These findings indicate that time providing support in the network (which could be associated with a strong sense of community), plus a history of sharing information/experience with others, are candidates for mechanisms of peer support in other online contexts.

Based on the current literature, it is reasonable to expect outdegree (sending messages) to have a larger effect size on participating in veterans online support groups over longer periods of time. However, indegree (receiving messages) could be expected to have a larger effect size when looking at shorter time intervals and more prominent on public-facing message boards. Overall, the literature appears to suggest that sending and receiving messages is contingent on timescale, design, and publicness of the platform.

Interactional Reciprocity

Giving and receiving support has been identified as one of the primary mechanisms driving online support groups (Pan et al., 2017). There is a body of literature describing the utility of reciprocity in building social connections (e.g., Leider et al., 2009; Lu et al., 2021; Sánchez-Franco & Roldán, 2015; Xu & Zhang, 2016, etc.). Applied to online spaces, reciprocity often takes the form of one user sending messages to another user who has previously sent them a message (i.e., reciprocating) on social networking platforms.

An analysis by Lu et al. (2021) examined online social support networks for people experiencing depression. Their sample consisted of 1,077 users participating in 74,986 posts over the span of 14 years. Networks were created for emotional and information types of communication among the users. Reciprocity was shown to be significant for both emotional and informational social support in exponential random graph models controlling for actor-level effects like gender and number of posts. Findings demonstrate reciprocity contributes to beneficial outcomes of online social support groups.

The downside to reciprocity may be found in its excessive presence between two individuals such that it inhibits the offering and receiving of support to others. A longitudinal analysis by Yang et. al (2018) sampled 90,965 user submissions in an online support group for persons with inflammatory bowel disease (n = 9,369) over 5 years. Results showed that the more one person reciprocated with the same person, the less likely they were to provide support to others in the support group. Findings suggest that there may be a tendency for social cliques to form and prevent new users, or users outside of the social clique, to integrate into the network if users are unwilling to communicate with other members.

Interactional reciprocity is evidenced as being an important endogenous network mechanism contributing to online peer networks. As a beneficent force, reciprocity contributes to social exchange of support. However, reciprocity may prevent the provision of support to others in the network. Based on the literature, it is reasonable to expect that reciprocity will be prevalent in online support groups for veterans.

Group Cohesiveness

Cohesiveness is a term used in social network analysis to describe subgroup clustering among ties and can be assessed through measures of transitivity or how interconnected a person is with their peers in a network. Transitivity describes a social network pattern where a person interacts with another person that has received an interaction from a person that they have interacted with (Holland & Leinhardt, 1970). Having more regular contact with a smaller group or subset of people in a network increases the strength of social ties within that group making a distinct subset of strong ties that are viable for social processes such as maintaining friendships while still capitalizing on other social benefits, such as having readily accessible peers, from the wider social network (Granovetter, 1973).

Social network analysis was used by Xu and Zhang (2016) to study the patterns and structure of discussions in an online health forum for people experiencing major depressive disorder (MDD). Approximately eight years of message board data were collected with 5,050 members, spanning 3,700 threads and 40,357 messages. Results showed that the MDD group had a high measure of local transitivity. Findings suggest that mutual support groups may possess characteristics, such as sharing identity or experiences (Lu et al., 2021; Ziebland & Wyke, 2012), that predispose them to having higher levels of transitivity than groups created for purposes other than mutual support.

A network analysis performed using bloggers on a popular blogging platform by Chiu et al. (2014) examined how the strength of friendship ties affected transitivity. Their sample consisted of 80,617 blogs collected over the span of eight months, containing 51,890 nodes and 201,392 edges. Results found that transitivity was most probable when actors in a transitive triad (e.g., actors A → B → C) had strong ties through repeated communication and was least probable when actor ties were weak, having experienced less communication. These findings suggest that frequency of communication plays an important role in maintaining close personal groups within online networks.

Implications exist for the role of transitivity in promoting over-involvement with others, resulting in a contagion-like effect which promotes socially undesirable outcomes. Peer contagion for depressive symptoms were studied by Zalk et al. (2010) in a longitudinal study in a community-based network of adolescence (n = 842). Researchers examined the prevalence of failure anticipation, a predictor of depression and hypothesized mechanism of peer contagion, in a sample of 355 females and 492 males with a mean age of 14 using. Surveys questionnaires were used to measure failure anticipation and depression along with peer nomination questions to construct social networks. The study suggests that peer attributes can have a contagion effect that is not limited to desirable social outcomes.

Evidence suggests that strong local transitivity is a reasonable indicator for subgroup cohesion within a larger social network (Chiu et al., 2014; Xu & Zhang, 2016). Tightly woven subsets of groups can be identified by the quality and/or quantity of their interactions which may promote beneficial social processes such as mutual support, or negative social processes leading to new or worsened pathology (Takahashi et al., 2009; Zalk et al., 2010). Based on the current body of literature, it is reasonable to expect that the veterans online support group will display transitivity supposing that the participation is reflective of mutual support rather than negative interactions.

Community Appraisal

Online spaces have introduced new lightweight forms of communication, such as upvotes, downvotes, likes, and a host of other symbols programmed into social networking platforms. These types of communications are called paralinguistic digital affordances (PDAs) and convey sentiment to an individual about how their messages or digital interactions are being perceived by the virtual community in which they are participating. Users of online platforms in turn evaluate themselves based on PDAs, which can affect their continued participation on a platform or in a group (Hayes et al., 2018). In the case of directional appraisal (e.g., upvotes and downvotes), negative appraisals correspond with negative emotional valence (Davis & Graham, 2021). In the absence of appraisal, a lack of interaction can lead to feelings of ostracism and negative emotionality (Hayes et al., 2018; Reich et al., 2018).

Positive Appraisal

Social networking platforms have been used as mediums for studying the phenomena of social support (see e.g., Hwang et al., 2014; Jenkins et al., 2021; Kahai & Lei, 2019; Liu et al., 2017; Maclachlan et al., 2020, etc.). Measures of perceived social support have been examined in relation to the presence of positive valence paralinguistic digital affordances. In a survey study (n = 323) of users active on five popular social media websites (Facebook, Twitter, Pinterest, Instagram, and LinkedIn), the quantity and message quality of PDAs were positively predictive of perceived social support and remained significant while controlling for individual psychological factors of loneliness, public self-consciousness, and self-esteem (Wohn et al., 2016). Results suggest that positive PDAs may provide an indication of social support in social networking platform use.

The impact of PDAs on users' satisfaction with their social media interactions lends itself to the notion that participation may also be affected by the presence and valence of community appraisals. A study by Zell and Moeller (2018) used a survey analysis (n = 311) to examine the effects of Facebook likes (i.e., positive appraisal) on an individual's perception of their interactions. Results showed that likes were better predictors of user satisfaction than the number of comments for interactions, regardless of if the comments were being perceived as positive by the receiver. This result suggests that some platforms or contexts may encourage the use of PDAs as a primary social metric through which users derive personal satisfaction.

Negative Appraisal

The ability to indicate counter-sentiment varies by online platform and the platform's intended function. For example, content aggregation platforms such as Reddit and Stack Exchange allow positive and negative sentiment to be expressed. In contrast, social media platforms such as Instagram, Facebook, and TikTok do not offer negative sentiment PDAs. Some cognitive and behavioral tendencies are evidenced among users of platforms where negative sentiment can be expressed. A study by Davis and Graham (2021) investigating engagement and emotional expression on Reddit found that downvotes positively predict negative emotional expression. They also found that negatively appraised interactions elicit more interactions (replies in general) than those positively appraised. Strong negative appraisal encourages interaction with counter-normative content despite the possibility for continued negative interactions. Looking at new users on Stack Exchange, Kang (2022) found negative appraisals decreased the individual's likelihood of continued participation on the platforms. The effect of negative appraisals on platforms where negative appraisals are possible suggest that in some cases there may be a brief period where greater attention is provided to the user who is being affronted. However, the influx of negative attention does not lend itself to continued participation over time.

Neutral Appraisal

Interactions on social media may often go unapprised for a variety of reasons ranging from disinterest from others to simply not being seen due to platform design (Grinberg et al., 2017; Hayes et al., 2018). The phenomenon has been framed as ostracism by Reich et al. (2018), who recruited a survey sample of 186 Facebook users to examine how the absence of likes compares to the presence of likes on measures of belongingness, self-esteem, positive affect, and negative affect. Results showed that users having never received a like were associated with lower sense of belongingness, self-esteem, negative affect, and higher negative affect. In a qualitative study using focus groups (*n* = 37), Hayes et al. (2018) further explored how the absence of PDAs may be perceived as ostracism. Question prompts were based on a modified ostracism experience scale asking participants about their experiences on Facebook, Instagram, and Twitter. A lack of PDAs from somebody meaningful to them were described as impacting their mood and behavior more. These findings suggest that participation in particular online platforms are influenced by getting PDAs from meaningful people and that participants will tailor their participation in a platform to meet social needs associated with PDAs. Findings from the focus groups found that many participants attributed lack of PDAs to platform algorithm idiosyncrasies rather than interpersonal feelings of ostracism.

The current body of literature suggests that the absence of PDAs is associated with ostracism but may be moderated by contextual factors such as the user's perception of platform-specific idiosyncrasies or the types of relationships involved. The studies above (Reich et al., 2018; Wohn et al., 2016; Zell & Moeller, 2018) focused on platforms, such as Facebook, where users are able to see who provided the PDA. Little attention has been given to platforms where users are anonymous or are otherwise unable to determine who provided an appraisal to their interaction.

Gaps in the Literature

As outlined above, there is an emerging body of literature investigating peer support and the role of online support groups in promoting veteran wellbeing. However, knowledge is limited in several areas. First, much of the existing literature examining veteran peer support is based on face-to-face interventions. Studies involving veterans in online support groups, and the virtual environments the groups exist in, remain underrepresented despite advancements in technology making access to online support more widely accessible. Of the studies that do exist examining aspects of online veteran support groups, most are qualitative and little quantitative information exists that provides insight into what the online support groups look like concerning user activity, what topics are being discussed, or the ratio of positive, negative, and neutral interactions over time.

Second, little information is provided about the social processes involved in promoting continued interaction with the online group. Information regarding network mechanisms involved in online support development, such as sharing information and experiences, interactional reciprocity, and group cohesiveness is alluded to but remains formally unmeasured. Studies looking at online support groups with other populations suggest that participation is a key aspect to becoming integrated into the support network. More information is needed to understand the role that network mechanisms and community appraisal play in promoting online support group participation.

Third, no study has examined how the social network constructs of information/experience sharing, interactional reciprocity, and group cohesiveness contribute to positive community appraisals for veterans which is indicative of peer support. The current body of literature suggests that receiving online peer support promotes increased participation in the online support groups, which bolsters social support networks, increases access to information, and facilitates wellbeing. Further elucidation on the role that structural network mechanisms play is likely to help fill gaps in the knowledgebase about which mechanisms underpin veteran peer support.

Lastly, no study has examined how the social network constructs of information/experience sharing, interactional reciprocity, and group cohesiveness contribute to negative community appraisals which the literature suggests fosters negative emotion and dissuades continued use of the online support group in the long-term. Provided that online support seeking is becoming increasingly more common, and evidence suggests that veterans more readily seek out fellow veterans for mutual support, research exploring how these mutually supportive relationships develop can improve future social work interventions to bolster access to peers. Social workers can use this knowledge to create or promote organizations/programs that act as primary or ancillary mediums for veterans to exchange mutual support. Professional peer support specialists can also benefit from an understanding of how online peer interactions transpire and create better-informed protocols for establishing presence in formal or informal online support groups.

Research Questions and Hypotheses

This dissertation aims to address these gaps in the literature by examining veteran peer support in the context of an online environment. It will assess how positive appraisal, negative appraisal, and neutral appraisal, are associated with structural network mechanisms and group participation. Interactional reciprocity, group cohesion, information/experience sharing are hypothesized to have interaction rates corresponding to their PDA valence. Past incidences of positive appraisal are hypothesized to increase the rate of positive appraisals (i.e., peer support) in conjunction with the network mechanisms of interactional reciprocity, group cohesion, and information/experience sharing. Inversely, prior incidences of negative appraisal are hypothesized to be positively associated with negative interactions, with the network mechanisms being positively associated with negative appraisals.

RQ1: What are the characteristics of the content and structure of user participation in the online support group?

H1: No hypotheses are advanced because the question is descriptive.

RQ2: How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity), and previous interactions that are appraised as either positive, negative, or neutral by the community relate to participation in the online support group?

H2(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be positively associated with participation.

H2(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be negatively associated with participation.

H2(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be negatively associated with participation.

RQ3: How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) and previous interactions that are appraised as either positive, negative, or neutral by the community the relate to peer support (positive appraisals) in the online support group?

H3(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be positively associated with peer support.

H3(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be negatively associated with peer support.

H3(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be negatively associated with peer support.

RQ4: How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity), and previous interactions that are appraised as either positive, negative, or neutral by the community relate to negative interactions in the online support group?

H4(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be negatively associated with negative interactions.

H4(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be positively associated with negative interactions.

H4(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be negatively associated with negative interactions.

In the following chapter, this dissertation’s sample, methods, and analytic strategy are described to test these hypotheses.

Chapter 4: Methods

This chapter details the research design, methods, and analytical techniques that were used to address the research questions and hypotheses posited at the conclusion of Chapter 3. The rationale for protecting the anonymity of the sample is provided before describing the anatomy of the digital platform and the subsequent data harvested for use. A detailed description of the data processing is then offered as a preface to the operationalization of variables derived from the data. Finally, network statistics are defined, and model parameters are specified for relational event analyses.

Design Overview

A longitudinal social network analysis design was used to examine how interactions within an online mutual support group for veterans unfolded over time, and how structural mechanisms affected peer interactions in the online support group setting. A letter from the institutional review board at the University of Texas at Arlington was obtained stating that the data used in this dissertation did not meet the criteria for human subjects research. Ethical considerations for the population under study included taking steps such as deidentifying usernames and redacting the support group name.

Ethics

Despite the public availability of data used in this research, it is important to highlight the potential ethical concerns regarding the veteran population being observed on the platform. Social work practice and research should strive to go beyond baseline ethical considerations when handling electronic data collected from populations that may be considered vulnerable because social workers are also charged with helping vulnerable populations. Accordingly, this section discusses considerations for user privacy, anonymity, and discoverability framed with the justificatory conditions for public health research framework (Childress et al., 2002).

