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Exploring the Role of Online Neighborhood Networks on Collective Efficacy and Fear of Crime

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ABSTRACT

Examining the Role of Online Neighborhood Networks on Collective Efficacy and Fear of Crime

By

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The proliferation of online neighborhood networks has significantly expanded the way neighbors interact. Recent work indicates that these platforms provide users with social benefits such as a sense of community and potential to mobilize but they may also be responsible for negative neighborhood mechanisms such as fear, tensions, and vigilantism. Still, their popularity calls for the need to better understand their role within the scope of neighborhood studies, including how to define and operationalize collective efficacy within these platforms, and their role in shaping individual perceptions of fear of neighborhood crime. This work seeks to address these issues by examining how online neighborhood networks influence attitudes of collective efficacy and fear of crime.

This mixed-methods research is divided into three studies. First, I conducted semi-instructed interviews to understand how online neighborhood network users conceptualize the meaning and function of these groups, and how traditional collective efficacy measures are perceived and understood in online neighborhood networks. Next, I applied the findings from my qualitative research to develop and validate an online neighborhood network efficacy scale by conducting both an exploratory and confirmatory factor analysis to determine a factor structure that addresses the construct. Lastly, I conducted a cross-sectional questionnaire and applied an

inverse probability weight model to estimate the effect of online neighborhood network use on reported fear of neighborhood victimization and estimate a log-linear model for the effects of frequency and magnitude of use on reported fear.

This study contributes to the neighborhood studies' literature in several ways. First, by providing a better understanding of online neighborhood networks' mechanisms and users' individual perceptions of their role in neighborhoods. Next, by developing an online neighborhood network efficacy scale that can be used to better determine online neighborhood networks' role in neighborhood outcomes. Finally, by creating both a specific 3-dimension measure of ONN use, and by applying causal methodology approach to isolate the effect of ONN use in fear of neighborhood victimization.

Examining the Role of Online Neighborhood Networks on Collective Efficacy and Fear of Crime

BY

MARIE-THERESE MOLINET LEYTE-VIDAL

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Criminal Justice & Criminology in the Andrew Young School of Policy Studies of Georgia State University.

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DEDICATION

Esta tesis doctoral primero se la dedico a mi esposo Fernando y a mis hijas, Bianca Isabelle y Penélope Rocío. Para Fernando…rien de rien. Para Bianca y Penélope…Espero que ustedes estén tan orgullosas de mí, como yo lo estoy de ustedes. Nunca dejen que nadie dictamine quienes son. Forjen su propio camino.

También dedico esta tesis doctoral a todas las mamás que deciden tomar las riendas, educarse, cambiar su vida, y volver a empezar, inclusive con el cansancio, el desvelo, y los sacrificios que conlleva. No se den por vencidas. Aunque la meta algunas veces se ve lejos, los logros saben mucho más dulce una vez que se logra llegar. Ustedes se lo merecen.

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CHAPTER 1: EXPLORING ONLINE NEIGHBORHOOD NETWORK (ONN) EFFICACY: HOW DO USERS CONCEPTUALIZE AND BUILD COLLECTIVE EFFICACY ONLINE

1.1 Introduction

The growing popularity of online neighborhood networks (ONNs) in recent years calls for the need to better understand their role as part of the neighborhood studies, including how to define and operationalize collective efficacy in these platforms to better understand their role in neighborhoods. This study seeks to address this issue by exploring users' individual perceptions of online neighborhood networks and their ability to generate efficacy beliefs in the online space. Furthermore, I examine whether the processes, indicators, and dimensions of ONN efficacy are distinct from traditional collective efficacy measures, so that future research can better capture collective efficacy in these platforms to analyze their impact on neighborhood outcomes.

1.2 Background and Research Questions

The space and relevance of online neighborhood networks is quickly growing. The most well-known online neighborhood network, Nextdoor, launched in 2011 and since amassed 290,000 neighborhoods in 11 countries and counts with over 27 million members (Nextdoor.com, n.d). Within the United States, Nextdoor claims it reaches 90% of neighborhoods and it's used in 1 out of 3 households. Researchers find that Nextdoor users have deep engagement with the platform, the preponderance of information is largely functional, and the site enhances community engagement (Masden et al, 2014). Nextdoor shares similarity with social media sites like Facebook and Twitter since individuals can engage by posting messages, reviews, and interact with others daily. Individuals have the option to consume content passively or actively. They can initiate a discussion or take part in one.

Nextdoor is not the only application trying to harness neighborhood relationships. The makers of the Ring video-doorbell also released the “Neighbors” application which allows users to connect with neighbors to learn, post, and comment about safety issues within their geo-defined areas all while sharing doorbell videos of the incidents being reported. Moreover, the application does not require that you buy a Ring camera, and the user is able to connect it to their own Facebook or Nextdoor network. Facebook launched a test-version of an application called Facebook Neighborhoods in October 2021 in Canada and aimed to launch in U.S. cities shortly after. However, the popularity of private neighborhood Facebook groups led the company to discontinue development (Hutchinson, 2021; Moon, 2022). Likewise, other applications such as WhatsApp are easy and popular ways to create private neighborhood groups (van Steden et al, 2022; WhatsApp, n.d.).

While these applications tend to market themselves as building safer and stronger communities by allowing its members to connect and communicate about different interests and issues including crimes or safety related events in their area, they have also been repeatedly criticized for harboring negative processes and outcomes such as profiling, discrimination, and digital redlining (Kurwa, 2019; Lambright, 2019; Payne, 2017; Taylor, 2020). However, little is known about the role of these online neighborhood networks and their users in shaping individual perceptions about their ability to coalesce, bring the community together, and keep neighbors safe.

While a wealth of criminological research examines individual and neighborhood correlates of collective efficacy and its outcomes (Sampson et al, 1997; Bursik & Grasmick, 2001; Convington & Taylor, 1991; Gibson et al, 2002; Hinkle & Weisburd, 2008; Mazerolle et al, 2010; McGarrell et al, 1997; Skogan, 1986; Skogan & Maxfield, 1981; Taylor & Convington, 1993; Wickes et al, 2017; Yuan & McNeeley, 2016)[1] and even though almost 20 years ago Sampson (2004) suggested that understanding these processes may lie in the study of online dynamics, little attention has been paid to these. Recent work suggests that not only online structures and interactions bypass obstacles found in offline dynamics, but online processes influence offline processes and outcomes (Ellison et al, 2010; Enjolras et al, 2013; Gil de Zuñiga, 2011; Gil de Zuñiga et al, 2017; Steinert-Threlkeld, et al, 2015; Tufekci & Wilson, 2012; Velasquez & Rose, 2015; Yin et al, 2016).

The following study seeks to better understand these processes in the online neighborhood network space by exploring the following questions: Is ONN efficacy conceptually and empirically distinct from traditional collective efficacy? Do online neighborhood networks mechanisms generate efficacy in a way that is distinct from traditional collective efficacy and what are the implications when measuring collective efficacy in ONNs? How are traditional collective efficacy measures such as trust, helpfulness, cohesiveness, and personal values identified and understood by ONN users?

1.3 Literature Review

1.3.a Online Neighborhood Networks

ONNs are restricted social media platforms designed to organize neighborhoods and connect neighbors online based on socio-spatially defined boundaries and identity verification (Coulton et al, 2013; Higgitt & Memken, 2001; Payne, 2017; Vogel et al, 2019; Vogel et al, 2020). Within these networks, neighborhood residents share information and resources about issues relevant to their neighborhood or community (Nextdoor.com; FrontPorchForum.com). ONN members primarily use the networks for either instrumental reasons such as getting help

[1] This is just a very tiny sample of the literature that addresses these topics which dates back to the 1970s and which emerged from social disorganization theory (Shaw & Mckay, 1982).

for something or expressive reasons such as sharing information relating to neighborhood events (De Meulenaere et al, 2021).

ONNs can be Facebook groups created and moderated by neighborhood residents, or they can be national and international platforms such as Nextdoor, Ring, and Front Porch Forum. There are also ONNs built for specific countries such as Neighbourly in New Zealand, Nebenand in Germany, Fuerenand in Switzerland (Renyi et al, 2018).

ONNs share many of the same characteristics as other social media platforms. Users asynchronously create profiles, can see who else belongs in their network, and can post labeled messages and comments. Most content is user-generated (Boyd & Ellison, 2007). One distinctive ONN feature is the membership protocols and the spatial delineation and formation of neighborhoods. The geographic boundaries in earlier ONN projects were outlined by the project creators. ONNs have several ways to spatially delineate and socially form a neighborhood. Vogel et al.'s (2020) ONN taxonomy notes that neighborhoods can be added and delineated by neighbors, the applications, or a combination of both. Neighbors join ONNs by providing verification of their neighborhood residency. Neighbors can also invite and engage others to become part of the online neighborhood. In some platforms, individuals can choose to expand their neighborhood activity to bordering neighborhoods and can expand their audience when the information in their posts has "cross-neighborhood relevance." Ultimately, a socio-spatial dynamic that bypasses the traditional geographic boundaries determines ONNs' delineation of neighborhoods (Coulton et al, 2013). This dynamic can provide expanded access once hindered by physical distance or barriers but can also create digital segregation and exclusion (Kurwa, 2019; Lambright, 2019; Payne, 2017). One online neighborhood may contain a cluster of offline neighborhoods. But the online population may not be an accurate representation of the offline community since the neighborhoods are precariously bounded online (Kurwa, 2019; Payne, 2017). Furthermore, invitation-only neighborhood forums such as the ones found on Facebook or even WhatsApp neighborhood groups can hinder accessibility even to some residents within a neighborhood (Farnham et al, 2015). Factors such as age diversity, home ownership, and neighborhood location influence neighborhood-level social media activity (Farnham et al, 2015).

1.3.b Neighborhood Collective Efficacy

Collective efficacy stems from socio-cognitive theory and Bandura's (1997) self-efficacy construct which was adapted and defined by Sampson et al (1997) as the "social cohesion among neighbors, combined with their willingness to intervene on behalf of the common good (p. 918)." Collective efficacy is also grounded on social capital theory (Cancino, 2005; Morenoff et al, 2001). Sampson et al's (1997) operationalization of collective efficacy captures social cohesion and trustworthiness, concepts that both Putnam (1995) and Coleman (1988) allude to. Sampson (2013) further argues that collective efficacy is a theory of process. He and his colleagues posit that while collective efficacy shares the dimensions of trust and social cohesion found in both definitions, operationalized collective efficacy assumes much more than simply a dense network of ties to achieve social control outcomes (Sampson, 2006). Collective efficacy differentiates between the social ties themselves, to the process of activating these ties to achieve outcomes (Sampson et al, 1999). Whereas Putnam (1995) argues that the density of social connections bolsters reciprocity and collective behavior, Sampson (2006) notes that social networks are not sufficient to exercise social controls. While social ties may predict collective efficacy, several studies conclude they are not "necessary or sufficient" in explaining spatial distribution of violence, and that collective efficacy is the principal mechanism explaining spatial distribution of violence (Mazerolle et al, 2010; Morenoff et al, 2001). Furthermore, Sampson (2013) explains that activated social ties, measured as neighboring activities or reciprocated exchange, and social cohesion are interrelated dimensions of collective efficacy.

The original collective efficacy scale (Sampson et al, 1997) included two dimensions consisting of 5 items each which examined individual attitudes about trust, cohesiveness, helpfulness, and values among neighbors, as well as items which present scenarios where neighbors may be expected to intervene. Sampson et al's (1997) scale has been adapted in several ways to assess the role of collective efficacy as one of the mechanisms that explains the difference in fear, violence, and between differences in neighborhood crime. According to several scholars, collective efficacy acts as a mediator between structural factors such as concentrated disadvantage, heterogeneity, and the outcomes outlined above (Maxwell et al, 2018; Morenoff et al, 2001; Sampson & Raudenbusch, 1999).

However, other researchers question the implied explanatory power of collective efficacy *vis a vis* the other social processes, social controls, and crime (Wickes, 2010). Some researchers suggest that density of social ties has a direct effect on collective efficacy (Carbone & McMillin, 2019) and plays a protective role in certain communities in hindering neighborhood violence (Feldmeyer et al, 2019). Others argue that collective efficacy is a construct distinguishable from social ties and social cohesion which produce varying effects (Wickes et al, 2013). Wickes et al (2017) found that individual-level social ties impact informal social control actions whereas collective efficacy and social cohesion did not. Hipp & Wickes (2018) measured neighboring activities (aka activated social ties), perceived social cohesion, and perceived collective efficacy. They found that neighboring activities and collective efficacy both had strong effects at individual and neighborhood level on informal social control. Social cohesion did not. Social control actions at an earlier point in time also significantly impacted residents' perceptions of neighboring and collective efficacy. Moreover, initial perceived crime and disorder problems significantly conditioned residents' perceptions of collective efficacy and social cohesion at a later point in time, yet the effects were not as strong under neighboring activities. Furthermore, the construct validity of collective efficacy has also been debated (Rhineberger-Dunn & Carlson, 2009). Some scholars posit that the dimensions of social cohesion and informal social control should be considered separate and distinct when operationalizing them (Kingston et al, 2009). Gau (2014) observed that social cohesion and informal social control have little to no significant relationship. Armstrong et al (2015) concluded that only social cohesion was associated with violence and neighborhood crime.

1.3.c Online Social Capital and Social Processes

Like collective efficacy research, social media research also utilizes social capital theory as an organizing framework to explain the online social processes. Resnick (2001) termed this online subset of social capital as "sociotechnical capital" and described it as the "productive combinations of social relations and information and communication technology (p.3)." Specifically, researchers attempt to parse out the effects of social media in *bridging* and *bonding* social capital and outcomes in online and offline behaviors (Bouchillon, 2014; Chang & Hsiao, 2014; Gil de Zuniga & Valenzuela, 2011; Hsu, 2014; Jin, 2015; Kwon et al, 2014; Valenzuela et al, 2009; Williams, 2019). Whereas, bonding social capital is exclusive and likely to develop among homogenous groups, relatives and close friends, bridging social capital is inclusive and outward-looking, and likely to foster weak ties (Granovetter, 1973; Putnam, 2000) [2]. Online social networks can foster bonding social capital (Bouchillon, 2014; Jin, 2015), but the effects are not as strong and are moderated by frequency and intensity of use (Chang & Hsiao, 2014; Liu

[2] Weak social ties as defined by Granovetter (1973) and explored by social media researchers are akin to the ties and networks described by Bursik & Grasmick (2001) in their parochial dimension of informal social control.

et al, 2016; Williams, 2019). Still, scholars note that social media is effective in facilitating bridging social capital by increasing and strengthening weak ties (Donath & Boyd, 2004; Ellison et al, 2007; Ellison et al, 2010; Liu et al, 2016). It also facilitates maintained social capital which allows individuals to maintain weak social ties from a previous community (Ellison et al, 2007). Frequency, network size, intensity of use, and type of content and activity also significantly moderate users' bridging social capital (Burke et al, 2011; Chang & Hsiao, 2014; Jin, 2015; Steinfeld et al, 2008; Su & Chan, 2018). Online network size and exposure are significantly associated with online and offline behaviors (Althoff et al, 2017; Gil de Zuñiga & Valenzuela, 2011; Kwon et al, 2014; Steinert-Threlkeld et al, 2015).