Justificatory conditions for public health research proposed by Childress et al. (2002) are considered in framing the use of data derived from web scraping in this dissertation. At the core of the justificatory conditions is an ideal of maximizing social benefit while preventing harm. Therefore, a reasoned understanding of benefit relative to risk is necessary to conduct ethically sound research. To aid in the task of framing relevant aspects of risk and potential benefit, social justice implications are considered in addition to justificatory conditions.

Most fundamental of the conditions is *effectiveness*, conveying the potentiality for the research to contribute to social benefit given the possibility for infringing on general moral or ethical considerations (Childress et al., 2002). The issue of effectiveness becomes a question of whether performing analyses on behavioral data from veterans in an online support group will be likely to improve outcomes for the veteran population. It is believed that this research will provide further insight into online support groups, how military veterans participate in them, and meaningfully inform interventions to improve wellbeing. Effectiveness is contingent on the intent to perform the research toward a determined and realistic goal. Here, the goal is both determined and believed to be realistic.

Social justice pertains to population-specific considerations regarding vulnerability, inequalities in power, and stigma. Military populations, particularly those still serving, have been identified by Schuman et al. (2021) as being vulnerable in the context of online research. They cite the servicemember’s inability to fully consent in making online posts due to military regulations, and potential harms that can arise regarding the servicemember or servicemember’s family if successfully reidentified. These are considerations applicable to the current study because it is possible that this research will sample data from persons still serving in the military in some capacity. However, privacy is important even for those who are no longer in active duty. For instance, the veteran population demonstrates higher a prevalence of potentially stigmatized conditions such as posttraumatic stress disorder and substance use disorders than the non-veteran population (Lee et al., 2018; Lehavot et al., 2018). In this dissertation protections such as deidentifying usernames and redacting the platform name are set in place to assure potentially identifying information is minimized through the principle of least infringement.

Least infringement applied to studies using big data means collecting and disclosing only the quality and quantity of information necessary to improve public health. This research has taken steps to mitigate risk in (1) querying data and (2) storing data related to online personas. A feature of the application programming interface (API) of the web scraper used in this research is the researcher’s ability to only collect data points of interest and exclude information that is considered superfluous. In this dissertation, the contents of submissions and comments were not collected, eliminating a vector of potential risk. Instead, only the relevant metadata was collected. This makes the dataset less laden with user disclosed information that could be used to triangulate a person’s identity. Further, usernames were assigned unique numbers after data extraction.

Proportionality more directly addresses moral and ethical risk. A prominent ethical issue in research using web scraped data is an inherent risk of violating consent, particularly in archival data where user deleted information may still be available (Proferes et al., 2021). Before data collection began, the online support group's community guidelines were checked to ensure that no policies were being violated by data collection activities. Presently, there is no stated restriction for data scraping or observational research on the discussion board. The platform explicitly permits data collection through its API, which the dataset utilizes in archival and data collection.

Retrieval of content created and then later deleted by individual users is made possible through third-party data archival and through the sharing of datasets. Concerns regarding user consent and user deleted data has been noted by the Committee of the Association of Internet Researchers (AoIR, 2019) for general online research, and for the platform specifically by Proferes et al. (2021) who suggested that the use of user deleted interactions on the platform denies individuals agency. The ethical issue of including cases of an individual's self-deleted history is partially addressed through web scraper's website, which allows platform users who know about the archive to request to have their data removed. Provided that minimal potentially identifiable information is collected, and none of the potentially identifiable raw data is being directly disseminated, the risk of analyzing user deleted data proportional to using the data toward a social benefit is deemed acceptable.

Necessity refers to the consideration of possible alternative strategies that would also be considered effective and meet acceptable proportionality, but with less potential moral or ethical criticism. A prominent ethical uncertainty in studies using web scraped data is obtaining informed consent from individual users as participants in research. Literature regarding the ethics of big data and informed consent provide ambiguity (Gerrard, 2021; Ioannidis, 2013), and necessity as a justificatory condition implies a degree of certainty regarding a moral or ethical status that is not presently widely agreed upon. Proponents of informed consent, even in the case of anonymized data, cite the possibility of reidentification which can bring harm to vulnerable populations (Anonymous, 2019; Mittelstadt & Floridi, 2016). This dissertation takes a position consistent with the underlying premise of reducing risk. A tenable solution to mitigate possible consent discrepancies, while protecting the anonymity of the support group and its constituents, is through cloaking procedures. Cloaking procedures entail the suppression of usernames, URLs, group names, and any other potentially revealing data that make reverse searching of users possible in research dissemination (Schuman et al., 2021). Accordingly, identifying information about the online support group have not been named in this dissertation to better protect the anonymity of the support group participants and abide the justificatory conditions for public health research.

The Online Support Group Examined in this Dissertation

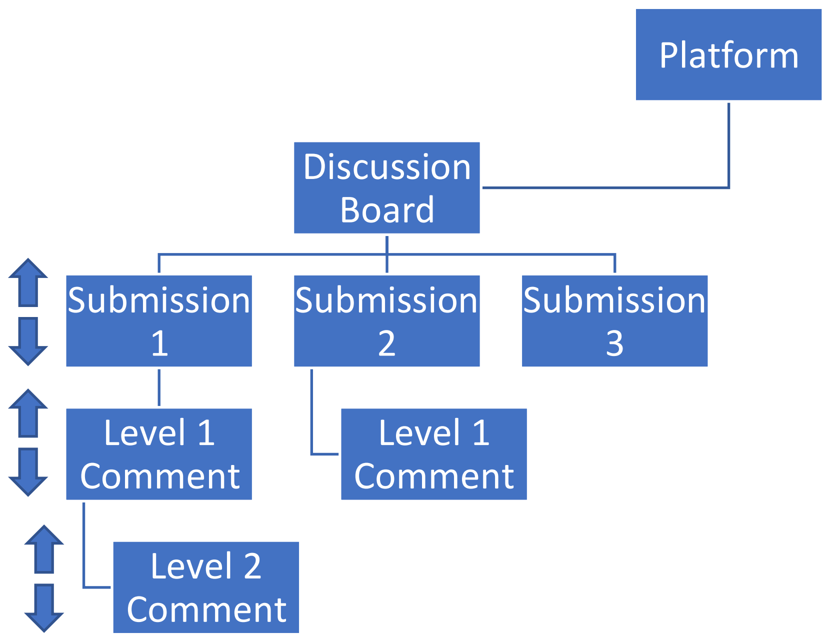
The online support group is hosted on the content aggregation platform Reddit (reddit.com) which invites user interactions through discussion threads. User interactions on the platform are designed to be anonymous and asynchronous. However, some insights are provided about the user demographics of the platform by referencing the official platform marketing analytics and additional third-party analytic sources. According to Reddit’s marketing webpage, in the year 2020 approximately 58% of users were age 18-34, 28% were age 35-49, and 19% were 45-65. Users were 44% female and 56% male. Data for ethnicity was unavailable from the official platform but market research from a third-party website (Sattelberg, 2021) indicates that 70% of users are white non-Hispanic, 7% black non-Hispanic, 12% Hispanic, and 11% other non-Hispanic.

Content on the platform is publicly viewable but requires that a user create an account to interact with the community. Interactions occur through users making submissions for others to comment on and for commenting on others’ discussion board submissions. Interactions between users are primarily text-based, having a high degree of cue absence (i.e., users not being able to determine social cues outside of interpreting message text). Data used in this dissertation were collected from a veterans' discussion board, which is an online forum that advertises itself as a space for veterans to have casual discussions and provide mutual support.

The platform's API is publicly accessible and provides lower-level access to the website interface for the purposes of automated tasks (e.g., harvesting data or creating a bot). Data used in this dissertation drew from three primary categories in the API: discussion boards, submissions, and comments (depicted in Figure 2). The platform hierarchy is outlined to provide clarity into how information was ordered during data retrieval.

Figure 2

Simplified Depiction of the Online Platform Hierarchy



Note. This example of the platform hierarchy is limited to 3 submissions and 2 comment levels to preserve ease of interpretability. The up and down arrows on the left-hand side of the figure represent the upvote and downvote buttons as they appear to the user through the platform interface.

On the platform, discussion boards contain a directory of user submissions that can be comprised of text, hyperlinks, or embedded multimedia (i.e., pictures and videos). Other users on the platform can vote and/or comment on the original submission (level 1 comment). Comments can also be made to existing comments within the submission that do not necessarily involve the original submitter (level 2). Comment levels may extend beyond two levels and become dense hierarchies of conversations within a submission. The interface is customizable by moderators of discussion boards, permitting information such as predefined topic categories to be obtained in addition to other interaction data.

Sample of Interactions

The unit of analysis for this research was a reply-based interaction on the discussion board (henceforth referred to as 'interaction'). The study population was comprised of all human-generated user interactions, defined as user comments responding to other submissions or comments on the discussion board. Therefore, each interaction involved both a sending and receiving discussion board user. Purposive sampling was used to select the timeframe for data collection, which included collecting all interactions within a specified timeframe. Selecting the timeframe was based on (1) availability of recent demographic information for the platform, (2) avoiding periods of macrolevel social phenomena that may create anomalous and non-generalizable results, and (3) the availability of complete retrievable metadata for the interactions.

The most complete and recent demographic information for the platform as a whole (see *The Online Support Group Examined in this Dissertation* section above) was available for the year 2020. However, the timeline selected included data from the year 2021 rather than 2020 due to the COVID-19 lockdown precautions in 2020 which may have induced higher than average social media usage and psychological stress (Awao et al., 2022) and could potentially affect the generalizability of results. Completeness of retrievable metadata for an interaction relied on the availability of relevant data points which included:

- Timestamp of exchanges
- Usernames
- Submission and comment scores
- Submission topic information
- Submission and comment id numbers
- Number of comments on the submissions

Exploratory analyses indicated that topic information became reliably available for user submissions between 2018 – 2022.

The timeline that provided that the most complete demographic information for the platform, avoided the height of COVID-19 lockdowns, and provided submission topic information (i.e., complete metadata) was the year 2021. As a result, the sample included all interactions on the discussion board that occurred between January 1st, 2021 and December 31st, 2021.

Exclusion criteria included interactions created by suspected automated users (bots) and those that had been deleted or removed by either the user or the platform. Posts and comments involving suspected bots were excluded from the sample using a list of 400 suspected bots compiled by a platform user and by referencing the forum moderator list to identify any moderator bots. In addition, posts where users were indicated as “deleted” or “removed” were excluded from the data. The final sample consisted of 172,223 interactions occurring between January 1st, 2021 and December 31st, 2021.

Data Collection

Raw data were extracted from the dataset using custom queries on the PushShift API (Baumgartner et al., 2020) used to scrape data from the platform available at https://pushshift.io/api-parameters/. The custom queries were built using syntax provided by the API manual to retrieve the necessary data pertaining to the information listed in the inclusion criteria. Collecting data for replies to submissions and replies to comments necessitated two separate commands for retrieval and, as a result, data for submission interactions and comment interactions were saved in separate CSV files. Each query was designed to retrieve only the information listed in the inclusion criteria.

Fields in the Raw Data

The two downloaded datasets contained information for submissions and comments, respectively. Fields found in each file contained information that was used to analyze participation in the OSG discussion board. Descriptions for each field and their accompanying data are listed below.

Submission Dataset

The raw submission dataset was comprised of (1) a timestamp, (2) author username, (3), upvote/downvote score, (4) the topic category indicated by the submitter, (5) a unique id number of the submission, and (6) number of comments on the submission.

Time. Time was natively represented by a timestamp in Unix time (see example in Table 2). Unix time relays the time in seconds that have passed since January 1, 1970, at 00:00:00 UTC and is widely used as a universal time in computing (Hauser, 2019). The Time in the submission dataset reflects the date and time that a submission was made to the discussion board.

Table 2

Example Submission Data

Time	Author ID	Submission ID	Score	Topic	Number of comments
1652561100	Example-user	1234	3	Question/ Advice	5

Author ID. Author ID was the platform username chosen by individual users. Usernames were unique and could contain letters and/or numbers. The Author ID in the submission data set refers to the username of the user who submitted content to the discussion board.

Submission ID. Submission ID is a unique identifying code consisting of letters and numbers that provided a reference to the submission to the discussion board. The Submission ID acted as a means for linking comments to submissions.

Score. Score was 1 plus the number of upvotes minus the number of downvotes (i.e., *Score* = 1 + upvote count – downvote count). A score of 1 is the default score for all new submissions. A score above 1 indicates that the submission received more upvotes than downvotes. Likewise, a score below 1 indicates that the submission received more downvotes that upvotes. A score of 1 may indicate that there was the exact same number of upvotes and downvotes or that the submission received no votes at all.

Topic. The discussion board required submissions to be self-categorized by the user into one of twelve categories (VA Disability, Question/Advice, GI Bill/Education, Healthcare, Article/News, VA Home Loan Question, Vocational Rehab Veteran Readiness, Employment, Tricare/ChampVA, St. Clair, Moderator Approved). Accordingly, each user submission contained information for the intended topic category of the submission discussion.

Number of Comments. Number of Comments was the sum count of comments, including comments to comments, within a submission.

Comment Dataset

The raw comment dataset contained similar information to the submission dataset. A notable difference included the Parent ID which referenced the submission or comment that the comment was replying to. Table 3 provides an example of comment data.

Table 3

Example Comment Data

Time	Author ID	Comment ID	Parent ID	Score
1652561160	Example-user	12345	1234	2

Time. As in the submission dataset, time was natively represented by a timestamp in Unix time. Time in the comment dataset represents the date and time a comment was made to a submission or a comment.

Author ID. Author ID was the platform username chosen by individual users. Author ID in the submission data set refers to the username of the user who replied with a comment to a submission or a comment.

Comment ID. Comment ID was a unique identifying code consisting of letters and numbers that provided a reference to the comment the discussion board.

Parent ID. The Parent ID provided a unique code that permitted the linking of comments to their parent submission (via Submission ID) or comment (via Comment ID). Only records in the comment dataset have a Parent ID field.