Social networks afford users with social capital components where they can increase potential resources and make action possible through a system embedded in "social cues" (Ellison & Vitak, 2015) [3]. Common features on social networks such as the personal profile, the public display of social connections, and the user-generated content, create bridging social capital by fostering social exchange and interactions, facilitating information-sharing, and encouraging association with weak ties (Ellison & Vitak, 2015; Gil de Zuñiga & Valenzuela, 2011; Surma, 2016). These attributes facilitate trust and the transformation of latent ties into weak ties (Ellison et al, 2007; Grabner-Krauter & Bitter, 2015)[4]. The process is reciprocal since as weak ties are strengthened, trust is nurtured, and so is the motivation to communicate, exchange information, seek support, and even mobilize (Haythornthwaite, 2002; Grabner-Krauter & Bitter, 2015; Hsu, 2015; Steinert-Threlkeld et al, 2015).

[3] While Ellison & Vitak (2015) refer to Putnam's definition of social capital theory, their claim is based on Lin's (2001) definition of social capital as "resources embedded in a social structure that are accessed and/or mobilized in purposive actions" (Lin, 2001 as cited in Ellison & Vitak, 2015, p.212).

[4] Ellison et al (2007) borrowed the term "latent ties" from Haythornwaite (2005) who describes latent ties as ties that are "technically possible but not yet activated" (Haythornwaite, 2005 as cited in Ellison et al, 2007, p. 1162).

Researchers also concede that the online and offline spheres are interconnected and share some similarities (Chakyo, 2014). Online social network structures parallel offline social network structures (Dunbar, 2016; Dunbar et al 2015). Yet, heavy social media users have a more diverse social network and a larger social capital advantage than those that solely interact offline (Hampton et al, 2011). Moreover, the evidence suggest that online and offline social capital are distinct in effects and outcomes (Gil de Zuñiga & Valenzuela, 2011; Gil de Zuñiga et al, 2017). Online social capital is more likely to predict offline social capital than the other way around (Gil de Zuñiga et al, 2017; Yin et al, 2016). According to Gil de Zuñiga et al (2017), online social capital predicts both online and offline civic participation more strongly than offline social capital. Online social processes create access to weak ties that bypass the spatial and temporal barriers found in face-to-face discussions (Ellison et al, 2010; Gil de Zuñiga, 2011). Previous evidence suggests that offline relationships precede online connections (Liu et al, 2016). However, recent findings indicate that individuals use social media rather than offline relationships to initiate and broaden both types of social networks (Gonzalez, 2017; Standlee, 2019). Specifically, among ONNs, studies find that users do not envision ONNs as a substitute for face-to-face social interaction among neighbors and may be unwilling to seek social support through the platforms (Vogel et al, 2020; Vogel et al, 2021). However, this may be dependent on an individual's engagement with the ONN and their online sense of community (De Meulenaere et al, 2020). Like previous social media literature, this implies that individuals perceive ONN processes and dynamics as distinct and overlapping with offline processes.

1.3.d Defining and Operationalizing Collective Efficacy Online

Multidisciplinary work in political science and communication studies, indicates that aspects of collective efficacy can be generated and sustained in social media and can lead to offline collective action (Enjolras et al, 2013; Steinert-Threlkeld, et al, 2015; Tufekci & Wilson, 2012; Velasquez & Rose, 2015). Yet, the definition and operationalization of online collective efficacy in social media research has continuously varied across studies. Some work has adapted Sampson et al's (1997) collective efficacy conceptualization and indicators and applied it online to measure online outcomes. Recent studies have adapted traditional collective efficacy indicators and applied them specifically to the online environment to measure outcomes of online perceptions such as online fear of crime (Lee & Park, 2022). The social control indicators of collective efficacy have also been adapted to measure individuals' perceptions of others' actions to stop attack messages online (Costello et al, 2017). Likewise, online collective efficacy has been defined as "online community cooperation" to analyze the effect of efficacy on the spread of hateful content on Twitter (Ozalp et al, 2019).

ONN studies also vary in how online efficacy is defined and operationalized. While factors of collective efficacy can be found in the research, they are not unified under a single theory that explains the mechanisms that lead to or discourage online collective efficacy in these platforms. Moreover, it is not entirely clear whether neighborhood collective efficacy precedes online collective efficacy, vice versa, or if there is a reciprocal relationship and if ONN users distinguish between the online processes and the neighborhood processes. In one of the first examinations of ONNs, Kavanaugh et al (2005) developed a scale to measure offline collective efficacy and concluded that collective efficacy mediated ONN use, yet it did not consider any perceptions of efficacy beliefs within the ONN itself. Hampton's (2010) content analysis of one of the first ONNs, i-Neighbors, examined both dimensions of collective efficacy as defined by Sampson et al (1997) through a direct observation exchange of messages on the platform which deviated from how collective efficacy is usually measured in neighborhood studies. The study concluded that the internet and the message exchange within the platform could facilitate neighborhood collective efficacy but did not make any distinctions regarding processes or collective efficacy from an online perspective.

Recent quantitative work finds that ONNs can generate aspects of trust and social cohesion which are hallmarks of collective efficacy. ONN use has been associated with fostering participation, peer support, mobilization intentions, and a sense of community both online and offline which is facilitated by online neighboring behavior (De Meulenaere et al, 2020; Vogel et al, 2020; Vogel et al, 2021). Collective efficacy measures have also been used to explain online outcomes such as ONN use (De Meulenaere et al, 2023; Yong-Chan et al, 2019) and dependency on social networking sites (2019). Robaeyst et al (2023) explored social cohesion for ONNs expanding Sampson et al’s (1997) measures to better operationalize and explain differences in perceived support, sense of community, and reciprocal exchanges through ONN communication practices. Yet, the researchers also noted that the quantitative method stops short of being able to capture all possible dimensions of social cohesion.

1.4 The Current Study

Overall, social media and collective efficacy research indicate that, not only could online and offline social processes be empirically distinct and result in different outcomes, but that collective efficacy could be dependent of individual level perceptions, marginal social processes, and neighborhood dynamics. This has implications for studying collective efficacy in online neighborhood networks. Before attempting to measure collective efficacy in the ONN environment and integrate it to neighborhood studies’ models we must first understand what, if any, are the unique online processes and individual perceptions of ONNs, to then be able to define ONN efficacy, and consider how best to operationalize it rather than attempting to apply previous measures of collective efficacy that may lack validity within the online context.

This study will address these issues and contribute to both the ONN and criminological literature by 1) qualitatively exploring whether collective efficacy in online neighborhood networks is both conceptually and empirically distinct, from traditional collective efficacy, 2) understanding individual perceptions of online neighborhood networks interactions and how these generate and sustain individual collective efficacy beliefs and 3) identifying the processes occurring online that could generate, sustain, or undermine ONN efficacy.

1.5 Data and Methods

1.5.a Design

The study was done by conducting and analyzing semi-structured interviews with ONN users. The questions were drawn from a three-part interview guide. The first two parts of the guide were designed to obtain substantive information about the respondent's neighborhood setting, a detailed description of their use of online neighborhood networks, an explanation of the composition of the ONNs, their online neighbors, whether they were distinguishable from their physical neighbors, and if they overlapped.

Once these parameters were established, the interview focused on questions that would elicit responses from the participants about their perceptions of collective efficacy in their online neighborhood networks. The ONN efficacy questions were grounded on the items found in Sampson et al's (1997) collective efficacy study. Those items ask individuals their level of agreement to whether they believe their neighbors are trustworthy, cohesive, get along, and have the same values. They also ask individuals about whether they expect neighbors to intervene as a form of informal social control. While there has been some debate on the construct validity of these scales and whether they even tap into the same construct, the in-depth interview process provides an opportunity to treat each indicator as stand-alone and consequently analyze whether they indeed belong to a unidimensional construct or whether as some have theorized should be distinctly operationalized. It also overcomes the limitations of previous quantitative examinations since it is impossible to determine through these close-ended items the process that explains these attitudes and whether online processes and attitudes are analogous to those offline processes and attitudes.

To both better explain online efficacy processes and behaviors and explore whether online efficacy could deviate conceptually from traditional efficacy, the questions were framed for the interviewees to explain *how* these perceptions are harnessed or hindered online. For example, interviewees were asked “Describe what makes your online neighbors trustworthy” for the trust measure and “Describe how your online neighbors show that they are a cohesive group”. If the answer was not substantive enough, they were asked to provide more detailed examples. Furthermore, they were also asked the opposite of the initial questions (i.e. “Describe how your neighbors *cannot* be trusted?”) to understand what processes lead to the decreased trust online. Online data also gives individuals the opportunity to witness and read about possible social control actions that others are taking. Therefore, social control action questions for those in online neighborhood networks can focus on what individuals *perceive* are outcomes based on the information they gather through posts and online conversations.

1.5.b Sample

Individuals were the main unit of analysis. A total of 23 participants were successfully recruited via snowball sampling from four different Georgia counties: Cobb County, Fulton County, Henry County, and Clayton County. Snowball sampling has been previously used in qualitative research for recruiting online, maximize representativeness, and find hidden populations (Baltar & Brunet, 2012). It relies on the participants and their social network. Most recruits already have prior knowledge of the dynamics of the interview before sitting down with the researcher which can lead to the discovery of "covert dynamics of the social system" (Noy, 2007).

An initial sample was recruited via Facebook Groups with residents from Cobb County, GA. Cobb County is the 3rd largest county in the state of Georgia with a population of approximately 766,000 residents with a diverse socio-economy makeup. The county's demographic factors are like the state of Georgia with a predominantly white population (60%). Black residents make up 28.8% of the resident population, slightly lower than the overall Black resident population in the state (32.2%). The county also has a larger population of Latinos (13.3%) than the rest of the state (9.9%). Cobb County's poverty rate is 8.6% making it the lowest in the state (American Community Survey, 2020).

Eligibility requirements to participate in the initial sample was to be over 18 years of age, a Cobb County resident, to own or rent a home, and use one or more of the following online neighborhood networks: Nextdoor, Neighbors, Facebook private neighborhood group, or a WhatsApp private neighborhood group. An estimated 36 Facebook groups were identified in Cobb County that could serve as recruitment sites. During October 2022, requests for permission to recruit in the Facebook Groups were sent over a period of seven days. I initially requested access to post on ten groups with five groups allowing the posts that same day. After three days, access to post on another ten groups was requested. If the Facebook Group did not respond to the first request, it was followed up with a second request three days later. After three more days, another 16 groups were contacted. In some cases, approval to be added to the groups itself was necessary since some groups were closed. Groups were comprised of several different populations and interests in the area.

A total of 8 groups approved the recruitment posts, two groups denied the request, and 26 groups never responded or left the post pending for approval (see Appendix A for list of groups). A post in one of the groups had to be deleted due to bringing many ineligible participants and spammers. The recruitment post included information about the goal of the study, the estimated time that the interviews would take, the incentive for participating if they qualified, contact information, and a link to a Qualtrics to answer eligibility questions. Due to limitations in Qualtrics each Facebook group could not have a dedicated Qualtrics link to be able to identify where the possible participant was coming from since once the link was used once by someone in the group, Qualtrics would deem them as ineligible due to "duplicate response". The eligibility screener asked participants for their zip code, their city, the online neighborhood groups they belonged to, best days and times to contact them for an interview, their preferred mode of participation (via Zoom or face-to-face), and their contact information. After initial testing and verifying the data quality with Qualtrics it was discovered that several individuals were trying to gain eligibility even though they did not reside in Cobb County so checks were put in place to avoid receiving ineligible entries such as, getting excluded if they put in a non-Cobb county city, a non-Cobb County zip code, and/or a mismatch between zip code and city. Furthermore, check geo-data location information provided by Qualtrics was continuously checked to ensure that the individuals resided in or around the Cobb County area since it was difficult to estimate an exact geo location with the data provided by Qualtrics. Those who did not pass the data quality checks were rerouted to an exit message saying that they did not qualify. A total of 171 individuals attempted to fill out the information to be interviewed. Qualtrics found that there was a total of

86 duplicate respondents and 11 potential bots. A total of 79 participants passed the automated data quality checks, a total of 58 individuals were deemed to be in the metro-Atlanta area, and a total of 20 were confirmed to live in or near Cobb County based on the geo-data information. I contacted each initial eligible participant via GSU email and text as I received their information. Once the date and time of the interview was coordinated with the participant, they would receive the Georgia State University Informed Consent Form to read before participating. From this initial recruitment effort, a total of 7 individuals were successfully recruited. Following the initial recruitment, the initial sample was told that if they knew someone that would be interested in conducting the interview, to provide them contact information so that they could contact the researcher about participating. They were further told that they did not have to live in Cobb County.

A total of 19 participants were recruited through the initial participant pool with participant #2 referring 3 individuals, and participant #3 referring 2 individuals. The rest of the participants were recruited via participants after the initial sample with participant #6 referring to 1 individual, participant #9 referring 7 individuals, and participant #11 referring a total of 6 individuals. Two participants declined to report who recruited them, only identifying them as a friend. Lastly, out of the 19 participants, two of them were initially recruited and contacted for interviews but later decided not to participate.

1.5.c Data Collection and Analysis

Prior to recruitment, the initial interview guide was reviewed by two qualitative experts to assess and recommend any changes that would help elicit responses from the interviewees and reduce interview fatigue. The guide was also pilot tested with 6 individuals from various demographic groups in different parts of the country[5]. The final instrument contained a total of 30 initial questions and was divided for participants into 5 sections: questions about their physical neighborhood (6 questions), questions about their use of online neighborhood groups (6 questions), questions about online collective efficacy (12 questions), and questions about social control actions witnessed online (7 questions). Additionally, there were 6 demographic questions at the end of the interview.

The semi structured interviews took place between October 24 and November 17, 2022 via Webex. This style of interviewing allows participants to guide the direction of the interviews and fore themes and categories to emerge that the questions did not address. This method also allowed for skipping or deleting some questions that brought forth redundancy or that created some confusion among the participants. Following Stern & Porr (2011) the questions became more focused on exploring the processes and perceptions tied to online neighborhood network efficacy, rather than how offline social control actions are interpreted in an online environment.

Participants were first read the Informed Consent Form and asked to audibly agree to participate. Audio of the interviews were recorded along with the automated closed-caption transcript provided by Webex. No video of the interviews was recorded to protect participants' privacy. Interviews took approximately 45 to 60 minutes, with a few lasting only about 30 minutes. These shorter interviews were given by participants that belonged to an online neighborhood group but reported not engaging with the platforms or spending less than 5 minutes on them each time. After completing the interviews participants were notified that they would receive the $75 Amazon gift card at the email address they provided.