Score. As in the submission dataset, score was the sum of the number of people who upvoted and downvoted a comment. A score of 1 is the default score for all new comments. A score above 1 indicates that the comment received more upvotes than downvotes. Likewise, a score below 1 indicates that the comment received more downvotes that upvotes. A score of 1 may indicate that there was the exact same number of upvotes and downvotes or that the comments received no votes at all.

Preprocessing for Network Analysis and Relational Event Modeling

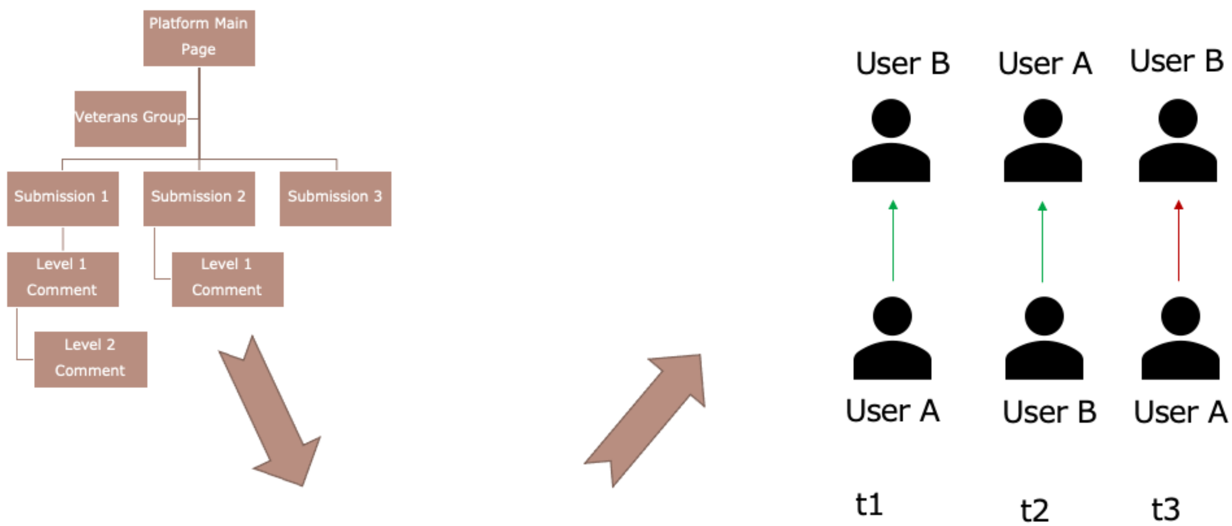
After data cleaning, additional processing of data occurred prior to final analyses. Preprocessing was necessary to link comments to submissions and comments to other comments in a way that could be used in static social network analysis for descriptive analyses in RQ1 and relational event modeling (REM), a dynamic subset of social network analyses used in RQ2 – RQ4.

Creating Network Data

In the preprocessing phase, data from the submission and comment files were joined by the ‘Comment ID’ and ‘Submission ID’ values. In each subsequent interaction, the “ego” was set to be the user who sent the comment and the “alter” was set to be the user to whom the comment was posted (i.e., egos sent interactions to alters, who were the receivers of the interactions thereby creating a network edgelist (see Figure 3)).To ensure the final network dataset contained all interactions, each comment was linked recursively to each Parent ID (i.e., submission or comment) in the raw dataset. Linking Comment IDs to Parent IDs resulted in a series of dyadic reply-based interactions that comprise the network edgelist (Figure 3). The network edgelist that was created provided a necessary format for relational event modeling and a convenient format for constructing a static network achieved by removing the exact time information.

Figure 3

Converting Submission and Comment Data into Network Edgelist



Time	Ego	Alter	Score
1652561100	User A	User B	3
1652561160	User B	User A	2
1652561220	User A	User B	-1

Figure 3 shows an example case of three events between a submitter and a commenter (i.e., dyadic events between two users) with interactions occurring one minute apart. The edgelist in Figure 3 shows one commenter (User B) receiving a positive comment from User A at time 1 (t1), where User B then responds to User A with a positive comment at time 2 (t2), and User A responds back to User B with a negative comment at time 3 (t3).

REMs dictate that the onset of time is exogenously determined (Butts, 2008), making 0 the starting point for all subsequent events in the model. Accommodating the onset time of 0 using seconds as the time increment was achieved by subtracting each Unix timestamp by the first timestamp (Table 4). Of the 172,223 interactions in the preprocessed data, there were 663 (0.38%) that were recorded simultaneously. Instances of exact time matching were handled by adding one second to events to differentiate their occurrence with minimal effect to the overall timeframe. For example, two events that happen at 09:00:00 have been ordered as 09:00:00 and 09:00:01. The communication event pushed forward by a second was randomly selected. This manner of handling simultaneous event times is anticipated to have minimal effect on model outcomes.

Measures

Measures in this dissertation are derived from information in the raw and processed data, and social network analysis statistics derived from the resulting network. This section contains description of topic categories and of community appraisals, how they are defined based on submission/comment score data and associated with peer support through the paralinguistic digital affordances framework.

Interaction Topics

Interaction topics for the submissions and comments included eight categories (1=*VA Disability*, 2=*Question/Advice*, 3=*GI Bill/Education*, 4=*Healthcare*, 5=*Article/News*, 6=*VA Home Loan Question*, 7=*Employment*, 8=*Other*). These categories were derived from the topic field in the raw datasets. Four categories from the raw datasets (Vocational Rehab Veteran Readiness, Tricare/ChampVA, St. Clair, Moderator Approved) were combined in the category *Other* by the researcher due to the sparsity of submissions and comments for the categories, thereby reducing the original twelve categories into eight.

Submission/Comment Community Appraisal

Interactions were conceptualized as being either peer support, neutral, or negative based on the submission/comment community appraisals. Specifically, peer support was conceptualized as submissions or comments receiving positive appraisal based on empirical literature for paralinguistic digital affordances (Hayes et al., 2018; Reich et al., 2018; Wohn et al., 2016). Negative appraisal was conceptualized as a submission or comment that received more downvotes than upvotes. Submissions and comments that received no community appraisal, or achieved an even number of upvotes and downvotes, were conceptualized as being neutrally appraised.

These conceptualizations of community appraisal for submissions and comments were operationalized as a categorical variable with attributes based on upvotes and downvotes for submissions and comments. Community appraisal scores for submissions and comments (taken from the "Score" field in the raw datasets) were categorically re-coded such that any score greater than one was considered to be peer support, any score less than one was considered a negative appraisal, and scores of exactly one were considered neutral. For example, a comment with a score of 20 would have met the criteria of being greater than one and therefore the community appraisal variable would have a value of "peer support." The continuous scores from the raw data were recoded into text values required for the analysis software Eventnet (Lerner and Lomi, 2020) where POS = *Peer support*, NEG = *Negative appraisal*, and NEUT = *Neutral appraisal*.

Table 4 shows the recoding of Unix time and community appraisal score using the three events from Figure 3.

Table 4

Example Network Data

Time	Ego	Alter	Submission/Comment Community Appraisal
0	User A	User B	POS
60	User B	User A	POS
120	User A	User B	NEG

Note. Time values are indexed to the first submission in the dataset representing the observational onset time of 0.

Analysis

This dissertation's analyses address the four research questions put forward to gain insight into an online support group for military veterans. Research question 1 (RQ.1): "What does user participation look like in the online support group?" was addressed by generating descriptive statistics for disaggregated discussion board data, and by constructing a static social network of the interactions across the one-year timeframe and generating descriptive statistics for the static network.

Research questions 2 – 4 (RQ.2, RQ.3, and RQ.4) ask how structural network mechanisms (i.e., the presence of specific local structural configurations of interactions) and previous interactions that are appraised as either peer support, negative, or neutral relate to: (RQ.2) participation in the online support group, (RQ.3) provision of peer support, and (RQ.4) posting negative submissions or comments. These research questions were addressed using REMs.

RQ.1: Descriptive Statistics and Visualization

RQ.1 was addressed by generating descriptive statistics for the aggregate online support group activity in 2021. Descriptive statistics for submissions and comments included the frequency and percentage of submissions by submission topic, comments associated with submissions by topic, interaction appraisal, and the distribution user participation in the discussion board disaggregated by calendar month. Static network descriptive statistics (i.e., the network of all interactions in 2021) were also calculated for the one-year network of interactions. Network statistics included average degree and standard deviation of indegree, standard deviation of outdegree, centralization, density, centralization, reciprocity, and transitivity. These descriptive statistics provide metrics for understanding the level of activity in the online support group network, the distribution of interactions within the network (i.e., the degree to which ties are associated with a few, highly active users versus distributed evenly across users), and the degree to which expected types of interactions (e.g., users responding to those who send them comments – or *reciprocity* – and users interacting with users that their alters interact with – or *transitivity*) exist in the observed network. Table 5 provides an overview of the descriptive statistics and a brief description of how the statistics are determined.

Table 5

Description of Network Statistics for the Aggregate Network of Interactions

Network Statistic	**Description**
Average Degree	Average number of incoming and outgoing interactions for each user.
Centralization	Proportion of users in the network connected to a single or a few highly connected user(s) (e.g., .00 means that all users are connected evenly to the others in the network, and 1.00 means that all users are connected to a single central user).
Reciprocity	Proportion of ties in the network that are reciprocated. See Figure 4 for an example of reciprocal symmetry.
Density	Proportion of all potential ties in the network that are present in the observed network.
Transitivity	Provides a description of how much local clustering there is in a network; ranging from 0 to 1, high transitivity scores indicate that there are clusters of densely connected local users in the network; transitivity is calculated as the proportion of three

	potentially connected users (as seen in Figure 4) that have a transitive structure (i.e., if A sends a tie to B and B sends a tie to C, then A also sends a tie to C).

Graphical illustrations for the aggregate interaction network were generated using the *Seaborn* library (Waskom, 2021) in Python3 to show the number of submissions, number of comments, and scores categorized by topic in the selected timeframe. A network visualization with 3 static subplots was created using the igraph library (v1.2.6; Horvát et al., 2022) in R to illustrate the evolution of the network over the course of the year.

RQ.2, RQ.3, and RQ.4: Relational Event Modeling

Relational event modeling (REM) was used to examine the association between structural effects in the online support group (see below for descriptions), community appraisals, and the rate of various types of engagement on the discussion board (i.e., general participation, peer support, and negative interactions). REM is suited to answering questions about how social interactions evolve over time and which structural mechanisms contribute to those social processes. A major point of differentiation between REM and other network analysis methods is its foundation in event history modeling (Blossfeld & Rohwer, 2001). Where other network analysis methods (e.g., stochastic actor-oriented models and temporal exponential random graph models) draw inference from simulated network structures based on panel data, event modeling uses a continuous history of interactions or event patterns between all actors by modeling the data directly. Because it is rooted in event history modeling, REM has the capacity to convey emergent communication patterns in online social networks (Foucault Welles et al., 2014).

Specifically, REM can model sequential processes and lend insight into the longitudinal interplay of causes and effects in social processes (Pilny et al., 2016).

Coefficients in the model are interpreted as the conditional log hazard of an event compared to all other possible outcome events in the model. Positive and significant coefficients indicate that the mechanism being measured is positively associated with the rate of a interaction (i.e., an event) in the online support group (i.e., any type of participation (RQ.2), peer support (RQ.3), or a negative interaction (RQ.4)); in contrast, negative and significant coefficients indicate that the proposed mechanism is inversely associated with the rate of the event in the online support group (Marcum & Butts, 2017).

In relational event modeling (Butts, 2008; Lerner et al., 2013) a rate function λ drives the stochastic component that allows for a risk set to be determined for event e in a sequence of events based on the past action of the source a (i.e., ego) of the event, target b (i.e., alter) of the event, type w of the event, and the time t that an event transpired. An event is a tuple containing the information for dyadic interactions at each point in time such that event $e_i = (a_i, b_i, w_i, t_i)$. The set of all e_i comprise the network *G*. Each timepoint in *G* is shaped by the history of events preceding the current event *t*. The hazard rate for an event (Lerner et al., 2020) is defined by Equation 1:

$$\lambda(a, b, w, t) = \frac{Prob(t \leq T + \Delta t \mid t \leq T)}{\Delta t} \qquad (1)$$

letting *T* denote the random time of the next event on the dyad of network actors (*a* and *b)* and type of event in the network. In the case of ordinal time sequences where the order of event occurrence is used for the indexing of events instead of exact time from 0, Butts (2008) illustrated that relational event networks can be modeled by a Cox proportional hazard model (Cox, 1972). The proportional hazard model provides inference for identifying factors that significantly increase or decrease the rate of dyadic events. A basic likelihood function (Equation 2) based on the Cox model with the network variables is defined by Lerner et al. 2020:

$$L(\theta) = \prod_{e_i \in E} \frac{\lambda_1(a_i, b_i, t_i, G[E;t_i];\theta)}{\sum_{ab \in R_{t_i}} \lambda_1(a_i, b_i, t_i, G[E;t_i];\theta)} \qquad (2)$$

where $G[E;t_i]$ is the event history of the network up to the i^{th} time in the network, R_{t_i} is the risk set for all possible events up to (but not including) the given time t, and Θ is model parameters estimated to maximize L. Alterations to this basic likelihood function are made for case-control sampling, which is discussed below.

Case-Control Sampling. An obstacle for relational event modeling has been the processing of a large number of events with many unique actors (Foucault Welles et al., 2014; Vu et al., 2015). Relational event modeling has often, if not mostly, been used with relatively small networks or subnetworks within larger networks (e.g., Butts, 2008; Leenders et al., 2016; Marcum & Butts, 2017; Meijerink-Bosman et al., 2022; Pilny, 2016; Schecter & Quintane, 2021). The latter case presents a potential problem for network analyses because interactions outside of the subnetwork may produce inaccurate network measurements (e.g., degree statistics) used in predictive models and provide inaccurate results (Lerner & Lomi, 2019). Accordingly, sampling that accounts for the nuances of event modeling has been explored in the form of case-control sampling by Vu et al. (2015) and expanded on by Lerner and Lomi (2020).