[5] The pilot interviews took place over 1 week and included 3 women, 3 men, 3 Latinos, 2 Whites, and 1 mixed race individual. The age range was 47-79.

One of the main concerns in following a grounded theory approach is the adequateness of the sample size vis a vis data saturation (Khaldoun & Le Navenec, 2018). To ascertain a large enough sample that would provide the richness for explaining online neighborhood network users' processes as well as relevant efficacy concepts (Charmaz & Thornberg, 2021; Kuzel, 1992), I handwrote field notes during the interviews and reviewed the notes after each interview. I estimated data saturation to have been reached by the 10th interview based on initial, preliminary coding of the data which suggested patterns of repetition in concepts discussed by the participants. A sample size of ten is also in line with previous qualitative methods research that indicates anything between 6-12 interviews having the most significant data and where significant themes are usually established (Guest et al, 2006; Morgan et al, 2002). However, to maximize variability in response across demographics and geographic areas and avoid prematurely stopping the data collection (Charmaz, 2006; Khaldoun & Le Navenec, 2018) I expanded the number of interviews to 23.

I transcribed the interviews over a period of four weeks using the closed-captioned transcriptions provided by WebEx as a starting point. While these transcriptions are not entirely clear or accurate due to audio issues, I downloaded them to a Word document, anonymized them by only including a number and the participants' initials to protect their privacy, and cross-checked with the audio recordings. I reviewed each interview for errors, formatted them, and re-transcribed. I made the decision to drop a total of four interviews from the analysis due to audio problems or for not providing any substantive responses. I qualitatively coded a total of 19 interviews using NVivo software and following a classic grounded theory approach[6]. Grounded theory is a conceptual framework and a method of analysis ideal for studying socio-

6 According to Holton's view of classic grounded theory, "attributing meaning is not the goal of grounded theory; rather, its goal is to offer the reader a conceptual explanation of a latent pattern of behaviour that holds significance within the social setting under study (Holton, 2007)".

psychological processes (Charmaz & Belgrave, 2014). It is a "study of a range of individual cases and extrapolates patterns from them to form a conceptual category (Charmaz, 2006: 188)." The goal of grounded theory is to develop theory through constant comparison of the data (Glaser & Strauss, 1967). According to Holton (2007) grounded theory's goal is "to offer the reader a conceptual explanation of a latent pattern of behavior that holds significance within the social setting under study (p.4)". Here, I applied a grounded theory method of analysis based on Strauss & Corbin (1992)'s iterative coding process: open, axial, and selective. Open coding refers to the initial coding of data where all the data is initially compared and categorized by line, sentence, or paragraph. Axial coding refers to the process of connecting categories and sub-categories with the aim of understanding the events that lead to a certain phenomenon. More focus is placed on actions and consequences. Lastly, selective coding is where the core category is selected and integrates all other categories and sub-categories into it. Selective coding provides the central phenomenon (Strauss & Corbin, 1992).

I coded the qualitative data collected from the semi-structured interviews in these three stages to extract key theoretical concepts, categories, and dimensions, to explore user perceptions of online neighborhoods groups, their online neighbors, as well as the origin and development of online neighborhood collective efficacy and the socio-psychological factors that support it. I expected that events and processes related to online efficacy would emerge since theory and literature suggest that online efficacy is possible (De Meulenaere et al, 2020; Vogel et al, 2020; Vogel et al, 2021). To avoid limiting the coding to assumptions of what constituted efficacy within ONNs, rather than assign a code relating to efficacy for each response to the indicator questions (i.e. what makes your neighborhood trustworthy), the coding scheme centered on applying multiple codes to texts to capture interwoven phenomena and processes. So, for example, within the trustworthy code, it was possible to also simultaneously code "helpfulness as trust" since for some of the participants, trustworthiness of the group was facilitated via the way they displayed helpfulness. In another example, texts that were coded as protection/security could also be coded under "trustworthiness" because a participant commented how individuals were trustworthy enough in the group for others to be able to post about being out of town while asked about how online neighbors shared resources to protect each other.

During the open coding phase of the project (Stern & Porr, 2011), I selected initial coding due to the exploratory nature of the study (Charmaz, 2014; Saldaña, 2021). Initial coding allows for several different coding methods to be used simultaneously during the first coding cycle. It is ideal for exploratory work to better understand the type of data that the researcher has before selecting a more focused approach for the subsequent coding stages (Saldaña, 2021). According to Charmaz (2014) it "allows the researcher to all possible directions suggested by the interpretation of the data (p.114)."

In the axial stage of coding the theoretical memos were used as part of the coding to understand the processes leading to or away from the efficacy categories and subcategories. Also at this stage, the multiple ways by which participants described a phenomenon were unified under the same code. For example, the code of "neighborhood watch" was created to categorize and unify when participants either explicitly called out the groups as a "neighborhood watch" or alluded to it in texts relating to awareness, neighborhood news, or when phrases like "everyone has eyes faced out" in the group, yet they all refer to the concept that the groups work to protect the neighborhood as a communal watch where everyone participates.

During the selective coding phase of the project (Thornberg & Charmaz, 2014; Stern & Porr, 2011; Strauss & Corbin, 1990), I reanalyzed all the categories, subcategories, and memos created and used theoretical coding to identify the core category which is "a key word or phrase that triggers a discussion of the theory itself (Saldaña, 2021: p.314)" and is what allows the researcher to integrate the data and the codes into a theoretical framework (Holton, 2007).

1.6 Findings

1.6.a Descriptives

Table 1 breaks down the demographic characteristics for participants. The sample was predominantly older, with most participants being over 44 years in age. Most participants were female (68%), homeowners (79%), and more than half were Black (53%). The median for years lived in neighborhood was seven. A majority of those interviewed described the neighborhood as, or synonymous with, quiet and many described their neighbors as private, friendly, and/or respectful. 42% also described their neighborhood as diverse. The median number of neighbors interviewees spent time with was three. Online neighborhood network use varied; however, many were not able to say how much time they spent. Answers ranged from less than five minutes a day to three hours a day. Over half of those interviewed (53%) use two or more online neighborhood groups.

All participants resided in the metro-Atlanta area. Most participants (73%) resided within Cobb County in the suburban cities of Smyrna, Acworth, Kennesaw, Mableton, Marietta, and Powder Springs. Cobb County is the 3rd most populous county in Georgia and is located northwest of the city of Atlanta.

Table 1. Summary Statistics for Interview Participants

Variable	**n**	**%**
home: own	15	79.0%
home: rent	4	21.0%
age:25-34	2	11.0%
age:35-44	5	26.0%
age:45-54	9	47.0%
age:55+	3	16.3%
race: white	6	32.0%
race: black	10	53.0%
race: latino	2	11.0%
race: asian	1	5.3%
gen: female	13	68%
gen: male	6	32%
education: some college	12	63.0%
education: college grad/postgrad	7	37.0%
income: under 50k	7	37.0%
income:50-70k	3	16.0%
income: 70-110k	5	26.0%
income: over 100k	4	21.0%
onnuse:nextdoor	13	68.0%
onnuse:facebook	6	32.0%
onnuse:ring	3	16%
onnuse:neighborhood	3	16%
onnuse:whatsapp/text group	8	42%
totalonns: 1	9	47%
totalonns: 2	6	32%
totalonns: 3	4	21%

The population grew at a rate of 1.6% to 1.8% per year between 2010 and 2019 (Knox, 2019). Smyrna, Marietta, and Mableton are the most populous and most diverse cities in the county with over 50% of the population identifying as non-White (Census, 2022) while Powder Springs is the smallest city with a population of 15,390 with over 50% of the population being African American. Poverty rates range from 6.34% in Powder Springs to 14.1% in Marietta. Acworth and Kennesaw's population are also smaller with 52.5% of Kennesaw residents and 54.3% of Acworth residents identifying as White. The poverty rate in Acworth is 8.63% while Kennesaw has a poverty rate of 12.5%.

The rest of the participants resided within Fulton County (Atlanta and Decatur) the most populous county in the state and with a poverty rate of 13.7%, Stockbridge in Henry County, and Rex in Clayton County. The city of Stockbridge located southwest of Atlanta is mainly composed of Black residents (66.4%). The poverty rate is 10.4%. The city has seen considerable growth with population tripling between 2000 and 2016. Meanwhile, Rex is a small less populated community also south of Atlanta with a predominantly Black population. The poverty rate in Clayton County is high with 18.9% of the population living below the poverty level.

1.6.b Conceptualization of ONNs

Users generate ONN efficacy beliefs based on how they conceptualize the networks. The conceptualization of the networks themselves is a core phenomenon to understand how ONN efficacy beliefs and perception develop. Online neighborhood network users primarily conceptualize the networks in two ways: as a neighborhood watch and as community within community. These conceptualizations of the networks inform all the beliefs rooted in ONN efficacy. Participants' perceptions are mainly shaped by the network they are using, the information delivered through them, and the primary function that the user themselves applies to it. Most participants (53%) discussed belonging to several groups, and they described the function that each one served for them. For example, those users who discussed belonging to Facebook private neighborhood groups or WhatsApp text groups for a small neighborhood audience such as their street, do not see the online neighborhood as just as place to find and communicate about incidents in the neighborhood, they conceptualize it as a place to connect with others, as well as share social events and experiences.

Neighborhood Watch. Like previous qualitative work which found that some online neighborhood groups developed a neighborhood watch style interaction (Masden et al, 2014; Pridmore et al, 2019), participants in this study also described events consistent with ONNs functioning as a neighborhood watch. The neighborhood watch identity is developed through the perceptions and expectations users have of neighbors posting about incidents or individuals that threaten their area. As LG, a Black female between the age of 35-44 living in the city of Smyrna described it,

> Because if anything goes on in the area, it's on Nextdoor, and it's on there, fast. And so, they really do. It's like a large neighborhood watch. And so, they really do try to be, Um, quick about anything discerning that they see, or they heard of what has happened, to put it out. So, people are aware (LG, Smyrna, Black, Female, 35-44).

The conceptualization of ONNs as a neighborhood watch doesn't just develop from what is being posted or responded to in the networks. Individuals also made salient the neighborhood watch dimension of ONNs through their recounting of the expectations they have specifically from those who belong to ONNs. Participants cited the duty to actively participate, report anything of concern to the neighborhood, report to the police, continue sharing, and follow-up with neighbors of the outcome. In other words, those who belong to the networks cannot take a passive approach, consuming information but not actively participating as "eyes and ears"

(Garofalo & McLeod, 1989). This deviates somewhat from traditional neighborhood watches where the work is done voluntarily and not everyone that lives in the neighborhood is tasked with and expected to participate in safeguarding and communicating with everyone (Kang, 2011). Those actively participating in neighborhood watches may receive some sort of training and work in conjunction with police departments (Garofalo & McLeod, 1989). Over half of those interviewed mentioned that their expectation for the online neighbors was that they would report on the site and alert others of what is going on. As individuals like KB, a white female homeowner living in Marietta explained, this expectation is enhanced by the communication facilitated in the online environment.

> The expectation would be If there'" lik', If there was a crime committed that somebody you know, does report it and then even if it's the police, but then if there's something going on, I want to know, like, um, It could be like, the car breaking thing, or a mile down the road…So those are I think the obligation is just to let your neighbors know if there's something going on. Or if I have a gas leak in my house, hopefully I'd go knock on my neighbor's door, and tell them to be careful, but it's just a way to communicate and to everybody. It's the 1 place that we can go to kind of to keep everybody up to date (KB, Marietta, White, Female, 45-54).

In other words, the price of admission for being part of these groups is the duty to participate and communicate with others as SP, a black female homeowner aged 45-54 in Atlanta, GA described.

> Well, my, my expectation of the, the community is to let others be aware of other, uh, neighbors, know what's going on. If my neighbor knows or sees that somebody is breaking into my house and it's on their ring and it's not on my ring And it's not my expectation is for them to communicate with me and let me know, and let the neighbors about what's going on. Communication is the key with me with the, the expectation that I expect from the Ring neighbors (SP, Atlanta, Black, Female, 45-54).

Community Within Community. The concept of community within community mainly emerges from the participants belonging to either or both a Facebook closed group for the neighborhood and/or a WhatsApp group for a smaller number of people. Two core dimensions in the conceptualization of ONNs as community within community are exclusivity and informational privilege which were informed by the level of privacy and topic within the online neighborhood groups. This stems from the selective and precarious nature of how ONNs are delineated. Neighborhoods can be added and delineated by neighbors, the applications, or a combination of both (Vogel et al, 2020). ONNs create a socio-spatial dynamic that bypasses the traditional geographic boundaries determines ONNs' delineation of neighborhoods (Coulton et al, 2013). This is somewhat distinct from how we conceptually and empirically consider traditional collective efficacy. Whereas traditional collective efficacy centers on the activation of weak ties, harnessed by bridging social capital (Granovetter, 1973; Putnam, 2000; Sampson, 2013), and measured through objectively geographically bounded areas (Sampson et al, 2006), ONNs rely on the cognitive perception of neighborhood (Stein, 2014) which can lead to more bonding social capital, thereby creating exclusivity and more homogeneous groups (Bouchillon, 2014; Jin, 2015). Both Facebook neighborhood groups and WhatsApp or other texting groups have gatekeepers to actively assure that outsiders do not join the groups or are by invitation only. At face value, this is no different from larger ONNs such as Nextdoor and Ring, however, in the Facebook and WhatsApp groups there is more scrutinizing as to who is joining and participating, leveraging exclusivity and informational privilege.

> Um, that 1, I am 1 of I think there's 4 moderators. I'm 1 of 4. So, um, we've got security questions that you have to answer in order to be approved to get in. You must live here. We do allow the children of the neighbors and mm. Hmm. Um…But you, you have to live here like, we had a son whose mom lived…we have a lot of family members outside the neighborhood. His parents live here and they'll try and join. And it's like, 'Yeah, no, you have to live here. We have enough cooks in the kitchen already.' (Kennesaw, Female, White, 25-49).

Exclusivity and informational privilege were even more salient in the WhatsApp and texting groups. Respondents who created or belonged to WhatsApp or regular texting group stressed that these were different from the regular neighborhood group where only some people that they know and interact with were able to participate and conversations could flow from the larger online neighborhood group to the text group or vice versa. For example, respondents used their text group to inform and comment on larger online neighborhood group issues keeping unwanted individuals and conversations outside the boundaries of that community within community. One respondent who had a group of 6-8 individuals in his text group explained.

> You know, you have to be political sometimes, so sometimes you don't want to share, you know, you don't want to look like a jerk for having a certain opinion. So, you keep it with your guy friends, you know. (Acworth, Male, White, 45-54)

However, the exclusivity and informational privilege made them feel stronger about not just the group, but their own community. When asked about their last thoughts on the online neighborhood groups they belong to, one respondent alluded to the need for exclusivity to build community.

> I'm more closely connected to the neighborhood group and my text group… (is there any other thoughts or comments that you would like to add about your online neighborhood groups?) Um, just how valuable and, uh, community building, they can be if they're, I would say, maybe making the smaller and more private, the group, the more community it will bring just because you get rid of some of that um, you have a bigger personal connection, so you're not gonna have as much of the negative conversations. The larger the group, the more hidden the person is and more trouble, they can be. (Powder Springs, Female, White, 45-54)

1.6.c Collective Efficacy Indicators as Manifested in ONNs

Trust. Community-based trust originates from participants' perceptions about the truthfulness of the information provided in postings and the sources of information either because of (1) the technological and privacy requirements needed to access the information and (2) from individuals sharing information and experiences that participants claimed were backed-up by evidence of some sort such as videos, photographs, or other online neighbors sharing they had the same experience. So, while they do not necessarily claim to trust the individual or individuals, they trust that the safeguards are there to trust the veracity of the information. In a sense, they did not see a reason to *distrust*.

> Hmm. I guess as they are putting it out, I'm *hoping* well, I guess, because they're, I'm just taking their word. It is. I mean, the, the Nextdoor app I trust it, I trust the app you have to, um…go by your identity, at the identity to the, um, before you can even post or before they even approve you to be a neighbor on there anyway (SMK, Acworth, Black, Female, 25-34).

Those that conveyed distrust in the networks (the lesser of the individuals) alluded to two sources of distrust. First, the inherent nature of online interactions where they don't really know the people they are interacting with. The other source of distrust is when a post does not seem to coincide in some way with reality or it is not backed up by evidence and the post may be done to, as one user put it, "start" something.

Helpfulness. Helpfulness through online neighborhood networks manifests in three types of posts. The first are "alert" posts dealing with incidents or individuals which may threaten or affect neighborhood safety. To users, the concept of see something, say something was related to the helpfulness of the online neighbors and to the tools (the ONNs) themselves.

> …um, just like, when they say people or they see somebody suspicious in the neighborhood, they let each other know to be aware of what's going on and send a text saying, "hey, this is a suspicious guy's walking around the neighborhood, knocking on doors. Uh, be mindful" or, I say, like, "hey, did I hear those gunshot? I hear, like, five, gun shots down the street," you know, they, they let, you know, so you could be aware of what's going on so you can be safe (CD, Rex, Black, Female, 45-54).

Helpfulness also manifested as posts related to activities that lead to collective charitable acts in cases of loss, tragedy or need (i.e. death, illness, fires, displacement, etc.). Online neighbors were also said to be helpful through posts that share resources such as recommendations or any kind of knowledge/advice sharing of any kind. The first type of helpfulness aligns with the conceptualization of ONNs as neighborhood watch while the other two align more closely with the conceptualization of community within community. Unlike traditional collective efficacy where helpfulness is measured as willingness but stops short of being able to measure whether people *actually* helped (people in this neighborhood are *willing* to help), individuals in these interviews were able to narrate specific instances where their online neighbors did something to help each other, even if it was just putting out the call for help. When asked about helpfulness, one individual described the aftermath of a house fire to illustrate his online neighborhood group as helpful.

> Uh, they had a fire, so they basically, you know, their home, home. Basically all, everything was burned out. And so, people posted on there a way for people to donate to this particular family. You know, either, um, physically physical items or like a through a GoFundMe kind of, kind of situation (CT, Acworth, White, Male, 55-64).

Cohesiveness. Cohesiveness was closely related to helpfulness, making these two concepts somewhat indistinguishable from each other. The offer to help and some sort of evidence that people did help, engendered perceptions of closeness among online neighbors. The ONNs therefore facilitate the process of need -> call for help -> positive response -> evidence and belief that they helped.

Individuals convey closeness on ONNs in three ways: Responsive behavior and helping actions, emotional support, and watching out for each other. While responsive behavior and watching out where already salient categories and derive from the two conceptualizations of ONNs, emotional support emerged here as something new and unique to cohesiveness. It's noteworthy that four individuals believed that there were times when there was no help offer of any kind but that online neighbors provided emotional "pick-me ups" as one person described it such as words of condolences, affirmations, prayers, or simply checking-in, which indicated to them that online neighbors were close.

Values. The online environment and the relative anonymity from the online neighborhood groups made it impossible for individuals to really convey the values that they shared with their online counterparts. However, the participants viewed shared values as those values relative to the community or the neighborhood. Three types of shared value were identified: Safe community, property value, and respect towards others. Participants characterized the shared value of a safe community with items like “watching out for each other” and “an environment where our children can grow.” Interviewees find that their online neighbors share their value of keeping up the property value through upkeeping the neighborhood, following rules, etc. Respect for others was characterized when there is a disagreement between neighbors, that it avoids getting created or escalated on the ONN and that neighbors will take the conversation offline. One caveat is that while the prompt was “Describe what values you and your online neighbors share”, interviewees in many instances alluded to visual neighborhood and neighbor cues, rather than online interactions to communicate what they perceived as shared values meaning that they may not have been able to cognitively identify values as an online characteristic. Yet, contrary to the difficulty among users when recalling shared values, individuals cited political differences as the overarching value that they did not share with online neighbors and referred to political discussions that occurred in the online neighborhood groups to support it.

1.6.d Security and Efficiency in ONNs

Security. Security, a factor that tends to overlap and facilitate the three other factors of helpfulness, cohesiveness, and trust, has two dimensions: perceptions of safety and protective actions[7]. The protection dimension is derived from the sharing of three types of posting activity. First, traffic-related posts (accidents, unsafe driving, etc.) that lead to individuals to change their

[7] While traditional collective efficacy scales do not measure security, rather expectations of social controls (a component of the safety, protection, and fear in neighborhoods), previous qualitative work suggests that online neighborhood groups are primarily used (and marketed) to function as neighborhood watches. I include safety and protection prompts to test these assumptions and to understand how users conveyed not just expectations, but also to online interactions that led to offline actions and outcomes.

route or seek out the culprits of unsafe driving within their neighborhood. Another is suspicious posts which offer information about individuals or activities that are deemed suspicious or sometimes criminal by the original poster and allows others to follow up, make people aware or warn them of being careful, taking measures to protect themselves (not opening the door, looking out for someone, etc.) and avoid a potential threat. This dimension of protection is also reliant on visuals (pictures or videos) that accompany the posts. Finally, the third way individuals conceptualize protection through online neighborhood groups is related to services. Individuals view online neighbors protecting each other through vetting a service (recommendation or criticism) or offering a service from a source of trust and/or authority.

The dimension of safety is experienced by online neighborhood group users through increased awareness of what is going on in or near their neighborhood. This increased awareness comes through the form of alert posts, which may include pictures or videos of the situations, reminders of what to do and avoid, and follow ups to ease people's concerns. In fact, awareness emerged repeatedly as a salient conduit to safety and protection.

> It makes me feel safe because if a share is shared with everyone, you know, what's going on, it shows you things, it shows you people are doing bad things that they shouldn't be doing. And it just alerts you and just keep aware of what's going on (SP, Atlanta, Black, Female, 45-54).

Efficiency. One core category in online efficacy which contributes to the positive perceptions of online neighborhood groups is the facilitation of quick, up-to-date information and rapid response, particularly when dealing with potential security issues in the community. However, it was salient for other types of information as well, such as missing pets or car accidents. This easy access to information was also a main reason for joining and reading online posts and it is enhanced by notifications throughout the day. Many cited text or email notifications to first engage with the platform when they found something to be relevant to them.

Participants described instances where the quick spread of information led to perceived outcomes in the neighborhood. The crowd-sourced neighborhood knowledge, and the rapidness with which the information spreads was even seen as a potential deterrent for neighborhood crime. For example, one woman described the exchange happening in the WhatsApp group she belonged to when an individual showed up in the neighborhood and exposed himself to one of the women in the group which led to the individual being apprehended by the police.

> Well, like, when they have the creeper, you know, the 1st thing that someone did was call the police. They got a case, let everybody know the case number, The person that was working on, working on it, so everyone has that information. They, um, posted the tag number, what type of car it was, What the what the guy look like, So. They'll, you know, people knew who it was so any time he came to the neighborhood. People like, oh, you know, "I saw him make sure you call the police (TM, Kennesaw, Black, Female,45-54)

Online Discord. Even though online neighborhood networks are predominantly conceived by users as something beneficial, positive, and useful for neighbors, participants repeatedly referred to discord in online interactions as a source of tension, disengagement, and even fear. Online discord was the primary reason cited for finding them unhelpful, divisive, and reduces the ability for the group to solve or deescalate issues. Discord includes negativity, bickering, complaining, and infighting. Most individuals find that the negative interactions come from a small minority in the groups. However, the severity of online discord was related to the use, perceptions, and even behaviors within and outside online neighborhood networks. The ability to have online negativity, threats, and complaints spill over to offline actions was a concern for some users. One user described how an online interaction about proposed cityhood for their town turned into a source of fear and concern for her safety.

> I had posted a comment on a group… but it was not pro or against the city. It was saying, I hope people pay this much attention after this is over about what the problems were, and a man commented negatively and then he said…he commented on the upcoming fundraiser I had and said, I guess he said, 'Maybe I'll see you there' and that felt, um, awkward and unsafe. (JG, Powder Springs, White, Female, 45-54)

While most cases were not as extreme or threatening as the one above the negativity and complaints online was perceived as a proxy for inaction and a missed opportunity for deescalating face to face a neighborhood situation.

> So, you'll see the, the kind of mean, mean spirited, you know, things that if you have an issue, you should actually go talk to the neighbor and say, 'Hey, can you not do this versus just blasting it on Facebook?' (KB, Marietta, White, Female,45-54)

1.7 Discussion

To date, criminological literature has mostly ignored the way collective efficacy develops in online neighborhood networks and its role in other neighborhood processes. This research aimed to understand how collective efficacy is generated and sustained in online neighborhood networks, how traditional collective efficacy indicators are manifested in the online environment and whether the online mechanisms generate efficacy in a way that is distinct from traditional collective efficacy.

The findings here highlight that while ONN efficacy is derived from traditional collective efficacy theory, the processes by which efficacy is generated in ONNs and the individual perceptions about the function that ONNs play at the larger neighborhood level, suggests the need to define ONN efficacy as a distinct construct. Thus, we are better able to empirically measure it by developing scale items that avoid conflating efficacy built through ONNs and efficacy built through offline interactions. Hence, ONN efficacy may be defined as social cohesion characterized by informational privilege, perceived sense of security, and facilitated by the efficiency of online interactions. This definition simultaneously grounds ONN efficacy in collective efficacy theory but considers the processes and individual perceptions that can be generated and observed in the online space. This definition also aligns with other researchers' findings that the dimensions of collective efficacy as a construct vary, is dependent of other processes and dynamics and as previously operationalized may lack validity (Hipp & Wickes, 2018; Rhineberger-Dunn & Carlson, 2009). Future research should similarly confirm or falsify whether ONN efficacy as defined here indeed is a higher ordered construct or if its dimensions of social cohesion, security, and efficiency should be considered distinct and produce different outcomes (Armstrong et al, 2015; Gau, 2014; Kingston et al, 2009; Wickets et al, 2013; Wickes et al, 2017).

This exploration suggests that online neighborhood networks generate online collective efficacy beliefs grounded in the individual conceptualization of the networks. By conceptualizing networks as a neighborhood watch, individuals build their expectations around the functional application of the platforms as a means of neighborhood protection and social control where everyone has the responsibility to participate. By conceptualizing the platforms as a community within community, the platforms represent a type of bonding social capital where access to information is considered privileged, and exclusivity generates stronger ties (Bouchillon, 2014; Jin, 2015). Both conceptualizations can be interconnected and salient to individuals, depending on number of platforms used, size of the platform, and purpose of engagement with the platform (Chang & Hsiao, 2014; Liu, 2016; Williams, 2019). While social media scholars find that social media networks may create bridging social capital(Donath & Boyd, 2004; Ellison et al, 2007; Liu et al, 2016), this study finds that ONN efficacy presumably depends more heavily on bonding social capital which is rooted on the unique characteristics of these platforms including the membership protocols, the ability to digitally redline others, and the reliance on more localized and exclusive communication (Coulton et al, 2013; Farnham et al, 2015; Kurwa, 2019; Lambright, 2019; Payne, 2017; Vogel et al, 2019; Vogel et al, 2020). Or as De Meulanere et al (2020) posits, bridging behavior is possible but is "contingent upon one's subscription to and compliance with the emergent group norms (p.492)". The findings here support this claim as evidenced by individuals' expectations of duty to participate, report, substantiate, and avoid discord within the groups to be considered trustworthy. The dual conceptualization of the networks and the saliency of awareness as a conduit for both, support De Meulenaere et al's (2020) findings that awareness mediates ONN use and sense of community. However, the extent to which bonding or bridging capital is generated also depends on the type and size of the ONN individuals engage with. Furthermore, the findings here also parallel from Wickes' (2010) examination of how, lacking strong ties and relationships, communities can build collective efficacy. Like Wickes, I find that the symbolic envisioning of a community, in this case digitally, through the ongoing posts, information exchange about behaviors or actions taken by others, particularly as it relates to neighborhood security, activates social cohesion.

The indicators of trust, helpfulness, cohesiveness, and values are analogous to offline collective efficacy, but they tap into mechanisms unique to the online environment. These indicators are all rooted in the evidentiary information users recall about others' responsive behaviors and actions. Traditional collective efficacy is grounded on the premise that social control actions are unobservable, and the language applied to the scale items address that inherent unobservability. Yet, the online environment overcomes this obstacle, at least from an individual, subjective, self-report perspective. An ONN efficacy scale can leverage this by including items that specifically address this plausible observability. For example, an ONN efficacy scale item could be "My online neighbors help others in need" rather than "My neighbors are willing to help". Furthermore, a future ONN scale should include items that specifically measure efficiency as a factor since the ability to effectively communicate neighborhood incidents were response or actions were expected enhanced perceptions of ONNs.

This differs from other collective efficacy scales that do not measure the way that the communication is transmitted and its relationship to the latent construct.

Moreover, in the online environment it is difficult to disentangle social cohesion and its indicators from the security factor since not only does security tap into feelings of safety and protection, but it permeates and somewhat shapes every other factor. This implies that even though a sense of community and social cohesion are generated in ONNs, it is principally driven by an individual need to keep themselves and the community safe. This aligns with Sampson's (2017) theory that collective efficacy does not need strong ties or association it just needs weak ties to be activated and the shared belief of the neighborhood's (or in this case the ONN's) capability to achieve community safety. However, the online social mechanisms demonstrated here do move away from Sampson's (2017) argument that neighborhoods require to be defined ecologically. The proliferation of ONNs and the choices individuals now make of what their neighborhood looks like online and who they interact with has implications for how we conceptualize and measure efficacy online. The effects of efficacy produced online may extend further through a spillover effect than it could without the advantage of social media communications (Ozalp et al, 2019). On the other hand, the ability to spread misinformation and discord further and more effectively than offline neighborhood interactions may also have a more sizeable negative effect for communities such as the ones Pridmore et al (2019) and Steden & Mehlbaum (2022) found in WhatsApp Neighborhood Crime Prevention Groups.