Case-control sampling takes the analyzed set of events happening at a timepoint and compares the events happening to a subset of events not happening at that timepoint rather than the set of all possible events not happening at that timepoint (Borgan et al., 1995). Using conventional verbiage – cases (events) are compared to non-events (controls) arising in the same time frame. Case control sampling necessitated regarding time as a sequential unfolding of events (referred to as the *ordinal* case by Butts, (2008)) as opposed to a strictly ordered series of events where time-from-onset establishes an absolute hazard rate (the *interval* case). See Lerner et al. (2020) for complete sampling equation notation regarding the likelihood function in the case of case-sampling.

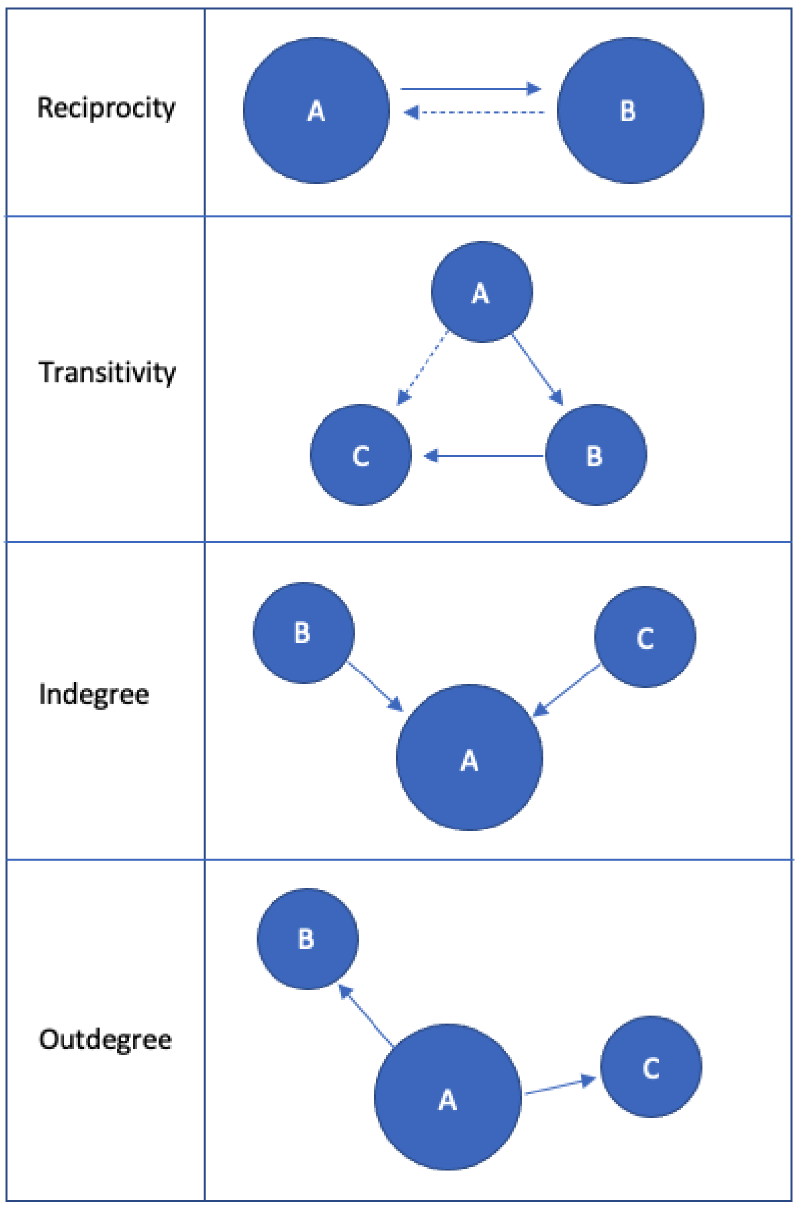
This analysis used the case control sampling implementation by Lerner and Lomi (2020) included in their event network analyzer software *Eventnet*. This software requires that number of control cases for comparing to realized events must be selected. For general use cases with many observed events the recommended number of controls are between two to ten (Lerner and Lomi, 2020). In the REMs for this dissertation, five control cases were selected per event. This was selected based on the suggested number of controls by Lerner and Lomi (2020).

Network Structural Effects

As noted above, the REMs used in this dissertation to answer RQ.2-4 include parameter estimates (i.e., Θ) for *structural effects.* Structural effects correspond to some of the social network terms introduced in the descriptives (RQ.1) section above for describing a static network in its entirety. However, in the case of REMs, the network characteristics are examined in smaller, local configurations to determine if local characteristics in a network influence the propensity for a user to participate in the online support group (RQ.2) or to engage in particular types of interactions (i.e., peer support (RQ.3) or negative interactions (RQ.4)). For example, it is reasonable to assume that if one user had a history of sending comments to another user, the tendency for them to continue to do so in the future is increased. This effect is the network structural effect of *outdegree.* Similarly, a user with a history of receiving comments would continue to have a higher rate of receiving more comments, which is the network structural effect of *indegree*. Users who invite responses, for example by asking questions, could be expected to receive more responses than users who make close-ended remarks. This effect reflects the structural effect of *reciprocity*. Active users in the support group network may be observed to stay engaged in discussion threads by replying to other users to whom the people they have already replied to have commented. This is the structural effect of *transitivity*. Below, visualizations for each of these structural effects are provided in Figure 4.

Figure 4

Visual Representations for Structural Effects (i.e., Reciprocity, Transitivity, Indegree, and Outdegree)



Statistics for Network Structural Effects

Each of these structural effects are network variables that are used as analogues for sociological constructs in this dissertation (detailed in Chapters 2 & 3). The structural effects of these sociological constructs can be described mathematically and are presented below as they are implemented in REM.

Indegree and Outdegree. Relational event models account for recency of past senders to future senders by indegree and outdegree statistics (Lerner et al., 2017) described in the equations that follow (Equations 3 and 4):

$$indegree_i(A,B) = \sum_{B' \neq A} \quad type_{i-1}(B',A) \quad (3)$$

$$outdegree_i(A,B) = \sum_{B' \neq A} \quad type_{i-1}(A,B') \quad (4)$$

where A represents the source actor, B the target actor of an event, and *i-1* is the previous instance of the interaction type for the dyad. Indegree and outdegree effects are employed in relational event modeling to represent directed ties among actors over time for interactions (peer support, negative, neutral). Outdegree and indegree network statistics provide the sum count of interactions for a pair of actors' community appraisal types over the span of a specified timeframe, accounting for their half-life weightings (discussed at the end of the network statistics section). For example, if actor A posted only two peer support interactions to actor B (i.e., actor A was the sender and B was the receiver), then actor A's outdegree for peer support interactions would be 2 in the dyadic context. From the receiving perspective, actor B would have an indegree of 2 having been contacted twice by actor A.

Reciprocity. Interactional reciprocity is conceived in REM as response of actor B to an incoming action from actor A. Notionally represented in Equation 5 as

$$reciprocity_i(A,B) = type_{i-1}(B,A) \quad (5)$$

This statistic for reciprocity used by Lerner et al. (2017) reflects the number of times actor B responded to actor A after actor A initiated a communication with B. A positive reciprocity statistic indicates that actors in the network tend to engage in mutual exchanges rather than just speaking to others or just being spoken to. Conversely, a negative parameter reflects that actors in the network tend not to respond to initiators of communication.

Network Transitivity. Any group of three individuals in a network, whether they are connected or not, is a triad. Transitive triads are ones in which the ego closes a 3-way connection (Figure 4). For example, a transitive triad occurs if user A has commented to B and B comments to C then A, will in turn, comment to C. The tendency toward transitivity in a network can be seen where two people who have ties a third person are more likely to be tied to each other than those who do not have a peripheral (i.e., third) person to broker social ties (Holland & Leinhardt, 1970).

The transitivity coefficient in this dissertation provides an indication of how involved an individual is in a cohesive local social network (i.e., where the alters tend to be connected to one another), which may be indicative of greater subgroup group cohesiveness. The implementation for the transitivity coefficient is based on the equation (Equation 6) used by Lerner et al. (2017)

$$transitivity_i(A,B) = \sqrt{\sum_{C \neq A,B} \quad type_{i-1}(A,C) \cdot type_{i-1}(C,B)} \quad (6)$$

where C represents a third user outside of the AB dyad interacting with user A. Transitivity, along with the other structural network statistics outlined in this section, must be considered in conjunction with the half-life of network interactions.

Half-Life of Interactions. The effects of interpersonal events in everyday life can decay given enough time and if the relationships are not maintained with relative frequency. The same principle can be applied to online interactions and in the context of social network analysis. For example, the effect of ties between actors can be considered constant or to decay over time within a moving temporal window supporting the supposition that social events have a general period of activity for which their effects are most salient before they begin to decay (Lerner & Lomi, 2020; Meijerink-Bosman, 2022). Network statistics can be thought to return to a pre-interaction paradigm after half-life weights return to 0 where previous interactions among users are seen as less salient in their social effects. For the relational event modelling in this dissertation, a data-driven approach to determining the value of the half-life weighting for the interactions was used by assessing the time difference between user interactions in the support group discussion board. The time difference between interactions suggests that an approximate median value for submitting or commenting in the online support group is once every 8 days. Accordingly, a half-life parameter (Lerner & Lomi, 2020) of 4 days was used to weight activity in the network such that an event's weight begins at 1 on the day it was posted then becomes .5 four days later, then .25 sixteen days after the event, and 0 when a threshold of <.01 is achieved at 20 days.

REM Assumptions

Butts and Marcum (2017) outline three assumptions for REM.

1. All events have been recorded and the onset is exogenously determined.
2. Events are temporally ordered, and events cannot occur at the exact same time.
3. Event hazard rates and support statistics are piecewise constant.

Each of the three assumptions were met. Related to the first assumption, there is a reasonable belief that the data recorded by the platform and collected by the web reflect all events within the sample frame. The onset of communication events was exogenously determined by the researcher as beginning at a specified timestamped communication (i.e., January 1 at 00:00:00).

Regarding the second assumption, temporal order is verifiable through timestamped data. A very small minority of interactions (0.38%) occurred simultaneously, indicating that REM is appropriate for this data as opposed to a dynamic (i.e., high simultaneity) framework such as the Stochastic Actor-Oriented Model (Butts & Marcum, 2017).

Finally, changes in hazard rates occur at realized endogenous events or at exogenous time events (i.e., be piecewise constant) in this analysis. Realized events, such as submissions or comments, are theorized to affect the propensity of future events that individuals engage in based on their history of interactions in the network. Therefore, all three assumptions were met prior to statistical modeling.

Specifying and Fitting the Relational Event Models

Specification for RQ.2 – 4.

The REMs were specified to include the structural effect predictor variables (i.e., indegree, outdegree, reciprocity, and transitivity) which included the weight of an actor's history of participation in different types of interactions (i.e., peer support, negative, and neutral) as the predictor variables.

Model 1: RQ2. This dissertation's second research question (RQ.2) was, "*How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity), and previous interactions that are appraised as either peer support, negative, or neutral by the community relate to participation in the online support group?"* The dependent variable for Model 1 is the observed event of any community appraisal type (peer support, negative, neutral). The independent variables for Model 1 include structural effect statistics for outdegree, indegree, reciprocity, and transitivity for each type of community appraisal type (e.g., in the notation of the analytic software used, POS.outdegree, NEG.outdegree, NEUT.outdegree). The half-life for the interaction effects for peer support was set for 4 days. The half-life for effects of neutral interactions was set for 4 days. The half-life for effects of negative interactions was set for 4 days.

Model 2: RQ3. This dissertation's third research question (RQ.3) was, ***"****How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) and previous interactions that are appraised as either positive, negative, or neutral by the community the relate to peer support (positive appraisals) in the online support group?****"*** The dependent variable for Model 2 is observed peer support events. The independent variables for Model 2 include structural statistics for outdegree, indegree, reciprocity, and transitivity for each type of community appraisal type (e.g., POS.outdegree, NEG.outdegree, NEUT.outdegree). The half-life for the interaction effects for peer support was set for 4 days. The half-life for effects of neutral interactions was set for 4 days. The half-life for effects of negative interactions was set for 4 days.

Model 3: RQ 4. This dissertation's forth research question (RQ.4) was, *"How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity), and previous interactions that are appraised as either positive, negative, or neutral by the community the relate to negative appraisals in the online support group?"* The dependent variable for Model 3 is observed negative events. The independent variables for Model 3 include structural statistics for outdegree, indegree, reciprocity, and transitivity for each type of community appraisal type (e.g., POS.outdegree, NEG.outdegree, NEUT.outdegree). The half-life for the interaction effects for peer support was set for 4 days. The half-life for effects of neutral interactions was set for 4 days. The half-life for effects of negative interactions was set for 4 days.

Constructing and Fitting the Models. Relational event models to answer RQ.2, RQ.3, and RQ.4 were constructed using the Eventnet software (Lerner & Lomi, 2020) to produce REM risk sets and were fit using the *survival* R library to evaluate relational event proportional hazard models. Assessing model fit was accomplished by examination of the Wald statistic ($p < .05$) which determined if the parameterized model significantly differs from the null model. Additionally, the pseudo-R-square score based on the partial likelihood ratio statistic to obtain an inference about improvement from the null model in the fitted model. A concordance score was used to determine the overall predictive accuracy of the model. Concordance scores above 0.5 indicate that that the model is successful in distinguishing survival times between groups and can be evaluated to have increasingly successful predictive power as the score approaches 1 (Gönen & Heller, 2005).

Chapter Conclusion

This chapter outlined the research design, methods, and analytical techniques that were used to address the research questions. Sample selection, data collection, and variable operationalization were detailed with respect to the prerequisite ethics considerations. The next chapter will present the results for the descriptive statistics for RQ.1 and relational event models for RQ.2 – RQ.4.

Chapter 5: Results

This chapter presents the results from descriptive and model-based analyses outlined in Chapter 4. Descriptive analyses include calculating frequencies for topics, submissions, comments, and aggregate network statistics to address RQ.1. Model-based results include the parameter estimates from relational event models addressing RQ.2 – RQ.4.

Describing the Support Group (RQ.1: What are the characteristics of the content and structure of user participation in the online support group?)

Description of the support group addresses RQ.1 and is divided into two sections. The first section includes an overview of the distribution of topics and comments. Frequencies of community appraised types of interactions are described and a visualization for the monthly distribution of interactions are presented. In the second section, descriptive results for the aggregate 2021 static network are provided.