1.7.a Limitations

This study contains several limitations. This study was conducted in several metropolitan counties around Atlanta, GA and is not generalizable to a larger population. The development of online collective efficacy may be different in smaller cities in rural areas where ONNs are not as prominent. Next, recruitment for the study was initially conducted online and on one large social media site (Facebook). It may be that individuals who use Facebook are more likely to be more connected and have a more positive perceptions of ONNs and social media overall. They may also have more collective efficacy beliefs both online and offline than those. Moreover, Facebook users may be using (and did in the sample) Facebook neighborhood group which suggested a smaller platform and stronger ties than those formed in platforms like Nextdoor or Neighbors.

1.8 Conclusion

Future online neighborhood network research should develop measures that better operationalize ONN efficacy to better understand its role in fear, violence and between neighborhood differences in crime. With the advantage of observable behaviors and perceived outcomes available online, research should also focus on how these online neighborhood networks achieve collective action, not just collective efficacy beliefs. The next step for neighborhood research should be methodologically focused in “digital-ecometrics”, combining Raudenbush & Sampson’s (1999) ecological assessment of neighborhoods with an examination of their digital counterparts.

This study reveals an important implication to the study of neighborhood crime and safety. With collective efficacy beliefs being generated online, it raises the question of what happens in neighborhoods with low offline collective efficacy. Does the introduction and use of ONNs in disadvantaged neighborhoods offer the opportunity for neighbors to come together and take collective action to decrease neighborhood crime? These findings indicate that if online neighborhood networks can quell discord, avoid disengagement, and encourage active participation, they can be an important tool to generate collective efficacy attitudes that translate into collective neighborhood action.

CHAPTER 2: DEVELOPING AND VALIDATING AN ONLINE NEIGHBORHOOD NETWORK EFFICACY SCALE

2.1 Introduction

In recent years, the wide reach of online neighborhood networks (ONNs) has changed the way neighbors communicate and address neighborhood issues. ONNs, such as Nextdoor, Neighbors, WhatsApp Neighborhood Groups, and Facebook neighborhood groups, allow community residents to share information pertinent to their surroundings and community. Among other uses, ONNs facilitate the sharing of crime and safety information, including individual users' first-hand experiences, data collected from home or neighborhood surveillance systems, law enforcement agencies, and even second-hand information posted by users. These platforms provide an opportunity to understand if and how individuals develop beliefs about their online neighbors' ability to come together and resolve issues that impact neighborhood outcomes.

Sampson et al. (1997) defined neighborhood collective efficacy as "social cohesion among neighbors combined with their willingness to intervene on behalf of the common good" (p. 918). The instruments traditionally used to measure collective efficacy assume that neighbors form weak ties through repeated interactions to make decisions about their sense of personal trust towards them, the personal values they share, and their shared level of cohesiveness (Sampson, 2006b). Social control is operationalized as an expectation since it assumes that individuals may not have witnessed or have evidence to determine whether neighbors have intervened or the actual community outcomes of those interventions (Sampson, 2006b). Furthermore, traditional measures of collective efficacy are primarily rooted in the premise that collective perceptions of social control are formed by visual cues such as disorder (Raudenbush & Sampson, 1999) within geographically bounded spaces (Sampson, 2006b). Yet, the nature of the interactions within an online neighborhood environment raises questions about if and how individuals develop collective efficacy beliefs in the online space and whether they are distinct from offline processes and outcomes.

2.2 Research Questions

While recent studies have attempted to capture the elements associated with collective efficacy online, questions remain as to exactly how ONN efficacy should be defined, how best to operationalize measures of ONN efficacy, and if it is or should be distinguishable from offline collective efficacy. This study seeks to lay the foundation for developing a new instrument to accurately measure online collective efficacy by exploring the following questions: (1) how can collective efficacy be conceptualized and operationalized in a communal space that lacks the physical characteristics and structural factors found in traditional neighborhood studies, and which includes interactions and possible perceptions outside the traditional neighborhood boundaries, (2) does social cohesion operate distinctly from social cohesion offline and what measures are best for capturing this construct in the online space, and (3) given the debate on the traditional measurements of collective efficacy and considering the advantages of real-time information in the online environment, would an instrument measuring social controls in the digital space be able to operationalize items that measure individual perceptions of social control actions rather than expectations of social control actions?

2.3 Background and Theoretical Framework

2.3.a Collective Efficacy and Neighborhood Studies

The construct of collective efficacy within criminology stems from social capital theory (Cancino, 2005; Coleman, 1998; Morenoff et al., 2001; Putnam, 1995). Bandura's (1997) self-efficacy construct is defined as "the beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). Collective efficacy theorists incorporate the subjective notion of belief in one's capabilities to organize and execute actions and extend it to a collective belief by community residents. Sampson et al. (1997) define collective efficacy as the "social cohesion among neighbors, combined with their willingness to intervene on behalf of the common good" (p. 918). The theory originally operationalized two dimensions of social capital theory that Coleman (1998) and Putnam (1995) allude to: social cohesion and trustworthiness. Sampson et al.'s (1997) original collective efficacy scale was a combination of two separate scales with distinct measures based on their assertion that two factors tapped into the same latent collective efficacy construct while the third factor of willingness to intervene is assumed to be "enhanced under conditions of mutual trust and cohesion" (p. 920). This theory of process (Sampson, 2013) seeks to explain the relationship between social processes, structural factors, and neighborhood outcomes.

Some researchers argue that collective efficacy is the principal mediating mechanism between neighborhood racial and economic composition and the spatial distribution of violence (Mazerolle et al., 2010; Morenoff et al., 2001; Sampson et al., 1997). Yet, some researchers find the assumptions, conceptualization, and operationalization of collective efficacy to be problematic (Hipp, 2016). Conceptually, Wickes (2010) argues that collective efficacy is dependent on individuals' belief of the community concept and that a social network and resources are required to maintain perceptions of collective efficacy. Operationally, the construct validity of collective efficacy has also been challenged (Rhineberger-Dunn & Carlson, 2009). While some studies indicate that collective efficacy is a one-factor construct (Brunton-Smith et al., 2018), some scholars posit that the dimensions of social cohesion and informal social control should be considered separate and distinct (Kingston et al., 2009). Gau (2014) observed that social cohesion and informal social control have little to no significant relationship. Armstrong et al (2015) concluded that only social cohesion was associated with violence and neighborhood crime. Carbone & McMillin (2019) found that the traditional collective efficacy instrument lacks independent variables of strong social ties and neighborhood perception. Hipp (2016) also notes that collective efficacy is dependent on time and space and theorized that perceptions of other neighborhoods may impact individual perceptions of their own neighborhood.

Some researchers suggest that density of social ties has a direct effect on collective efficacy (Carbone & McMillin, 2019) and plays a protective role in certain communities in hindering neighborhood violence (Feldmeyer et al., 2019). Others argue that collective efficacy is a construct distinguishable from social ties and social cohesion which produce varying effects (Wickes et al., 2013). Wickes et al. (2017) found that individual-level social ties impact informal social control actions whereas collective efficacy and social cohesion did not. Hipp & Wickes (2018) measured neighboring activities (i.e., activated social ties), perceived social cohesion, and perceived collective efficacy. They found that neighboring activities and collective efficacy both had strong effects at the individual and neighborhood level on informal social control. However, social cohesion did not. Social control actions at an earlier point in time also significantly impacted residents' perceptions of neighboring and collective efficacy. Moreover, initial perceived crime and disorder problems significantly conditioned residents' perceptions of collective efficacy and social cohesion at a later point in time, yet the effects were not as strong under neighboring activities. Additionally, the construct validity of collective efficacy has also been debated in the field (Rhineberger-Dunn & Carlson, 2009). Some scholars posit that the dimensions of social cohesion and informal social control should be considered separate and distinct when operationalizing them (Kingston et al., 2009). Gau (2014) observed that social cohesion and informal social control have little to no significant relationship. Armstrong et al. (2015) concluded that only social cohesion was associated with violence and neighborhood crime. Recent work has veered away from the traditional collective efficacy scale to better conceptualize collective efficacy and resolve some of the aforementioned issues. Hipp (2016) and Hipp & Wickes (2017) detached collective efficacy from social cohesion, with collective efficacy operationalized as the traditional dimension of expectations for social control.

2.3.b Characteristics of Online Neighborhood Networks

Early iterations of online neighborhood networks have been around since the 1990s (Carroll & Rosson, 1996). While ONNs now share many of the same features as other social media platforms such as user-created profiles, crowd-sourcing information, and being able to post and respond to comments and messages (Boyd & Ellison, 2007), they are uniquely characterized by spatial delineation, identity verification, and hyperlocal content (Coulton et al., 2013; Higgitt & Memken, 2001; Konsti-Laakso, 2017; Payne, 2017; Vogel et al., 2019; Vogel et al., 2020). According to De Meulaenaere et al. (2021a), online neighborhood network use can be characterized in two ways: expressive and instrumental (De Meulenaere et al., 2021a). Expressive use includes active use of the platforms for sharing content that may be of communal interest and engaging with others in a supportive manner while instrumental use of the platform includes informational support and tangible requests such as mobilization support (De Meulenaere et al., 2021a; Ellison et al., 2014; Gibbs et al., 2019). Online neighborhood networks' distinct features allow the facilitation of neighbors' exchange of information in real-time without having to overcome physical geographical boundaries that may have created a real or perceived obstacle in the past (Coulton et al., 2013; Zayed, 2015).

2.3.c Understanding ONNS within Social Media Theory

Social media theory also utilizes social capital theory as an organizing framework to explain the online social processes. Social media theory posits that social media platforms afford users with what Resnick termed sociotechnical capital which they describe as the "productive combinations of social relations and information and communication technology" (p. 3). Online social networks can foster bonding social capital (Bouchillon, 2014; Jin, 2015) and is effective in facilitating bridging social capital by increasing and strengthening weak ties (Donath & Boyd, 2004; Ellison et al., 2007; Ellison et al., 2010; Liu et al., 2016). Social networks provides social capital components where users can increase potential resources and make action possible by being "embedded in a system that is rich with social cues" (Ellison & Vitak, 2015, p.213).[8] Common features on social networks, such as the personal profile, the public display of social connections, and the user-generated content, create bridging social capital by fostering social exchange and interactions, facilitating information-sharing, and encouraging association with weak ties (Ellison & Vitak, 2015; Gil de Zuñiga & Valenzuela, 2011; Surma, 2016). These attributes facilitate trust and the transformation of latent ties into weak ties (Ellison et al., 2007; Grabner-Krauter & Bitter, 2015).[9] The process is reciprocal since as weak ties are strengthened, trust is nurtured, and so is the motivation to communicate, exchange information, seek support, and even mobilize (Alberici & Milesi, 2013; Enjolras et al., 2013; Grabner-Krauter & Bitter, 2015; Haythornthwaite, 2002; Hsu, 2015; Nekmat et al., 2015; Steinert-Threlkeld et al., 2015; Tufekci & Wilson, 2012; Velasquez & Rose, 2015). However, social media structures and

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[8] While Ellison & Vitak (2015) refer to Putnam's definition of social capital theory, their claim is based on Lin's (2001) definition of social capital as "resources embedded in a social structure that are accessed and/or mobilized in purposive actions" (Lin, 2001 as cited in Ellison & Vitak, 2015, p.212).

[9] Ellison et al. (2007) borrowed the term "latent ties" from Haythornwaite (2005) who describes latent ties as ties that are "technically possible but not yet activated" (Haythornwaite, 2005 as cited in Ellison et al., 2007, p. 1162).

dynamics could also lead to negative outcomes such as digital ostracism, decrease in social cohesion, and decrease in social capital (Ryan et al., 2017; Stieglitz & Ross, 2022).

Online neighborhood groups' structure and dynamics operate similarly to other social media and provide many of the same psycho-social benefits at the neighborhood level (De Meulenaere et al., 2020; Farnham et al., 2015; Vogel et al., 2020a; Vogel et al., 2021). These platforms' potential for providing various means of support (e.g., informational, emotional, and tangible) in a controlled environment, combined with the highly local relevant shared content, may foster strong ties, community awareness, social connectedness, participation, and a sense of community for its members both online and offline (Page-Tan, 2018; De Meulenaere et al. 2021b; Gibbs et al., 2019; Mamonov et al., 2016; Vogel et al., 2020a). Research suggests that ONNs may foster social cohesion. De Meulanere et al (2020) found that users who actively engaged in a neighborly manner within ONNs had a stronger sense of community both online and offline and sense of community was associated with perceived offline local social support. These dynamics and social benefits mainly extend to those who with the platforms in an active manner (De Meulanere et al., 2020; De Meulanere et al., 2021b). Yet, online neighborhood networks' unique structures may lead to dynamics and attitudes not necessarily found in other, more inclusive, open platforms (Masden et al., 2014). The haphazard way that physical neighborhood boundaries are delineated (Vogel et al., 2020) instill a level of exclusivity and in-group identification that could lead to negative community outcomes such as digital redlining, segregation, and a deterioration in social cohesion (Kurwa, 2019; Lambright, 2019; Payne, 2017; Ryan et al., 2017). For example, invitation-only neighborhood Facebook groups can hinder access even to some neighborhood residents (Farnham et al., 2015). Moreover, studies exploring the use of online neighborhood networks for neighborhood surveillance have also found that they can elevate what the "dark-side" of social cohesion (van Steden & Melhbaum, 2022). Research suggests that using online neighborhood networks specifically for crime watch may lead to the blurring of boundaries between police and citizens while increasing tension among both groups, racial profiling, normalizing so-called suspicious activity, and fostering possible vigilante actions, and high level of discord and distrust among those participating in the networks (Mols, 2021; Mols & Pridmore, 2019; Pridmore et al, 2019; van Steden & Melhbaum, 2022; Velez, 2019).

2.3.d Theoretical Framework for an ONN Efficacy Scale

Extant work in political science, education, and communications indicates that efficacy is not only possible online but is distinct in its operationalization due to the online communication practices (Costello & Hawdon, 2018; Glassman et al., 2021; Lee & Park, 2022; Miller et al., 2023; Ozalp et al., 2019; Velasquez & Rose, 2015). Moreover, the need to understand collective efficacy within online neighborhood networks was initially proposed by Hampton (2010) from early iterations of online neighborhood network platforms. Recent work by ONN researchers also signals the need for understanding and developing a theory of online neighborhood network efficacy (De Meulenaere et al., 2020; De Meulenaere et al., 2021; De Meulenaere et al., 2023; Robayest et al., 2022; Vogel et al., 2021). However, no theoretical organizing framework has been available to define, conceptualize, and measure online neighborhood network efficacy.

I then situate online neighborhood network efficacy in Sampson's et al.'s (1997) collective efficacy theory of neighborhoods, and Bandura's social cognitive theory of mass communication which denotes the ability of mass media for producing a socially constructed reality, vicarious influencing, and abstract modeling that can create or alter perceptions and behaviors. This is especially true in the online environments "members are (or can be) active agents in the creation of productive communities (Glassman et al., 2021, p.2)." Therefore, the possibility to develop socially constructed symbolic communities outside strict geographical boundaries, with the capacity to broadly disseminate and document behaviors and outcomes, and which allows its members to guide and model behaviors manifested in an interpersonal social network, then highlights the need to define online neighborhood network efficacy as a distinct construct rather than just a derivative of collective efficacy.

Hence, online neighborhood network efficacy can be defined as social cohesion characterized by informational privilege, perceived sense of security, and facilitated by the efficiency of online interactions (Molinet, n.d.). This definition place emphasis on the processes by which efficacy is generated and communicated in ONNs and considers individual perceptions about the function that ONNs play within neighborhoods, while recognizing it as a distinct process from collective efficacy in neighborhoods. This means that like Bandura's self-efficacy theory, we can construe collective efficacy as domain-specific where efficacy online may not always equate to efficacy offline or vice-versa (Bandura, 1997). Based on this framework and definition we are better able to empirically measure ONN efficacy by developing scale items that avoid misidentifying perceptions efficacy produced through ONNs and efficacy produced through face-to-face neighborhood interactions (Armstrong et al, 2015; Gau, 2014; Kingston et al, 2009; Wickets et al, 2013; Wickes et al, 2017) as well as any behavior patterns that may arise specifically from the use of online neighborhood networks (Bandura, 2001).

2.4 The Current Study

The primary motivation for the current study centers on the need for: (1) an online neighborhood network efficacy instrument and (2) the need to distinguish between traditional collective efficacy and online neighborhood network efficacy. While previous research suggest that social cohesion and sense of community can be generated in ONNs, less is known about how it interacts with online neighborhood network users' expectations for their online counterparts' ability to exercise social control within physical neighborhoods. This study seeks to (1) determine if online collective efficacy is a salient measurable construct among online neighborhood network users and (2) assess the factor structure of items relating to trust, cohesiveness, and helpfulness, usually found in traditional collective efficacy scales. Specifically, I will conduct both an exploratory factor analysis and a confirmatory factor analysis to determine a factor structure for an ONN efficacy scale and attempt to develop a reliable and valid measure that contributes to future research on the role of ONNs on crime deterrence and neighborhood violence research.

Conceptually, the same empirical framework used by Sampson et al (1997) which sought to combine two scales into one, is applied here to develop and test an ONN efficacy scale. The exploratory factor analysis is grounded in previous qualitative work (Molinet, n.d.) which found that ONN efficacy deviates from traditional collective efficacy in the conceptualization of trust online, the identification of values, the generating of safety and protection beliefs, and in the networks' ability to effectively spread alerts about perceived threats to neighbors. Next, the confirmatory factor analysis seeks to confirm through a larger sample the factors and items extracted to create the scale derived from the exploratory factor analysis. This study hopes to bridge the online neighborhood network literature and the criminological literature by operationalizing collective efficacy online so that we can better measure the effects of online neighborhood networks on criminological constructs such as fear and variations in neighborhood crime.

2.5 Data and Methods

2.5.a Design

The study draws from previous qualitative work by Molinet(n.d.) which found that ONN users conceptualize ONNs primarily in two ways. First, as a neighborhood watch which is consistent with other work by Masden et al (2014) and Pridmore et al (2019) and aligns with neighborhood watch literature (Garofalo & McLeod, 1989; Kang, 2011). The neighborhood watch conceptualization was characterized by users' expectations that anyone who is part of ONNs needs to actively participate and report in any situation that may pose a threat to the neighborhood. Second, ONN users view the network as a community within community which was characterized by the exclusivity provided through membership protocols and the access to informational privilege. This was particularly salient for users who participated in smaller, more intimate ONNs such as WhatsApp groups or Facebook groups. While the factors of trust, cohesiveness, and cohesiveness usually found in traditional collective efficacy scale were also salient, they were facilitated by security which individuals expressed as perceptions of safety marked by increased awareness of events and surroundings and/or by perceptions of neighborhood protection derived from the posting of 3 types of incidents: traffic-related posts, suspicious activity posts, and service recommendations. Lastly, the study also found that efficacy was facilitated by the efficiency of online communication especially with regards to security-related neighborhood issues. The study also found that personal/community values are more difficult to operationalize in the online environment. While participants were able to detail values that they did not share with other ONN users, it was more difficult to identify shared values.

2.5.b Variables

Item development was based on the findings from data gathered through the qualitative interviews conducted from the aforementioned study that indicate that there are several factors relevant to the construct of online neighborhood network efficacy (Appendix A). This is necessary to later conduct an accurate factor analysis that avoids missing relevant factors and measures spurious ones (Fabrigar et al., 1999).

The goal was to test as many indicators as possible that specifically referred to online processes and perceptions while avoiding extreme multicollinearity between the items. The variables of trust, cohesiveness, and values were operationalized based on how individuals spoke about developing these constructs in the online space. For example, trust in online neighborhood networks is centered on information relayed through the ONNs, rather than trust developed from personal connections to other so a measurable item was created to address this conceptualization of online trust. Shared values were derived from shared community safety and value as well as respect to others within the online space, so three items were created to address all three aspects. Some items were directly extracted from verbatim descriptions that users provided such as "My ONN is like a large neighborhood watch" and "My ONN is like a community within a community". These two items simultaneously test and validate the global dimensions of ONNs as well as their significance within the ONN efficacy factors. Moreover, all the variables referred specifically to either online neighbors or online neighborhood networks to avoid confusion between neighbors that are interacted with online to neighbors that are personally known.

2.5.c Exploratory Factor Analysis

A total of 610 individuals were recruited via Prolific in March 2023. These types of online crowdsourcing recruitment platforms have been found to recruit samples like those in traditional psychology, while also providing an older more diverse participant pool (Behrend et al., 2011). Prolific has been found to have the best data quality in the online research platform field (Peer et al., 2022) and the most representative sample, particularly for questions about attitudes and experience (Tang et al., 2022).

There were no eligibility requirements other than living in the United States and being fluent in English. Everyone in the sample was screened for eligibility within the instrument based on age, living arrangements, and use of online neighborhood groups. Respondents who did not meet the criteria were ineligible to complete the online neighborhood network efficacy questionnaire and were re-directed to questions on neighborhood fear of crime and collective efficacy. To reduce social desirability bias and to avoid attracting respondents who are more likely to be engaged in online neighborhood networks (Chang & Krosnick, 2009) the survey recruitment prompt did not mention online neighborhood networks, rather described the study as one about neighborhoods.

A total of 242 individuals were eligible to answer the online neighborhood network efficacy with six individuals failing attention checks. The final sample consisted of 236 individuals.

The questionnaire was designed to (1) assess possible differences in offline neighborhood efficacy and online efficacy as well as (2) to develop a scale that appropriately captures online neighborhood network efficacy. The instrument contained a total of four sections and 40 close-ended survey items about use of online neighborhood networks, their perceptions about online neighborhood networks, and general demographic questions.

The 33 observed variables were divided into two scales with Likert-type items. The first measure asked respondents to indicate their level of agreement to items related to safety, protection, trust, helpfulness, community values, and cohesiveness. In the second measure, respondents indicated the level of truthfulness to items relating to the efficiency of the ONNs in communicating neighborhood-relevant situations. The questionnaire included six reverse-coded items.

Prior to conducting the research, the questionnaire was sent to 10 Georgia State University doctoral candidates to assess comprehension and length of time. The average time for answering the questionnaire was six minutes. These data were used to set up the median time for questionnaire completion in Prolific. The questionnaire was also reviewed by Dr. Kat Albrecht for comprehension and attention checks. The instrument was also released to a small sample (n = 20) of Prolific users to assess for any issues including questionnaire flow, skip pattern errors, attention check placement, and comprehension issues. After all issues were resolved, the survey was released in three separate batches to control for any other issues during sampling and to determine whether enough participants were able to complete the online neighborhood network use questionnaire. Prior to answering the questionnaire, participants were shown an informed consent form which stated that continuing with the questionnaire they were acknowledging participation. They were also asked for their Prolific identification to be able to manually review each response. For web-panel respondents a $2 incentive was provided for completing the survey.

The analytical procedure for the exploratory factory analysis follows Watkins' (2018) recommendations for best practices. I coded and analyzed the data using various statistical R packages.[10] The final sample of 236 observations is initially assumed to be sufficient to conduct factor analysis and develop an instrument based on the number of items and expected number of

[10] Psych, Lavaan, QuantPsych

factors (Hair et al., 1998; Kline, 2023).[11] However, there is no rule of thumb for sample size in exploratory factor analysis with some studies suggesting that at least a $n = 50$ could be sufficient (Barrett & Kline, 1981), while others recommend a minimum of 5:1 ratio for subject/item (Gorsuch, 2014; Hatcher, 1994) and yet others a minimum of $n = 300$ as a "good" sample size (Comfrey & Lee, 1992). More recent work suggests that communalities are one of the most relevant factors to determine whether the sample size is appropriate for a valid and reliable analysis (MacCallum et al, 1999; MacCallum et al, 2001). I generated a correlational matrix and conducted normality tests to avoid skewed results and overestimation.

Before conducting factor analysis to develop a scale, three tests are conducted to determine the adequacy of 1) factor analysis and 2) correlation between items. Bartlett's test and a Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy are conducted to avoid violating assumptions related the strength of the relationship among the variables (Howard, 2016; Watson, 2017). Bartlett's Test is a highly reliable statistical method to discover "potentially spurious data (Tobias & Carlson, 1969:376)." Correlational analysis is also conducted to explore the associations to eliminate items that may highly correlate with each other (Watson, 2017). The correlational analysis also helps determine which type of rotation should be performed, oblique or orthogonal (Tabachnick & Fiddell, 2007).

An exploratory factor analysis (EFA) with a Promax rotation was selected rather than confirmatory factor analysis (CFA) to determine the factor model. Due to the exploratory nature of the data, the EFA is initially more appropriate due to being an unrestricted measurement model that allows the researcher to explore the relationship between observed variables and model these with latent variables (Goretzko et al., 2021). The Promax rotation was selected due

[11] In Hair et al's (1998) Table of Loadings for Practical Significance factor loadings of .50 requires a minimum sample size of 100.

to most of the correlations among the variables at or exceeding .32 (Tabachnick & Fidell, 2007). Pre-determining the number of factors is not necessary for exploratory factor analysis (Kline, 2023), however, a 3-factor model for online neighborhood efficacy was hypothesized based on Molinet(n.d.). Lastly, I estimated Cronbach's alpha to test reliability of the final scaled items.

2.5.d Confirmatory Factor Analysis

I collected the sample for the confirmatory factor analysis in a similar manner to the EFA sample, via survey responses on Prolific in July 2023. Individuals who participated in the first survey were excluded. The two individual scales were modified to allow for more variation and to minimize measurement error by omitting the choice of "don't know" in items relating to communication efficiency items and "neither agree nor disagree" in the items relating to cohesion and security.

The number of initial responses for analysis was 448. A total of 25 observations were dropped before the analysis either because of missing attention checks or due to a technical glitch in the survey which impeded a few individuals from completing the survey. The final sample size was 423 observations. This sample size, along with a ratio of 24 observations per variable makes it suitable for factor analysis (Myers, Ahn & Jin, 2011). Like in the exploratory factor analysis, I conducted normality testing, KMO test, and Bartlett's test of sphericity to confirm that the data followed a normal distribution and that the items were adequate for factoring. Lastly, I estimated Cronbach's alpha to measure internal consistency of the scale items.

2.6 Results

2.6.a Exploratory Factor Analysis

Table 2 provides summary statistics for the participants in the exploratory factor analysis. The 236 participants completed all items so there was no missing data. Most respondents were married, white, homeowners, between the ages of 25 and 44. Table 3 includes descriptives for online neighborhood network use. On average, individuals visit ONNs 14 times per week. The average time individuals reported spending on ONNs a week was 31 minutes. Most respondents belong to the ONN Nextdoor and/or to a private Facebook neighborhood group. The distributions for reading, responding, and publishing posts per week suggests that while most are passive users with close to 80% reading more than three posts per week, not many are active users that respond or publish any content to the ONNs with 93% responding to 0-2 posts per week and 99% publishing 0-2 posts per week. The correlation matrix indicated that there was no evidence of multicollinearity and most of the variables resulted in over .30 correlations making it an adequate structure for factor analysis (Table 4). I removed one item to avoid multicollinearity with two other items (Grewal et al., 2004; Hoyle, 212; Kline, 2023).

The individual distribution of the variables and the average of each of the scales for skewness and kurtosis were examined. Most of the items did not have significant skewness or kurtosis. Mardia's test for both averaged scales indicated that there was some kurtosis in the security and social cohesion questions and skewness in the distribution of the efficiency items. After identifying and deleting two outliers in the data, the average for the efficiency items indicated no skewness or kurtosis. The items measuring security and cohesion indicated no skewness and only mild kurtosis. QQ plots were also used as a supplemental measure and indicated normality in the distribution of the averaged data (Fig.1 & Fig.2).

Bartlett's test of sphericity was highly significant ($\chi^2(234) = 426.62$, $p < .0001$) indicating that the correlations are non-random. KMO statistic was .93 with individual values between .81 and .97, making it an excellent structure for factor analysis (Table 5). The parallel analysis, scree plot and eigenvalues initially suggested that a four to six factor model would be appropriate.