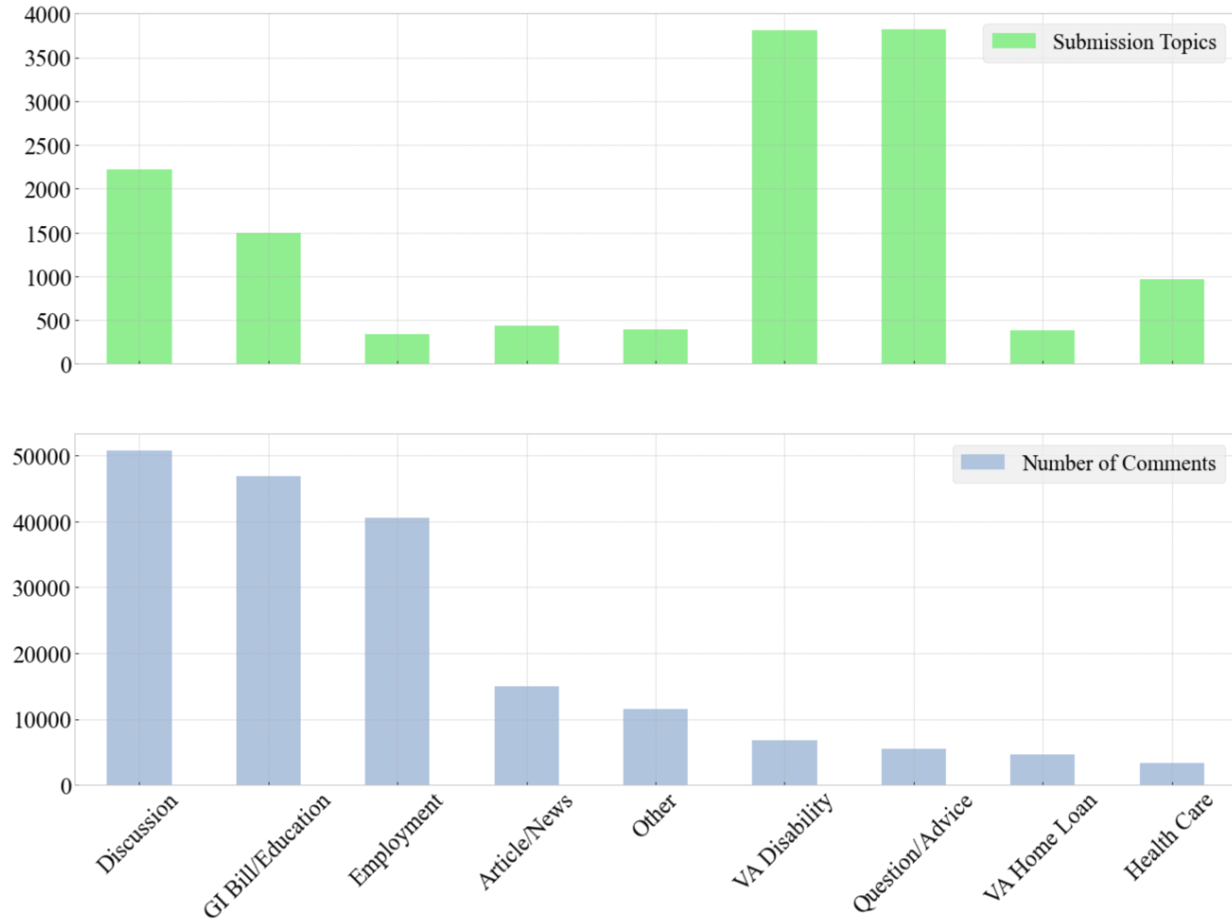
Submissions and Comment Topics

The study included 13,954 user submissions (i.e., initial posts to the discussion board) and 170,892 comments made by 19,684 unique users. As shown in Figure 5, the total number of submissions and comments vary by the topic of discussion. The submissions with the highest number by topic were ‘Question/Advice’ (*n* = 3,815) accounting for 27.3% of all submissions and ‘VA Disability’ (*n* = 3,806; 27.3%), with ‘Employment’ having the least number of submissions (*n* = 341; 3%).

Topics having the highest number of comments were ‘Discussion’ receiving 50,731 comments and accounting for 30% of all comments, followed by ‘GI Bill/Education’ (*n* = 46,859; 27%) and ‘Employment’ (*n* = 40,476; 24%). The topic category receiving the fewest number of comments was 'Health Care' with 3,313 comments, accounting for 2% of all comments.

Figure 5

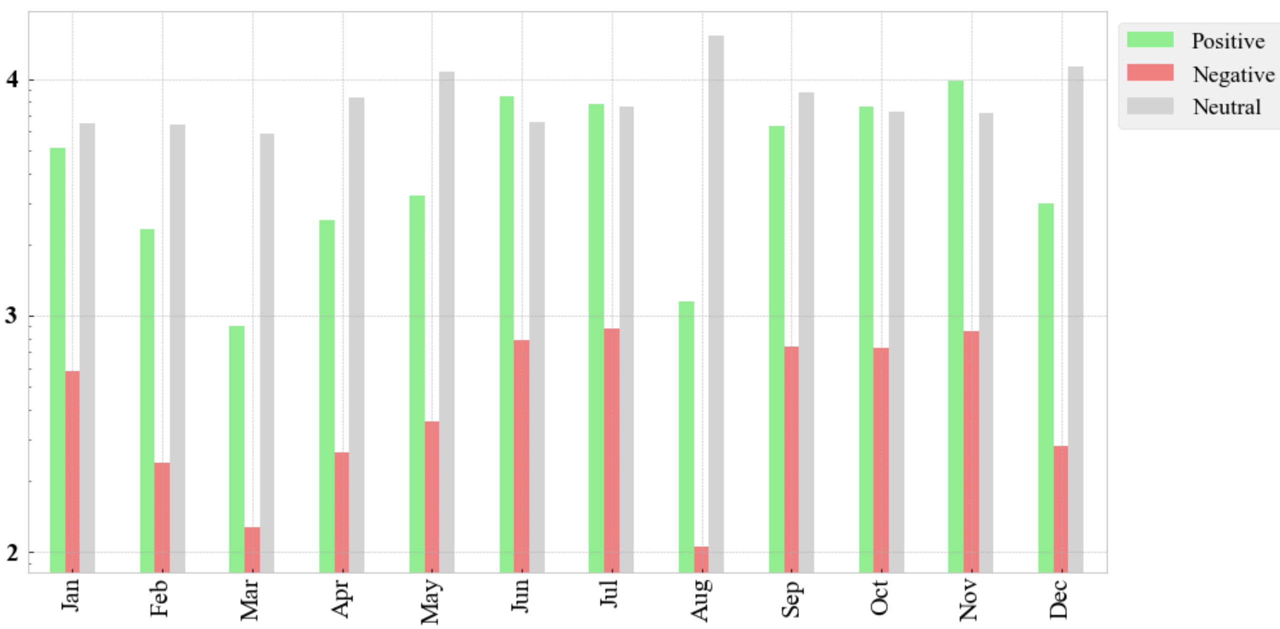
Total Number of Submissions and Comments in the Support Group



The aggregate distribution for all interactions in 2021 showed that a large proportion (61.6%) were neutrally appraised. Peer support was the second most common type of interaction (34.8%) and negative interactions the least common (3.6%). Figure 6 shows the types of interactions plotted with month on the x-axis and number of interactions on the y-axis. The monthly distribution of appraised interactions shows that neutral interactions tended to be the most prominent type of interaction each month. Positive interactions were the second most prominent type of interaction each month, and negative interactions the least prominent.

Figure 6

Monthly Distribution of Community Appraised Interactions



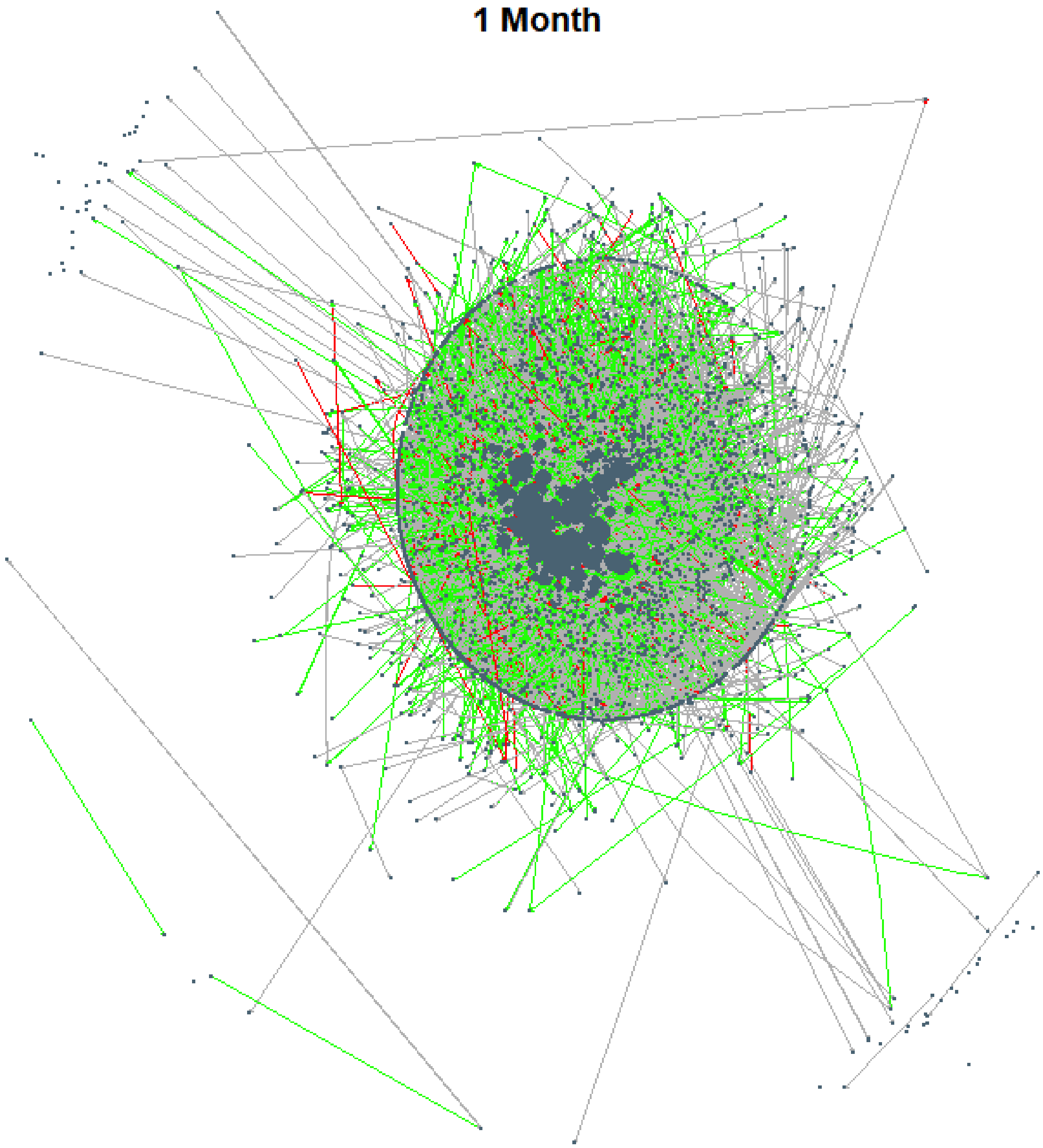
Note. The number of monthly interactions is presented using a log scale on the y axis to provide better visualization of peer support and negative appraisals relative to neutral appraisals.

Static Network Description

The static directed network was comprised of 19,684 users and 142,483 interactions (Figure 7 – Figure 9). Users in the network sent and received an average of 7.24 interactions. There was greater variability for the number of interactions received (*SD* = 43.68) than sent (*SD* = 27.19). Centralization of the network was 0.15, indicating that interactions in the network tended to be dispersed more evenly across the network of users than sent and received by a relatively small number of prominent users. Tie reciprocity was 0.52, indicating that more than half of the interactions between users are reciprocated in the static network. The density statistic (0.0004) showed that there were relatively few interactions among users in network considering the number of people users had the option of interactions with. Transitivity (0.02) indicated that there were relatively few transitive triangles occurring in the static network.