Table 2. EFA Participant Summary Statistics

	N	%
Home Ownership		
own	156 / 236	66%
rent	80 / 236	34%
Age		
18-24	17 / 236	7.2%
25-34	98 / 236	42%
35-44	61 / 236	26%
45-54	34 / 236	14%
55+	25 / 236	10.7%
missing	1 /236	0.4%
Race / Ethnicity		
White	194 / 236	82%
Black	13 / 236	5.5%
Latino	15 / 236	6.4%
Asian	12 / 236	5.1%
missing	2 /236	.8%
Gender		
female/nonbinary/trans/other	120 / 236	51%
male	116 / 236	49%
Education		
HS or less	19 / 236	8.1%
some college	52 / 236	22%
4-year degree	110 / 236	47%
post graduate	55 / 236	23%
HH Income		
under 50k	59 / 236	25%
50-80k	52 / 236	22%
80-110K	43 / 236	18%
over 110k	82 / 236	35%
Marital Status		
married	142 / 236	60%
not married	94 / 236	40%

Table 3. ONN Use Summary Statistics

Continuous Variables	**M / (SD)**	**Min Max**
Visits p/week	14 (16)	0 100
Minutes p/week	31 (45)	0 351
Categorical Variables	**N**	**%**
ONN Groups		
nextdoor	150 / 236	64%
neighbors	49 / 236	21%
fb_onn	81 / 236	34%
whatsapp_onn	12 / 236	5.1%
Other_onn	12 / 236	5%
# of ONN Groups		
1	171 / 236	72%
2	62 / 236	26%
3	3 / 236	1.3%
Posts read p/ week		
none	3 / 236	1.3%
1-2	49 / 236	21%
3-5	93 / 236	39%
6-9	41 / 236	17%
10+	50 / 236	21%
Post Respond per week		
none	146 / 236	62%
1-2	74 / 236	31%
3-5	14 / 236	5.9%
6-9	1 / 236	0.4%
10+	1 / 236	0.4%
Publish per week		
none	194 / 236	82%
1-2	40 / 236	17%
3-5	2 / 236	0.8%

Table 4. Correlational Matrix

	onn 1_1	onn 1_2	onn 1_3	onn 1_4	onn 1_6	onn 1_7	onn 1_8	onn 1_9	onn 1_11	onn 1_12	onn 1_13	onn 1_14	onn 1_15	onn 1_17	onn 1_18	onn 1_19	onn 2_1	onn 2_2	onn 2_3	onn 2_5	onn 2_6	onn 2_8	onn 2_9	onn 2_11	onn 2_14	onn 2_15	onn 2_16	sus	tress	breaks	drive	accs	children	pets
onn1_1	1	0.49	0.47	0.45	0.48	0.6	-0.55	0.28	0.58	0.36	0.45	0.46	-0.47	0.57	0.46	0.55	0.51	0.56	-0.49	0.23	-0.48	0.38	0.49	0.54	0.45	0.58	-0.49	0.23	0.14	0.13	0.18	0.18	0.26	0.19
onn1_2	0.49	1	0.36	0.41	0.41	0.41	-0.47	0.38	0.32	0.19	0.44	0.43	-0.28	0.51	0.4	0.42	0.46	0.35	-0.39	0.39	-0.32	0.32	0.36	0.44	0.3	0.42	-0.38	0.26	0.21	0.23	0.24	0.18	0.25	0.22
onn1_3	0.47	0.36	1	0.46	0.44	0.67	-0.33	0.24	0.73	0.41	0.52	0.5	-0.32	0.5	0.25	0.43	0.39	0.61	-0.33	0.38	-0.31	0.39	0.36	0.5	0.43	0.58	-0.38	0.38	0.28	0.3	0.16	0.13	0.27	0.18
onn1_4	0.45	0.41	0.46	1	0.37	0.5	-0.36	0.35	0.48	0.34	0.45	0.49	-0.18	0.51	0.32	0.36	0.63	0.44	-0.32	0.3	-0.22	0.35	0.31	0.56	0.38	0.62	-0.32	0.17	0.2	0.17	0.24	0.17	0.2	0.23
onn1_6	0.48	0.41	0.44	0.37	1	0.46	-0.3	0.22	0.4	0.27	0.36	0.46	-0.27	0.44	0.21	0.31	0.38	0.44	-0.24	0.23	-0.29	0.28	0.34	0.39	0.43	0.41	-0.31	0.32	0.23	0.24	0.26	0.29	0.31	0.28
onn1_7	0.6	0.41	0.67	0.5	0.46	1	-0.37	0.3	0.78	0.5	0.45	0.52	-0.35	0.5	0.34	0.47	0.44	0.56	-0.43	0.35	-0.37	0.37	0.38	0.57	0.47	0.64	-0.43	0.43	0.31	0.32	0.22	0.22	0.32	0.19
onn1_8	-0.55	-0.47	-0.33	-0.36	-0.3	-0.37	1	-0.23	-0.36	-0.21	-0.41	-0.38	0.48	-0.38	-0.61	-0.55	-0.43	-0.4	0.51	-0.11	0.5	-0.24	-0.49	-0.5	-0.34	-0.47	0.54	-0.19	-0.05	-0.05	-0.12	-0.12	-0.12	-0.13
onn1_9	0.28	0.38	0.24	0.35	0.22	0.3	-0.23	1	0.26	0.09	0.21	0.3	0.03	0.28	0.26	0.21	0.28	0.17	-0.06	0.33	-0.09	0.32	0.16	0.27	0.24	0.31	-0.2	0.17	0.19	0.15	0.19	0.08	0.11	0.26
onn1_11	0.58	0.32	0.73	0.48	0.4	0.78	-0.36	0.26	1	0.46	0.45	0.49	-0.32	0.46	0.34	0.44	0.41	0.57	-0.41	0.38	-0.33	0.39	0.35	0.57	0.42	0.62	-0.39	0.42	0.3	0.29	0.17	0.15	0.25	0.15
onn1_12	0.36	0.19	0.41	0.34	0.27	0.5	-0.21	0.09	0.46	1	0.27	0.28	-0.17	0.32	0.19	0.22	0.25	0.48	-0.3	0.25	-0.28	0.35	0.31	0.39	0.43	0.47	-0.17	0.36	0.28	0.25	0.19	0.06	0.24	0.09
onn1_13	0.45	0.44	0.52	0.45	0.36	0.45	-0.41	0.21	0.45	0.27	1	0.51	-0.25	0.49	0.36	0.44	0.48	0.39	-0.31	0.32	-0.24	0.32	0.31	0.49	0.31	0.43	-0.32	0.18	0.14	0.12	0.21	0.23	0.14	0.24
onn1_14	0.46	0.43	0.5	0.49	0.46	0.52	-0.38	0.3	0.49	0.28	0.51	1	-0.24	0.5	0.28	0.34	0.48	0.43	-0.28	0.32	-0.22	0.43	0.36	0.57	0.4	0.53	-0.3	0.28	0.18	0.19	0.22	0.24	0.3	0.19
onn1_15	-0.47	-0.28	-0.32	-0.18	-0.27	-0.35	0.48	0.03	-0.32	-0.17	-0.25	-0.24	1	-0.34	-0.33	-0.56	-0.23	-0.34	0.67	0.03	0.72	-0.12	-0.43	-0.35	-0.34	-0.35	0.64	-0.24	-0.09	-0.06	-0.06	-0.12	-0.14	-0.12
onn1_17	0.57	0.51	0.5	0.51	0.44	0.5	-0.38	0.28	0.46	0.32	0.49	0.5	-0.34	1	0.3	0.44	0.59	0.51	-0.36	0.34	-0.37	0.44	0.46	0.51	0.45	0.56	-0.4	0.24	0.2	0.25	0.3	0.26	0.27	0.19
onn1_18	0.46	0.4	0.25	0.32	0.21	0.34	-0.61	0.26	0.34	0.19	0.36	0.28	-0.33	0.3	1	0.47	0.47	0.29	-0.41	0.18	-0.44	0.16	0.39	0.37	0.15	0.37	-0.49	0.1	0.03	0.07	0.1	0.09	0.04	0.2
onn1_19	0.55	0.42	0.43	0.36	0.31	0.47	-0.55	0.21	0.44	0.22	0.44	0.34	-0.56	0.44	0.47	1	0.37	0.42	-0.47	0.13	-0.59	0.3	0.55	0.44	0.35	0.48	-0.68	0.12	0.13	0.12	0.16	0.14	0.17	0.14
onn2_1	0.51	0.46	0.39	0.63	0.38	0.44	-0.43	0.28	0.41	0.25	0.48	0.48	-0.23	0.59	0.47	0.37	1	0.5	-0.37	0.39	-0.35	0.34	0.4	0.59	0.34	0.62	-0.39	0.2	0.19	0.19	0.23	0.2	0.13	0.29
onn2_2	0.56	0.35	0.61	0.44	0.44	0.56	-0.4	0.17	0.57	0.48	0.39	0.43	-0.34	0.51	0.29	0.42	0.5	1	-0.42	0.3	-0.38	0.46	0.47	0.51	0.52	0.63	-0.41	0.34	0.27	0.29	0.25	0.23	0.33	0.19
onn2_3	-0.49	-0.39	-0.33	-0.32	-0.24	-0.43	0.51	-0.06	-0.41	-0.3	-0.31	-0.28	0.67	-0.36	-0.41	-0.47	-0.37	-0.42	1	-0.12	0.68	-0.18	-0.49	-0.47	-0.29	-0.43	0.61	-0.27	-0.13	-0.08	-0.07	-0.02	-0.1	-0.14
onn2_5	0.23	0.39	0.38	0.3	0.23	0.35	-0.11	0.33	0.38	0.25	0.32	0.32	0.03	0.34	0.18	0.13	0.39	0.3	-0.12	1	-0.08	0.45	0.2	0.37	0.18	0.32	-0.11	0.38	0.32	0.35	0.23	0.18	0.19	0.31
onn2_6	-0.48	-0.32	-0.31	-0.22	-0.29	-0.37	0.5	-0.09	-0.33	-0.28	-0.24	-0.22	0.72	-0.37	-0.44	-0.59	-0.35	-0.38	0.68	-0.08	1	-0.23	-0.58	-0.4	-0.31	-0.39	0.76	-0.23	-0.08	-0.1	-0.12	-0.1	-0.17	-0.16
onn2_8	0.38	0.32	0.39	0.35	0.28	0.37	-0.24	0.32	0.39	0.35	0.32	0.43	-0.12	0.44	0.16	0.3	0.34	0.46	-0.18	0.45	-0.23	1	0.32	0.44	0.4	0.51	-0.2	0.28	0.22	0.25	0.27	0.18	0.3	0.2
onn2_9	0.49	0.36	0.36	0.31	0.34	0.38	-0.49	0.16	0.35	0.31	0.31	0.36	-0.43	0.46	0.39	0.55	0.4	0.47	-0.49	0.2	-0.58	0.32	1	0.47	0.41	0.47	-0.5	0.17	0.1	0.09	0.16	0.12	0.22	0.12
onn2_11	0.54	0.44	0.5	0.56	0.39	0.57	-0.5	0.27	0.57	0.39	0.49	0.57	-0.35	0.51	0.37	0.44	0.59	0.51	-0.47	0.37	-0.4	0.44	0.47	1	0.42	0.71	-0.41	0.29	0.18	0.16	0.14	0.19	0.24	0.16
onn2_14	0.45	0.3	0.43	0.38	0.43	0.47	-0.34	0.24	0.42	0.43	0.31	0.4	-0.34	0.45	0.15	0.35	0.34	0.52	-0.29	0.18	-0.31	0.4	0.41	0.42	1	0.57	-0.29	0.33	0.22	0.26	0.28	0.24	0.38	0.1
onn2_15	0.58	0.42	0.58	0.62	0.41	0.64	-0.47	0.31	0.62	0.47	0.43	0.53	-0.35	0.56	0.37	0.48	0.62	0.63	-0.43	0.32	-0.39	0.51	0.47	0.71	0.57	1	-0.43	0.34	0.23	0.25	0.2	0.24	0.31	0.14
onn2_16	-0.49	-0.38	-0.38	-0.32	-0.31	-0.43	0.54	-0.2	-0.39	-0.17	-0.32	-0.3	0.64	-0.4	-0.49	-0.68	-0.39	-0.41	0.61	-0.11	0.76	-0.2	-0.5	-0.41	-0.29	-0.43	1	-0.22	-0.12	-0.15	-0.13	-0.14	-0.21	-0.23
sus	0.23	0.26	0.38	0.17	0.32	0.43	-0.19	0.17	0.42	0.36	0.18	0.28	-0.24	0.24	0.1	0.12	0.2	0.34	-0.27	0.38	-0.23	0.28	0.17	0.29	0.33	0.34	-0.22	1	0.64	0.69	0.41	0.27	0.48	0.43
tress	0.14	0.21	0.28	0.2	0.23	0.31	-0.05	0.19	0.3	0.28	0.14	0.18	-0.09	0.2	0.03	0.13	0.19	0.27	-0.13	0.32	-0.08	0.22	0.1	0.18	0.22	0.23	-0.12	0.64	1	0.67	0.52	0.35	0.48	0.36
breaks	0.13	0.23	0.3	0.17	0.24	0.32	-0.05	0.15	0.29	0.25	0.12	0.19	-0.06	0.25	0.07	0.12	0.19	0.29	-0.08	0.35	-0.1	0.25	0.09	0.16	0.26	0.25	-0.15	0.69	0.67	1	0.46	0.37	0.56	0.46
drive	0.18	0.24	0.16	0.24	0.26	0.22	-0.12	0.19	0.17	0.19	0.21	0.22	-0.06	0.3	0.1	0.16	0.23	0.25	-0.07	0.23	-0.12	0.27	0.16	0.14	0.28	0.2	-0.13	0.41	0.52	0.46	1	0.54	0.39	0.32
accs	0.18	0.18	0.13	0.17	0.29	0.22	-0.12	0.08	0.15	0.06	0.23	0.24	-0.12	0.26	0.09	0.14	0.2	0.23	-0.02	0.18	-0.1	0.18	0.12	0.19	0.24	0.24	-0.14	0.27	0.35	0.37	0.54	1	0.44	0.28
children	0.26	0.25	0.27	0.2	0.31	0.32	-0.12	0.11	0.25	0.24	0.14	0.3	-0.14	0.27	0.04	0.17	0.13	0.33	-0.1	0.19	-0.17	0.3	0.22	0.24	0.38	0.31	-0.21	0.48	0.48	0.56	0.39	0.44	1	0.25
pets	0.19	0.22	0.18	0.23	0.28	0.19	-0.13	0.26	0.15	0.09	0.24	0.19	-0.12	0.19	0.2	0.14	0.29	0.19	-0.14	0.31	-0.16	0.2	0.12	0.16	0.1	0.14	-0.23	0.43	0.36	0.46	0.32	0.28	0.25	1