Figure 7

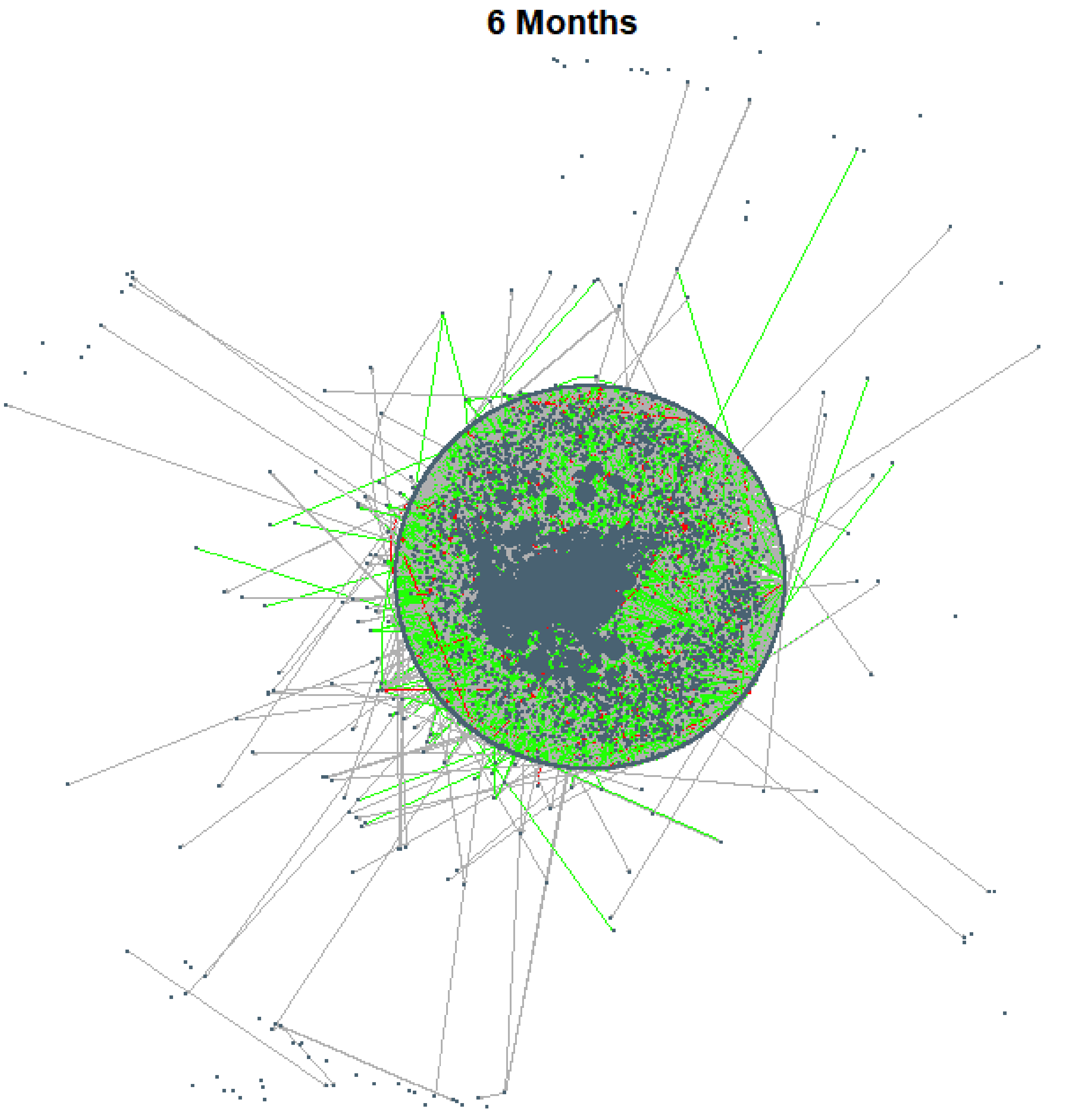
Static Interaction Network at 1 Month



Note. Node size corresponds to the node's degree in the network. Nodes with degree greater than 100 were excluded to improve visualization. Edge colors correspond with the type of community appraisal (green = peer support, red = negative, gray = neutral). *N* = 3,794 users and 13,133 reply-based interactions. At 1 month, the network shows a small number of high-degree users in the network as illustrated by the patches of gray nodes.

Figure 8

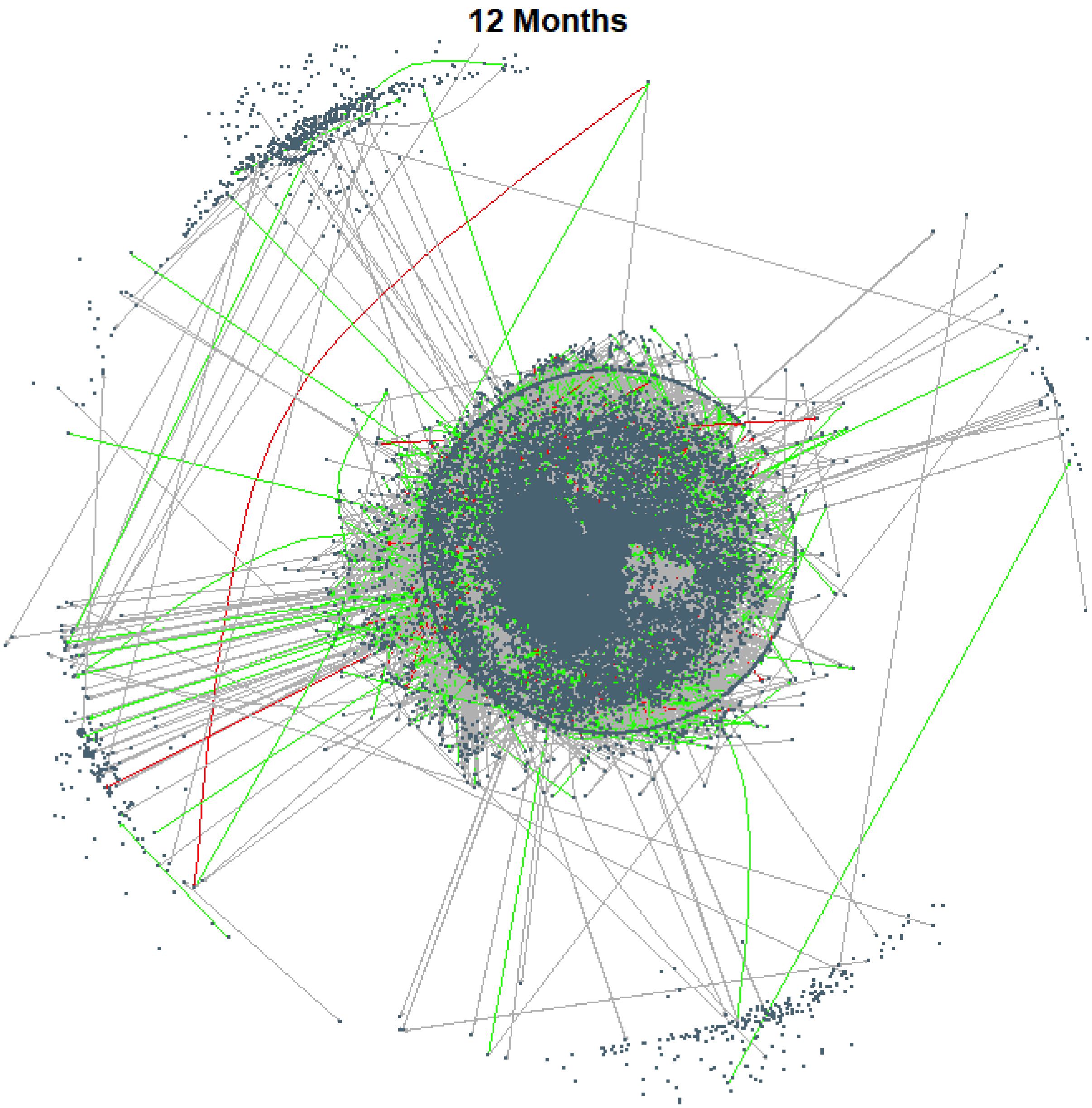
Static Interaction Network at 6 Months



Note. Node size corresponds to the node's degree in the network. Nodes with degree greater than 100 were excluded to improve visualization. Edge colors correspond with the type of community appraisal (green = peer support, red = negative, gray = neutral). *N* = 10,575 users and 56,554 reply-based interactions. At 6 months, the network shows a larger number of high-degree users in the network as illustrated by the patches of gray nodes.

Figure 9

Static Interaction Network at 12 Months



Note. Node size corresponds to the node's degree in the network. Nodes with degree greater than 100 were excluded to improve visualization. Edge colors correspond with the type of community appraisal (green = peer support, red = negative, gray = neutral). *N* = 19,684 users and 142,483 reply-based interactions. At 12 months, the network shows the largest number of high-degree users in the network as illustrated by the patches of gray nodes.

Relational Event Modeling

Relational event models 1-3 (addressing RQ.2 – RQ.4) provide inference for the historical rates of structural network mechanism on (1) online support group participation (all types of community appraised interactions), (2) peer support (interactions with positive community appraisals), and (3) negative interactions (interactions with negative community appraisals). The independent variables are structural network mechanisms (i.e., indegree, outdegree, reciprocity, and transitivity) thought to contribute to interactions of interest. Each structural network mechanism was coded by type of community appraisal for brevity in the results table (*POS* = peer support, *NEG* = negative, *NEUT* = neutral). Model coefficients are presented as hazard ratios (HR), which indicate the effect size that structural network mechanisms have on interactions. HRs greater than one indicate that the historical rate of the structural mechanism is greater than the control cases (i.e., interactions that could have happened given the history of the network). Likewise, HRs less than one indicate that the historical rate of the structural mechanism is less than the control cases. A HR equal to one indicates that the historical rate of the structural mechanism is equal to the control cases (i.e., suggests no meaningful effect). Goodness-of-fit indices are presented for each model and include the Wald test statistic, pseudo-R-square, and concordance score.

Table 6

Effects of Structural Network Mechanisms on OSG Participation, Peer Support Interactions, and Negative Interactions

	Model 1: Participation[a]		Model 2: Peer Support[b]		Model 3: Negative Interactions[c]	
Network Mechanism	HR	95% CI	HR	95% CI	HR	95% CI
POS.Indegree	1.04***	1.04, 1.04	1.04***	1.04, 1.04	1.05***	1.04, 1.05
NEG.Indegree	0.95***	0.95, 0.96	0.96***	0.95, 0.97	1.01	1.00, 1.02
NEUT.Indegree	1.02***	1.02, 1.02	1.02***	1.02, 1.02	1.01***	1.01, 1.02
POS.Outdegree	1.03***	1.03, 1.03	1.06***	1.06, 1.06	1.05***	1.05, 1.05
NEG.Outdegree	1**	0.99, 1.00	1.15***	1.15, 1.16	1.14***	1.13, 1.16
NEUT.Outdegree	1.02***	1.02, 1.02	0.98***	0.98, 0.98	0.99***	0.98, 0.99
POS.Reciprocity	1.76***	1.75, 1.78	1.90***	1.87, 1.92	1.69***	1.62, 1.77
NEG.Reciprocity	0.87***	0.85, 0.89	0.63***	0.60, 0.66	1.22***	1.17, 1.28
NEUT.Reciprocity	1.15***	1.15, 1.16	1.15***	1.13, 1.16	1.03	1.00, 1.07
POS.Transitivity	0.76***	0.74, 0.77	0.88***	0.85, 0.90	0.86***	0.81, 0.92
NEG.Transitivity	0.77***	0.70, 0.85	0.80*	0.67, 0.95	0.91	0.75, 1.10
NEUT.Transitivity	0.76***	0.75, 0.76	0.74***	0.72, 0.76	0.70***	0.66, 0.73
Wald[d]	285,820		109,840		12,408	
Pseudo-R-square	0.11		0.11		0.15	
Concordance	0.91		0.90		0.92	

*p<.05, **p<.01, ***p<.001
[a] *Number of events* = 172,223
[b] *Number of events* = 60,281
[c] *Number of events* = 6,087
[d] Wald test statistics are significant at $p<.05$

Model 1: Effects of Structural Network Mechanisms on OSG Participation

(RQ.2: How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) and previous interactions that are appraised as either positive, negative, or neutral by the community the relate to the rate of peer support (positive appraisals) in the online support group?). The parameter estimates for model 1 address the hypotheses for RQ.2 below:

H2(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be positively associated with participation.

H2(a) was partially supported by the finding that the more peer support messages a user received in the past (expressed by POS.Indegree), the more interactions of any appraised type they participate in (*HR* = 1.04; 95% *CI* [1.04, 1.04]; $p<.001$). Users who had received peer support in the past had a 4% higher rate for participating in any type of interaction when compared to the non-recipient control cases. Likewise, the more peer support messages a user provided to other users in the past (expressed by POS.Outdegree), the higher the rate of interactions there was for any appraised type in the future within the OSG (*HR* = 1.03; 95% *CI* [1.03, 1.03]; $p<.001$). Users with a history of reciprocating peer support (POS. Reciprocity) tended to engage in reciprocation in the OSG network (*HR* = 1.76; 95% *CI* [1.75, 1.78]; $p<.001$). Specifically, they had a 76% higher rate of engaging in reciprocation in the OSG network compared to the non-reciprocation control cases. For the transitivity parameter estimate (POS.Transitivity), users who send transitive peer support interactions (i.e., peer support to people that have received peer support from those users that they have sent support to) had 24% lower rate of closing a transitive triad in the OSG network compared to the control cases (*HR* = 0.76; 95% *CI* [0.74, 0.77]; $p<.001$).

H2(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be negatively associated with participation.

H2(b) was partially supported by the finding that the more negative messages a user received in the past (expressed by NEG.Indegree), the less interactions of any appraised type they tended to participate in (*HR* = 0.95; 95% *CI* [0.95, 0.96]; $p<.001$). Users with a history of reciprocating negative interactions (NEG. Reciprocity) tended to not engage in reciprocation in the OSG network (*HR* = 0.87; 95% *CI* [0.85, 0.89]; $p<.001$) and had a 13% lower rate of reciprocation in the OSG network compared to the reciprocation control cases. Likewise, the transitivity parameter estimate (NEG.Transitivity) indicates that users who send transitive negative interactions (i.e., negative interactions to people that have received negative interactions from those users that they have sent negative interactions to) have a 23% lower rate of closing a transitive triad OSG network compared to the control cases (*HR* = 0.77; 95% *CI* [0.70, 0.85]; $p<.001$). However, the rate for sending negative messages to others (expressed by NEG.Outdegree) was the same for interactions of any appraised type within the OSG and non-provider control cases (*HR* = 1.00; 95% *CI* [0.99, 1.00]; $p<.01$).

H2(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be negatively associated with participation.

H2(c) was largely unsupported, as only the estimate for transitivity (NEUT.Transitivity) was significant and less than one. This finding indicates that users who send transitive neutral interactions (i.e., neutral interactions to people that have received neutral interactions from those users that they have sent neutral interactions to) have a 24% lower rate of closing a transitive triad in the OSG network compared to the control cases (*HR* = 0.76; 95% *CI* [0.75, 0.76]; $p<.001$). In contrast to the hypothesized direction of effect, the hazard ratio estimate showed the more neutral messages a user received in the past (expressed by NEUT.Indegree), the more interactions of any appraised type they tended to participate in (*HR* = 1.02; 95% *CI* [1.02, 1.02]; $p<.001$). Similarly, the more neutral messages a user provided to other users in the past (expressed by NEUT.Outdegree), the more participation within the OSG (*HR* = 1.02; 95% *CI* [1.02, 1.02]; $p<.001$). Users with a history of reciprocating neutral interactions (NEUT. Reciprocity) tended to engage in reciprocation in the OSG network at a higher rate than the control cases (*HR* = 1.15; 95% *CI* [1.15, 1.16]; $p<.001$).

Model 1 demonstrated adequate model fit as determined by the Wald statistic, pseudo-R-square score, and concordance score.

Model 2: Effects of Structural Network Mechanisms on Peer Support

(RQ: 3 How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) and previous interactions that are appraised as either positive, negative, or neutral by the community relate to the rate of peer support (positive appraisals) in the online support group?).

The parameter estimates for Model 2 address the hypotheses for RQ.3 below:

H3(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be positively associated with peer support.

H3(a) was partially supported by the finding that the more peer support messages a user received in the past (expressed by POS.Indegree), the more peer support interactions they tend to engage in (*HR* = 1.04; 95% *CI* [1.04, 1.04]; *p*<.001). Users who had received peer support in the past had a 4% higher rate for engagement in peer support interactions when compared to the non-recipient control cases. Likewise, the more peer support messages a user provided to other users in the past (expressed by POS.Outdegree), the more peer support interactions they tended to engage in (*HR* = 1.06; 95% *CI* [1.06, 1.15]; *p*<.001). Users with a history of reciprocating peer support (POS. Reciprocity) tended to engage in peer support interactions (*HR* = 1.90; 95% *CI* [1.87, 1.92]; *p*<.001). They had a 90% higher rate of engagement in peer support compared to the non-reciprocation control cases. For the transitivity parameter estimate (POS.Transitivity), users who send transitive peer support interactions (i.e., peer support to people that have received peer support from those users that they have sent support to) have a 12% lower rate for closing transitive triads in peer support interactions compared to the control cases (*HR* = 0.88; 95% *CI* [0.85, 0.90]; *p*<.001).

H3(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be negatively associated with peer support.

H3(b) was partially supported by the finding that the more negative messages a user received in the past (expressed by NEG.Indegree), the less peer support interactions they tended engage in (*HR* = 0.96; 95% *CI* [0.95, 0.97]; $p<.001$). Users with a history of reciprocating negative interactions (NEG. Reciprocity) tended to not participate in peer support interactions (*HR* = 0.63; 95% *CI* [0.60, 0.66]; $p<.001$) and had a 37% lower rate for peer support interactions compared to the reciprocation control cases. Likewise, the transitivity parameter estimate (NEG.Transitivity) indicates that users who send transitive negative interactions (i.e., negative interactions to people that have received negative interactions from those users that they have sent negative interactions to) had a 20% lower rate of closing transitive triads in peer support interactions in the OSG network compared to the control cases (*HR* = 0.80; *CI* [0.67, 0.95]; $p<.05$). Unexpectedly, the more negative messages a user provided to other users in the past (expressed by NEG.Outdegree), the more peer support they tended engage in (*HR* = 1.15; 95% *CI* [1.15, 1.16]; $p<.001$).

H3(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be negatively associated with peer support.

H3(c) was partially supported as the more neutral messages a user provided to other users in the past (expressed by NEUT.Outdegree), the less peer support interactions they engage in (*HR* = 0.98; 95% *CI* [0.98, 0.98]; $p<.001$). Also, users who engage in transitive neutral interactions (i.e., neutral interactions to people that have received neutral interactions from those users that they have sent neutral interactions to) have a 26% lower rate for closing transitive triads in peer support interactions in the OSG network compared to the control cases (*HR* = 0.74; *CI* [0.72, 0.76]; $p<.001$). The more neutral messages a user received in the past (expressed by NEUT.Indegree), the more peer support interactions they tended to engage in (*HR* = 1.02; 95% *CI* [1.02, 1.02]; $p<.001$). Likewise, users with a history of reciprocating neutral interactions (NEUT. Reciprocity) tended to participate in peer support interactions (*HR* = 1.15; 95% *CI* [1.13, 1.16]; $p<.001$).

Model 2 demonstrated adequate model fit as determined by the Wald statistic, pseudo-R-square score, and concordance score.

Model 3: Effects of Structural Network Mechanisms on Negative Interactions

(RQ4: How do structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity), and previous interactions that are appraised as either positive, negative, or neutral by the community the relate to the rate of negative appraisals in the online support group?).

The parameter estimates for Model 3 address the hypotheses for RQ.4 below:

H4(a): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous peer support will be negatively associated with negative interactions.

H4(a) was largely unsupported, as only the transitivity parameter estimate (POS.Transitivity) suggested that users who engage in transitive peer support interactions (i.e., peer support to people that have received peer support from those users that they have sent support to) had a 14% lower rate for closing transitive triads in negative interactions in the OSG network compared to the control cases (*HR* = 0.88; 95% *CI* [0.81, 0.92]; $p<.001$). Conversely, the more peer support messages a user received in the past (expressed by POS.Indegree), the more negative interactions they tended to engage in (*HR* = 1.05; 95% *CI* [1.04, 1.05]; $p<.001$). The more peer support messages a user provided to other users in the past (expressed by POS.Outdegree), the higher the rate of negative interactions they engaged in (*HR* = 1.05; 95% *CI* [1.05, 1.05]; $p<.001$). Users with a history of reciprocating peer support (POS. Reciprocity) tended to engage in negative interactions (*HR* = 1.69; 95% *CI* [1.62, 1.77]; $p<.001$). They had a 69% higher rate of engagement in negative interactions compared to the non-reciprocation control cases.

H4(b): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous negative interactions will be positively associated negative interactions.

H4(b) was partially supported as the more negative messages a user provided to other users in the past (expressed by NEG.Outdegree), the more negative interactions they tended engage in (*HR* = 1.14; 95% *CI* [1.13, 1.16]; *p*<.001). Users with a history of reciprocating negative interactions (NEG. Reciprocity) tended to engage in negative interactions (*HR* = 1.22; 95% *CI* [1.17, 1.28]; *p*<.001) and had a 22% higher rate of engaging in the negative interactions compared to the reciprocation control cases. However, the parameter estimates for transitivity (NEG.Transitivity) and a history of sending negative messages (NEG.Outdegree) were non-significant.

H4(c): Structural network mechanisms (i.e., outdegree, indegree, reciprocity, and transitivity) associated with previous neutral interactions will be positively associated with negative interactions.

H4(c) was partially supported as the more neutral messages a user received in the past (expressed by NEUT.Indegree), the more negative interactions they tended to engage in (*HR* = 1.01; *CI* = 1.01, 1.02; *p*<.001). On the other hand, the more neutral messages a user sent to other users in the past (expressed by NEUT.Outdegree), the less negative interactions they tended to engage in (*HR* = 0.99; *CI* = 0.98, 0.99; *p*<.001). Users who engage in transitive neutral interactions (i.e., neutral interactions to people that have received neutral interactions from those users that they have sent neutral interactions to) have a 30% lower rate for closing transitive triads in negative interactions in the OSG network compared to the control cases (*HR* = 0.70; 95% *CI* [0.66, 0.73]; *p*<.001). The parameter estimates for reciprocity (NEUT.Reciprocity) were non-significant.

Model 3 demonstrated adequate model fit as determined by the Wald statistic, pseudo-R-square score, and concordance score.

Chapter Conclusion

This chapter provided the results to the research questions and hypotheses posited in Chapter 3 and further detailed in Chapter 4. Descriptive statistics results were provided to address RQ.1 and REM model results were provided to address RQ.2, RQ.3, and RQ.4. The next chapter will discuss the implications for the results and how they relate to social work theory, practice, research, and policy.

Chapter 6: Discussion and Conclusion

The purpose of this research was to explore an online support group for veterans and determine what structural mechanisms contribute to continued participation in the group, the development of peer support, and negative interactions. This was accomplished using the networked neo-ecological framework as a foundation for understanding the microsystem of the OSG. Data were obtained through an API for harvesting discussion board submissions and comments from an online platform and analyzed using a combination of descriptive statistics and network analyses. This chapter discusses the findings from the analyses in the context of the gaps in the literature regarding online peer support for veterans. Implications for social work practice, theory, research, and education are presented.

Describing the OSG

This research is among the first to examine what topics are being discussed in veterans' OSGs. Insight into what topics in the OSG are most or least discussed was achieved by examining the number of comments delineated by discussion topic. The disaggregated submission and comment data shows a discrepancy between topics that users made submissions for and topics that received the most conversation. Notably, the topics 'VA Disability' and 'Question/Advice' have the highest number of submissions (27.30% and 27.34% of submissions respectively) but among the lowest number of comments replying to the submissions (3.95% and 3.22% of comments respectively). In contrast, 'GI Bill/Education', 'Discussion', and 'Employment' have fewer users creating discussion threads in service of those topics but have the highest number of comments associated with them.

These findings suggest that there is a sizable contingent of veterans who visit the online support group looking to discuss disability claims, or to ask general questions, and who receive relatively little support regarding those topics when contrasted against other discussion topics. One possibility is that there are few veterans in the OSG who are knowledgeable about the process of making VA disability claims or who have answers to other more general questions which do not have a forum topic dedicated to them. It may be the case that the OSG is composed of younger veterans who have not needed to file disability claims related to their service, having joined the armed forces after the height of combat deployments between 2001 and 2012 (Tsai et al., 2012). Indeed, a more recent cohort of veterans may be more active in the OSG considering that a disproportionate number of comments are found in the 'GI Bill' and 'Employment' topic submissions – a possible indication of recent separation from the armed forces. Overall, the topic descriptions suggest that seeking informational support is among the most prevalent type of support sought in the OSG and that much of the activity in the OSG is by veterans who could be in the early stages of reintegration into society.

The prevalence of apparent informational support aligns with what Stana et al. (2017) found in their thematic coding of discussions topics in an OSG for veterans where they noted that informational support was the most common type of support provided. The characteristics of informational support identified by Stana et al. (2017) were (1) requesting personal disclosure, (2) providing personal disclosure, (3) requesting information, (4) providing information, (5) requesting advice, and (6) providing advice. The topic categories found in the OSG examined this dissertation research suggests that the content of the OSG in this dissertation research may reflect some of the qualitative aspects of Stata et al.'s findings.

Recoding scores into discrete interaction types (i.e., peer support, negative, and neutral) showed that most interactions within the OSG network were neutrally appraised. This finding suggests that the majority of submissions and comments either receive no community appraisal or receive an equal number of positive and negative appraisals. It is possible that this phenomenon is commonplace given the nature of content aggregation platforms but could also be explained by community-specific factors that have yet to be uncovered. Further research into support groups on similar types of platforms could serve as a useful metric for comparison using a similar approach that was taken in this research.

The static network degree statistics (i.e., sending and receiving messages) reveal that users connected with seven other users on average over the course of one year. To the researcher's knowledge, this is the first study to provide information about the size of veteran's online social support network in an OSG. A previous study by (Harris, 2021) showed that veterans' peer social networks were relatively small (average of three connections) compared to their non-veteran networks. Participation in OSGs, like the one examined in this study, has the potential to expand the number of peers a veteran is exposed to. Additionally, interactions in the OSG are geared towards peer support and may provide more benefit than general veteran peer connections which do not necessarily have an expectation of mutual support.

Participation in the OSG

Participation in the OSG has been defined as an interaction involving an interaction of any appraisal type. All structural mechanisms indicative of peer support (POS) were associated with increased participation in the support group except for transitivity. From the perspective of paralinguistic digital affordances, this result is largely congruent with previous research suggesting that positive appraisal is positively associated with continued participation on online platforms (Hayes et al., 2018; Zell & Moeller, 2018). All structural mechanisms indicative of negative interactions (NEG) are associated with decreased support group participation. This finding reflects the findings of previous studies into negative online interactions (Davis & Graham, 2021; Kang, 2022) and supports theoretical concepts of positive and negative proximal processes as employed in the networked neo-ecological framework.

Information Sharing (Indegree and Outdegree)

Receiving messages (indegree) and sending messages (outdegree) served as the structural mechanisms for the concept of *information sharing*. Previous literature investigating sending and receiving messages in OSGs found that sending messages was more strongly associated with OSG participation (Yang et al. 2018; Zhao et al, 2016) despite receiving messages being more common overall. Results from this dissertation’s REM for participation showed that, for positive and negative appraisal types for sending and receiving messages, the effect sizes on participation were similar. Users with a history of sending and receiving positive and neutral messages tended to participate in the OSG. Receiving negative messages had the opposite effect, while sending negative messages showed no effect. These findings indicate that the historical rate of sending messages and receiving messages do not differ substantially in OSG participation except for in the case of negative interactions. Future studies examining effects of sending and receiving messages in an OSG might consider measuring the historical rates of sending and receiving messages in conjunction with community appraisal to gain improved insight into how these factors influence participation.

Interactional Reciprocity (Reciprocity)

The analogous structural mechanism for *interactional reciprocity* was the social network analysis measure for reciprocity. Positive reciprocity showed the largest effect size for increasing the rate of participation in the OSG among all the structural network effects in the models. Although this finding applies specifically to having a history of positive reciprocal interactions, the result parallels previous research noting that reciprocity is positively associated with OSG participation (Pan, 2020). Negative reciprocity was associated with a negative rate for participation. The effect of negative reciprocity is in alignment with the finding of Kang (2020) who noted that negative appraisals show decreased continued participation on online platforms.

Group Cohesion (Transitivity)

The concept of *group cohesion* was based on the transitivity network statistic. In this study, transitivity indicates the likelihood that a user will send a message to a person who has received a message from a user that the original user messaged (i.e., close a transitive triad) relative to the control cases. Results of the REM for participation suggest that transitivity is not associated with participation. The effect of transitivity on participation is unexpected. Previous research suggests that OSGs could be expected to have high levels of local transitivity (Xu and Zhang, 2016) and having higher transitivity is indicative of identifying with characteristics of others, thereby fostering a tight-knit group (Lu et al., 2021; Ziebland & Wyke, 2012).

Possible explanations for this phenomenon might explained by neo-ecological theory. The veterans' OSG that was studied contained a high degree of anonymity. A study by Andalibi et al. (2018) found that support groups are often sought out for their anonymity and that anonymity is sometimes supplemented by users creating "throwaway" accounts different to their primary account to ask for or receive support regarding a sensitive issue. Existence of throwaway accounts is possible provided the relative ease of creating an account on the platform examined in this study. Throwaway accounts or multiple accounts used by the same person were not controlled for in this dissertation. Future studies could benefit from a mixed methods approach that asks users about their experiences to understand their perception of the group in addition to the observation of behaviors.

Development of Peer Support

Peer support REM results support the hypothesis that a history of engaging in peer support lends itself to engaging in future peer support interactions. Like in the case of participation, these findings are congruent with previous research indicating that positive appraisals are predictive of peer support and overall user satisfaction with the online platform (Wohn et al., 2016, Zell & Moeller, 2018).

Information Sharing (Indegree and Outdegree)

A history of sending peer support messages is positively associated with engaging in peer support events. The effect size between sending and receiving peer support messages is slightly larger than general participation in the OSG network with sending positive messages having a larger effect size in the peer support model. This result is congruent with previous research suggesting that sending messages has a larger effect size on OSG participation than receiving messages (Yang et al. 2018; Zhao et al, 2016). However, the outcome is specific to peer support rather than general participation. The distinction between general participation and positive participation (whether it be defined as peer support or otherwise) may serve as a useful heuristic for future studies looking at sending and receiving messages in OSGs.

Interactional Reciprocity (Reciprocity)

The effect of reciprocity for peer support interactions had the strongest effect among structural mechanisms for any interactions type. This result supports the existing literature which posits that reciprocity is a driving structural mechanism in OSGs (Lu et al., 2021; Pan et al., 2020). Negative reciprocity is not associated with peer support. These findings are consistent with previous literature on reciprocity on OSGs and lends support to the idea that a positive proximal process can be represented as a reciprocal exchange of positive interactions. Further, these findings support the theoretical supposition in neo-ecological theory that positive proximal processes can be associated with the concept of peer support (Navarro & Tudge, 2022).

Group Cohesion (Transitivity)

Group cohesion in peer support interactions had similar results to general participation but with weaker effects and larger confidence intervals. Significance values suggest that when users did close transitive triangles associated with appraisal interaction type, the effect was not associated with peer support.

Negative Interactions

Results from the negative interaction REM are generally reflective of previous research finding that negative experiences in online spaces tend to drive people away from platforms in the long-term, but not in the short-term (Davis & Graham, 2021). The measurement of interaction rates among users has provided additional insight into the behavior among users experiencing negative interactions.

Information Sharing (Indegree and Outdegree)

Receiving negative messages (negative indegree) was shown to have a non-significant result. The non-significant parameter estimate is interesting because a history of negative messages might be expected to be a driving force in negative interactions. A potential implication for non-significance of negative incoming messages is that there was likely not an abundance of retaliatory group interactions or “dogpiling” (Livan et al., 2017) that sometimes occurs in online social networks. This finding suggests that the phenomena of negative interactions in OSGs may not be due to receiving negative messages, and that future social work interventions or policies used in OSG interventions should continue to reevaluate the differential impacts of sending and receiving negative messages.

Interactional Reciprocity (Reciprocity)

Users were shown to have an increased rate for reciprocating negative interactions. This result makes sense in light of the literature on negative online interactions which note how negative interactions tend to increase responses temporarily (Davis & Graham, 2021). Unexpectedly, users with a history of engaging in positive reciprocity have higher rates of positive reciprocity than negative reciprocity in negative interactions. Finding that there is a history of both positive and negative reciprocity suggests that there may be a degree of volatility among some users in the OSG. A potential explanation is that most users are acting in good faith when participating in the OSG (i.e., are not being overt internet trolls) but, when confrontation occurs, users who sometimes act in a reciprocally supportive way also act in a reciprocally negative way. Continued study into the apparent volatility within negative interactions could provide insight into online conflict resolution or forum moderation policies.

Group Cohesion (Transitivity)

The negative group cohesion analogue (i.e., negatively appraised transitivity) was non-significant for negative interactions. The non-significant parameter estimate is likely a result of sparsity in transitivity among users in the OSG.

Implications for the Networked Neo-Ecological Framework

Methods in this research were based on modified neo-ecological theory to incorporate a social network paradigm and thereby a de facto set of analyses (i.e., social network analyses) to understand the evolution of behaviors within an online microsystem. The results from REMs suggest that the networked neo-ecological framework has some merit as the results largely reflect what is predicted by the framework – that positive reciprocal interactions foster the development of peer support and neutral/negative reciprocated interactions foster negative interactions (referred to as *functionally negative* proximal processes in Chapter 2). An unexpected result was that some structural mechanisms appraised as neutral were predictive of participation and peer support interactions.

Despite the effects of neutral predictors being weaker than positive predictors, the presence of some neutral effects being predictive of positive interactions warrants discussion.

Several possibilities emerge as being plausible explanations for the unexpected phenomenon: (1) the half-life parameter was set at 4 days, which is insufficient time for a feeling of ostracism to take effect (Hayes et al., 2018; Reich et al., 2018) and therefore be reflected in parameter estimates, (2) the effect of ostracism is not as strong as suggested by previous literature, (3) being ignored is a norm on the platform and users are more resilient to the lack of responses, and (4) the method of constructing a interaction network includes interactions that do not necessarily carry an expectation of community appraisal (e.g., a perfunctory comment appended to a long chain of comments) and therefore inflate the effects of neutral comments. All the above are not mutually exclusive, nor exhaustive explanations and require further study to provide improved insight into how neutrally appraised interactions fit into the neo-ecological and networked neo-ecological frameworks.

Implications for Social Work Practice

This research has contributed to a growing body of literature indicating that OSGs have the potential to be used as a valuable resource for veteran peer support. The utility of veteran peers as potentially important conveyers of social support is supported by literature indicating that group identity can be especially salient for military veterans (Albertson, 2019; Matthieu & Carbone, 2020; Tarbet et al., 2021). This dissertation research provides evidence-based findings for subject areas of potential need for veterans (i.e., more information about VA disability claims and miscellaneous information). Results suggest that there is opportunity for social work services within the VA, or that work with the VA, to facilitate an intervention that provides informational resources to veterans outside of conventional services. Possibilities also exist for the use of full-time peer support specialists or volunteers to embed themselves in large publicly accessible informal OSGs like the one examined in this study.

The neo-ecological theory provides a useful framework that helps to identify environmental features that can be used for differing types of online intervention. For example, findings in this study indicate that anonymity may be suitable for certain kinds of social support, such as informational support, but does not necessarily lend itself to building tightly knit communities. Similarly, asynchronicity may change the dynamic for time sensitive services such as online crisis intervention projects for veterans like the Stack Up program (Carras et al., 2021) which provides an important mental health crisis service to veterans who may be reluctant to seek out formal services and rely on online community efforts for immediate support. The effect that time has on online behavior has been noted in this research. For example, the rate of sending and receiving messages has been shown to have very similar effects on participation in the OSG whereas previous literature suggests that sending messages increases participation more than receiving messages. Social workers considering online interventions that aim to provide time sensitive services can benefit from gaining a better understanding how environmental context and time impacts behavior in an online environment.

One of the strongest effects observed in this research was reciprocation of peer support in participation in future peer support interactions. This finding indicates that online interventions should consider using a platform interface that is conducive to back-and-forth conversation between two people. In addition, platforms designed to bolster peer support might consider a private peer-to-peer messaging system to facilitate exchanges between users that are protected from public view so that users can have private conversations about sensitive topics. Social workers might consider focusing intervention efforts on publicly accessible platforms (with private messaging functionality) rather than exclusively private platforms. A potential downside to strictly private platforms with a through vetting processes is that support services become difficult to find (Yeshua-Katz & Hård af Segerstad, 2020). Most users on a publicly viewable platform may be “lurkers” who actively watch interactions but never participate. There is evidence that lurkers still benefit from passively observing OSG interactions (Uden-Kraan et al., 2008).

A benefit of OSGs is that the content is user generated so that users have the ability to seek out people or discussions that most appeal to them. Subgroups of veterans that tend to have a set of different experiences than the majority (e.g., female veterans and combat veterans) can more easily find one another and provide mutual support. This research was primarily interested in overall group behavior and therefore did not consider demographic-related differences. Future research into subgroup differences could provide useful insight into how veteran subgroups interact with each other and what topics of discussion are of more interest to some groups than others.

Implications for Social Work Research

This study has demonstrated that web scraping provides a means of obtaining large amounts of useful information about a veteran population with free and open-source tools that provide valuable insights that otherwise might not be obtainable through more conventional methods. For example, the current literature examining the potential needs of veterans have largely relied on surveys distributed by the VA to inform researchers and practitioners about topics veterans want to know more about (Sheahan et al., 2022; Tsai et al., 2019). Because previous literature finds that younger veterans reintegrating into society may not use institutions like VA due to lack of trust or interest (Littman et al., 2018), the needs of younger veterans may be better understood through where they congregate online what topics get discussed on social media platforms.

This dissertation contributed to a small but growing body of research using Lerner and Lomi’s (2020) Eventnet software and method of case-control sampling. Future social work research that aims to use relational event modeling to analyze large networks to analyze underserved populations can learn from, or use, some of the model specifications outlined in this research. Further, this dissertation has helped establish a precedent for identifying potential structural mechanisms of peer support that can be applied to other populations using online platforms as ad-hoc support groups.

The networked neo-ecological framework suggests a set of analytical methods for exploring how people interact and how behaviors evolve in online and offline spaces. Variables lending themselves to a taxonomy of online spaces have been presented in this dissertation as contextual elements for its findings (i.e., anonymity, synchronicity, publicness, and cue absence). These contextual elements can serve as a minimal example for what environmental variables may need to be considered when conducting research involving online groups. The networked neo-ecological framework is particularly suited to social work because of its theoretical foundations in ecological theory which considers the person in the context of their environment. Social work research often focuses on sociological niches involving underserved and underrepresented populations. Neo-ecological theory provides a robust theoretical foundation for considering groups and group identity where previous iterations of ecological theory had not. Future social work research using ecological theory can utilize the updated models to help adapt research to digital spaces.

Implications for Social Work Policy

An unexpected finding in this study is that a history of sending negatively appraised messages is associated with an increased rate in participating in peer support interactions. However, the effect for receiving negative messages is negatively associated with peer support interactions. A possible explanation for this phenomenon is that a learning curve exists where the negative judgment of outgoing messages is sufficient to correct unacceptable behavior but not dissuade users from engaging in peer support. Whereas when users receive negatively apprised messages there is a tendency away from engaging in peer support interactions.

Social work interventions that involve the use of message boards or OSGs could benefit from implementing policies that encourage engagement and beneficial outcomes. Previous research into social media intervention design has recommended removing the option for negative appraisals in support groups to avoid attrition and negative emotion resulting from seeking online support (Moreno & D'Angelo, 2019). Users may also benefit from a clearly defined scope for the use of the support group. A public charter that is available to users may reduce the number of overall negative appraisals or reduce reliance on community moderation.

Policy focusing on making online platforms more appealing to female veterans, such as implementing a dedicated subgroup in an online discussion, has the potential to help expand female veterans' social networks which evidence suggests may be smaller than male veterans' social networks (Campbell et al., 2021). Additionally, veterans in ethnic and racial minorities sometimes experience discrimination based on race or ethnicity during active-duty service which can result in negative mental health outcomes (Carlson et al., 2018). Having a dedicated subgroup within a discussion board for veterans who are members of historically marginalized groups can serve to provide a safe space for these veterans to share their experiences and engage in mutual support.

Implications for Social Work Education

To the best of the researcher's knowledge this study is the first to use neo-ecological theory as a framing device for empirical research. The neo-ecological model may serve as a useful educational tool as a supplement to the traditional ecological systems heuristic often used in social work education. There are some aspects of the traditional ecological model that do not withstand the test of time. For example, understanding that a person can exist in multiple microsystems nearly simultaneously has implications for how environments can change based solely on a person's directed attention. A way to make sense of complex social systems is much needed as digital environments emerge as a part of everyday life.

Limitations

This study took an observational approach which has inherent limitations. Message removal due to admin moderation or self-removed messages could affect the effect size of structural network mechanisms on interaction types and result in information bias. Only public-facing messages were accounted for when constructing the social networks used in this study. A private message system exists on the platform where individual users can exchange messages without others being able to read them. The findings of this research can therefore only relay information about what messages are publicly exchanged.

Another possible limitation is selection bias. This study only examines a group of veterans on one platform that skews toward a young male demographic. The findings of this research do not likely convey generalizable information for older veterans, female veterans, and veterans in racial minority groups because platform demographics suggest that users of the platform tend to skew younger, male, and white. Further, the generalizability of the behavior observed in this study is limited due to the platform-specific features shaping the structural mechanisms driving the behavior within the OSG context. The rates of behaviors for other groups within the studied platform were not examined and therefore the effect of the platform cannot be properly controlled for. Inferences about development of peer support are limited to the sample in this study.

A methodological limitation exists for relational event modeling regarding the assumption that all actors in the network were able to see and interact with one another, thereby creating a representative risk set. It may be the case that the platform’s content aggregation algorithm made some users less visible than others at some points in time and consequently some users were unable to interact. User visibility at any given time is difficult to account or control for without knowledge of the proprietary algorithms used by the platform for displaying users posts. The risk sets used by models in this research likely do not provide a completely accurate representation of all the interactions that could have happened in the network's history.

Future Directions

Future research into OSGs for veterans can benefit from a mixed-methods approach to better understand the motivations for observed behaviors. Subgroups of veterans that often have unique experience or needs such as female and combat veterans could benefit by being considered independently from the veteran population at large. Creation of break-away have the potential to provide specialized spaces for less common or less discussed issues arising from military service.

Dual setting network analyses that account for the digital and physical domains of life could provide additional insight into peer and social support networks. The methods introduced in this study are capable of examining how digitally supplemented social support can affect network size, interaction valence, and strength. Interventions looking to bolster peer or social support could benefit from understanding how digital and physical support networks interact.

Conclusion

OSGs have been suggested to have the potential to strengthen social support networks for veterans and create a space to provide mutual support based on shared military identity and experiences. Findings in this dissertation research have contributed to the existing literature on veteran OSGs by providing insight into what is being discussed in a veteran OSG and how participation, peer support, and negative interactions develop. These findings can be used into inform social work interventions. Policy implications exist for determining which behaviors are permitted in support group spaces to maximize the potential for peer support and reduce the potential for negative interactions. Findings in this dissertation also present evidence for some potential mechanisms of peer support for veterans in a response to the question: “Veteran Peer Support: What are the Mechanisms?” posed by Oh and Rufener (2017). Peer services and support specialists within the VA could expand their reach by embedding themselves in larger ad-hoc veterans support groups like the one examined in this dissertation to help address questions about benefits or solicit information about programs at the VA. Similarly, veterans organizations that work outside of the VA that aim to bolster social support can benefit from the information presented in this dissertation.

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