Figure 1. Normality Plot for Cohesion and Security Factors

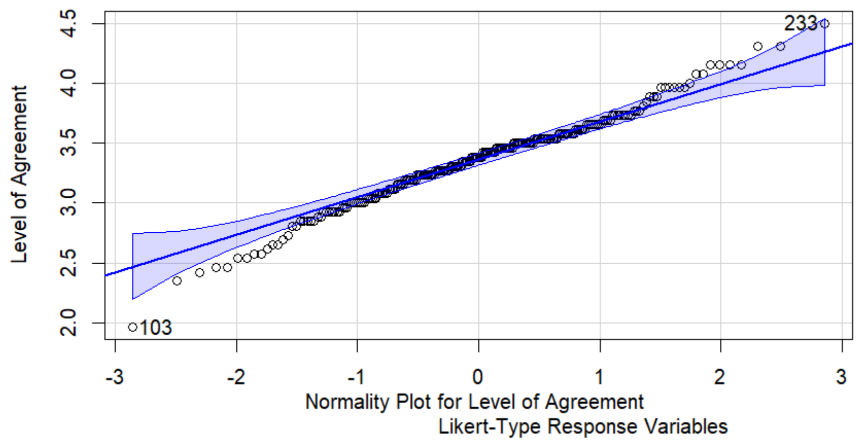


Figure 2. Normality Plot for Efficiency Factor

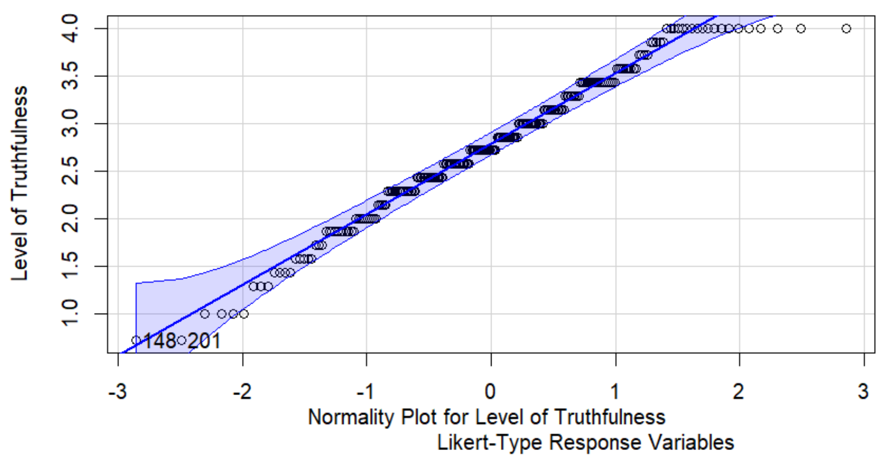
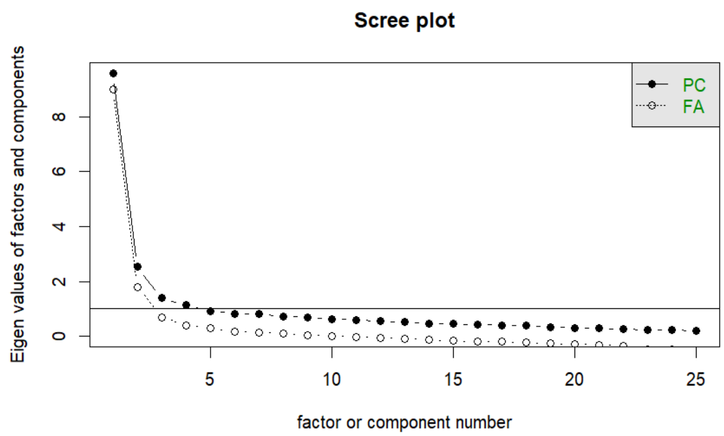


Table 5. KMO Values

Var.1	.97	Var.9	.90	Var.17	.95	Var.25	.95	Var.33	.88
Var.2	.94	Var.10	.94	Var.18	.92	Var.26	.93	MSA	.93
Var.3	.93	Var.11	.96	Var.19	.90	Var.27	.88		
Var.4	.94	Var.12	.88	Var.20	.89	Var.28	.88		
Var.5	.96	Var.13	.96	Var.21	.92	Var.29	.87		
Var.6	.95	Var.14	.92	Var.22	.95	Var.30	.88		
Var.7	.94	Var.15	.93	Var.23	.97	Var.31	.81		
Var.8	.85	Var.16	.91	Var.24	.94	Var.32	.90		

The initial rotation indicated that the measures that were reverse coded and negatively correlate with efficacy were showing up as a method factor and were excluded. After excluding these measures, the parallel analysis and the scree plot yielded a 3-4 factor model (Figure 3) while the eigenvalues suggested a 4-factor model.

Figure 3. Parallel Analysis Graph and Scree Plot



While the 4-factor model provided slightly better TLI, RSMR and RMSEA, one factor did not contain at least three items loading at .40 or more. Also, three items in the 4-factor model cross-loaded, leading to concerns of overfactoring. Therefore, I retained the 3-factor solution. A 2-factor model and a 1-factor model were also examined but they turned out to be highly inadequate based on fit statistics. Final loadings for the 3-factor model appear in Table 6. The proportional variance for each factor is as follows: The first factor which taps into dimensions of social cohesion accounts for 23% of the explained variance, the second factor comprised of safety and protection indicators accounts for 13%, and the third factor of efficiency in communicating neighborhood related threats accounts for 12%. Cumulative variance for all three factors was 48%. Factor correlation was adequate with all factor correlations under 60%. Cronbach's alpha demonstrated high internal consistency among all items (α = .92.7) indicating strong reliability among the items. At least 4 indicators loaded onto each factor making them excellent structure for scale construction.

2.6.b Confirmatory Factor Analysis

Table 7 and Table 8 provide the summary statistics for the confirmatory factor analysis. Respondents were mainly older (*M* = 41, *SD* = 13), homeowners (63%), and identified as women/other (58.2%). Respondents were in large part racially diverse with 43.5% being a race or ethnicity other than white (54.1%). The majority of individuals had at least some college education (92.9%).

Most respondents indicated that they belong to a Nextdoor (63%), Facebook (35%), or Neighbors (23%) group and 91% of respondents use 1-2 groups. Respondents spent less time than on these networks than other social media sites. While users in social media platforms like Twitter, Facebook, and Instagram spend about 30 minutes per day (Dixon, 2023), respondents reported spending an average of 31 minutes per week on ONNs. Overall, participants are heavily engaging with the platforms in a passive manner with 53% reading between 1-6 posts a week and 46% reading over seven posts a week. Generally, however, participants are not engaging with the platform in a heavily active manner with almost half (48%) responding to less than one post a week and 40% responding to 1-3 posts a week. Publishing posts is even less common with 57% not posting anything in a month and 31% publishing 1-3 posts a month.

Mardia's test for multivariate normality indicated mild non-normality and there was no evidence of true outliers skewing the data, so I conducted Maximum Likelihood Estimation with robust standard errors. Barlett's test and KMO results were both highly significant confirming that the data were adequate for factor analysis. Correlational matrix (Table 9) indicated that the observed variables are significantly correlated but there was no evidence of extreme multicollinearity which led me to retain all variables for the analysis (Kline, 2016). I retained a second-order factor model which provided the overall best fit statistics and suggests a good fit (Table 10). While the 3-factor model was statistically equivalent, the model indicated that a high co-variance of over .95 between two of the factors meaning that they were tapping into the same latent construct.

The second-factor model had poor absolute fit, as indicated by the significant chi-square test, $\chi^2(116) = 329.278$, $p = < .001$. However, the chi-square is highly sensitive to larger sample sizes (Babyak & Green, 2010) which could lead to misspecification when not considering other fit indices.

The CFI value with robust standard errors was just under .95 for the second-order factor model, suggesting a good fit (Hu & Bentler, 1999). The robust SRMR value at < .05 indicated a close fit. while the robust RMSEA value of 0.75 suggests that it is an acceptable but not close fit (Hu & Bentler, 1999). However, it may simply reflect the number of loaded items per factor and sample size (Kenny & MacCoach, 2003; Marsh et al., 2004). Cronbach's alpha also demonstrates high internal consistency among the items (α:93.5) indicating high reliability. All but one item had a standardized factor loading of higher than .60 meaning that the items correlate highly with the factors. I also examined a 2-factor model which indicated mediocre model fit based on an RMSEA of over .80 and the 1-factor model indicating poor model fit. Parameter estimates for the second-order factor model appear in Table 11 while Figure 4 depicts diagram of the best fitting model with fully standardized estimates. The average variance extracted for all the factors was above .50, indicating convergent validity among the factors (Table 12). Finally, Figure 4 provides a visual representation of the parameters, variances, and co-variances of the model.

Table 6. EFA Factor Loadings and Commonalities*

*Items that scored at >=.40 and had a communality of >=.40 are in bold	**Coh**	**Sec**	**Eff**	**h2**
My online neighbors provide information I can trust	**0.61**	0.27	0.11	**0.56**
My online neighbors care about our community	**0.66**	0.08	0.09	**0.43**
My online neighbors share resources that keep me safe	0.30	**0.52**	0.01	**0.55**
My online neighbors come together to help in tragedies	**0.67**	0.09	0.04	**0.49**
My online neighborhood group(s) is my primary source of information for my neighborhood	0.42	0.16	0.13	0.36
My online neighbors provide information that helps protect me	0.32	**0.52**	0.07	**0.62**
My online neighbors care about our property values	0.45	0.14	0.15	0.22
Crimes have been stopped thanks to my online neighborhood group	-0.05	**0.66**	0.06	**0.43**
My online neighbors share helpful recommendations	**0.66**	0.05	0.08	**0.43**
I know what is going on in my community thanks to my online neighbors	**0.58**	0.15	0.03	**0.48**
My online neighborhood group is like a community within a community	**0.68**	0.09	0.04	**0.57**
My online neighbors respect each other	0.55	0.18	0.12	0.38
My online neighbors help others in need	**0.79**	0.03	0.05	**0.56**
My community is safer thanks to my online neighborhood group	0.29	**0.55**	0.03	**0.60**
My online neighbors watch out for each other	**0.59**	0.30	0.08	**0.59**
My online neighborhood group(s) is like a large neighborhood watch	0.33	0.24	0.13	0.33
Everyone can safely share their views in my online neighborhood group	0.44	0.29	0.14	0.37
My online neighborhood group is the first line of defense for anything happening around me	0.21	**0.44**	0.13	**0.43**
My online neighbors come together to protect each other	0.50	0.46	0.05	0.70
My online neighborhood group is the most efficient way to alert neighbors about- Suspicious Activity	-0.23	0.42	**0.66**	**0.62**
My online neighborhood group is the most efficient way to alert neighbors about Trespassers	-0.19	0.17	**0.77**	**0.59**
My online neighborhood group is the most efficient way to alert neighbors about Break-Ins	-0.23	0.19	**0.84**	**0.69**
My online neighborhood group is the most efficient way to alert neighbors about Unsafe Drivers	0.14	0.12	**0.62**	**0.43**
My online neighborhood group is the most efficient way to alert neighbors about Car Accidents	0.19	0.14	0.49	0.30
My online neighborhood group is the most efficient way to alert neighbors about Missing Children	-0.08	0.24	**0.56**	**0.42**

Table 7: CFA Summary Statistics

Variable	**N**	**%**		
home: own	268	63.0%		
home: rent	155	37.0%		
race: white	229	54.1%		
race: black	80	18.9%		
race: latino	49	11.6%		
race: asian	48	11.3%		
race: other	7	1.7%		
race:missing	10	2.4%		
gen: female/other	246	58.2%		
gen: male	174	41.1%		
gen:missing	3	0.7%		
education: HS or less	30	7.1%		
education: some college	124	29.3%		
education: ba	190	44.9%		
education: post grad	79	18.7%		
income: under 50k	116	27.4%		
income:50-80k	124	29.3%		
income: 80-110K	55	13.0%		
income: over 110k	123	29.1%		
income: missing	5	1.2%		
marital: married	211	50.0%		
marital: not married	212	50.0%		
	M	**SD**	**Min**	**Max**
age	41	13	19	77

Table 8. CFA ONN Use Summary Statistics

Variable	**M**	**SD**	**Min**	**Max**
visits p/week	4.7	4.8	0	50
minutes p/week	31	44	0	360
	N	**%**		
nextdoor	275	65.0%		
neighbors	96	23.0%		
facebook onn	146	35.0%		
whatsapp_onn	46	1.0%		
frontporch	5	1.2%		
onn_other	10	2.4%		
onngroups: 1	276	65.0%		
onngroups:2	111	26.0%		
onngroups: 3	30	7.1%		
onngroups: 4+	5	1.1%		
missing	1	0.2%		
read: none	5	1.2%		
read: 1-3	113	27.0%		
read: 4-6	109	26.0%		
read: 7-9	64	15.0%		
read: 10+	132	31.0%		
respond:none	204	48%		
respond:1-3	169	40.0%		
respond:4-6	30	7.1%		
respond:7-9	7	1.7%		
respond:10+	13	3.1%		
publishmonth: none	241	57.0%		
publishmonth:1-3	133	31.0%		
publishmonth: 4-6	35	8.3%		
publishmonth: 7-9	8	1.9%		
publishmonth: 10+	6	1.4%		

Table 9: Correlational Matrix

	onn1	onn2	onn3	onn4	onn5	onn6	onn7	onn8	onn9	onn10	onn11	onn12	sus	tress	breaks	drive	childre
onn1	1.00	0.69	0.59	0.67	0.63	0.53	0.58	0.50	0.47	0.55	0.43	0.45	0.48	0.42	0.44	0.38	0.36
onn2	0.69	1.00	0.62	0.79	0.65	0.55	0.67	0.51	0.44	0.53	0.48	0.40	0.48	0.44	0.45	0.34	0.36
onn3	0.59	0.62	1.00	0.60	0.59	0.44	0.49	0.49	0.52	0.51	0.32	0.48	0.41	0.29	0.35	0.26	0.22
onn4	0.67	0.79	0.60	1.00	0.67	0.57	0.64	0.55	0.46	0.55	0.46	0.45	0.52	0.47	0.49	0.37	0.40
onn5	0.63	0.65	0.59	0.67	1.00	0.55	0.56	0.52	0.47	0.54	0.39	0.48	0.43	0.38	0.39	0.34	0.34
onn6	0.53	0.55	0.44	0.57	0.55	1.00	0.59	0.48	0.45	0.56	0.46	0.51	0.41	0.41	0.39	0.30	0.37
onn7	0.58	0.67	0.49	0.64	0.56	0.59	1.00	0.53	0.44	0.53	0.60	0.38	0.52	0.47	0.49	0.41	0.35
onn8	0.50	0.51	0.49	0.55	0.52	0.48	0.53	1.00	0.41	0.52	0.33	0.40	0.52	0.44	0.47	0.38	0.33
onn9	0.47	0.44	0.52	0.46	0.47	0.45	0.44	0.41	1.00	0.50	0.34	0.66	0.43	0.38	0.39	0.27	0.27
onn10	0.55	0.53	0.51	0.55	0.54	0.56	0.53	0.52	0.50	1.00	0.54	0.44	0.47	0.40	0.42	0.39	0.33
onn11	0.43	0.48	0.32	0.46	0.39	0.46	0.60	0.33	0.34	0.54	1.00	0.25	0.39	0.39	0.37	0.37	0.28
onn12	0.45	0.40	0.48	0.45	0.48	0.51	0.38	0.40	0.66	0.44	0.25	1.00	0.36	0.32	0.35	0.25	0.25
sus	0.48	0.48	0.41	0.52	0.43	0.41	0.52	0.52	0.43	0.47	0.39	0.36	1.00	0.78	0.80	0.61	0.56
tress	0.42	0.44	0.29	0.47	0.38	0.41	0.47	0.44	0.38	0.40	0.39	0.32	0.78	1.00	0.80	0.60	0.58
breaks	0.44	0.45	0.35	0.49	0.39	0.39	0.49	0.47	0.39	0.42	0.37	0.35	0.80	0.80	1.00	0.60	0.60
drive	0.38	0.34	0.26	0.37	0.34	0.30	0.41	0.38	0.27	0.39	0.37	0.25	0.61	0.60	0.60	1.00	0.51
children	0.36	0.36	0.22	0.40	0.34	0.37	0.35	0.33	0.27	0.33	0.28	0.25	0.56	0.58	0.60	0.51	1.00

Table 10. Fit of Models Tested

Model Name	χ^2	*df*	*p*	CFI	TLI	SRMR	RMSEA	90% CI RMSEA
Second Order	329.278	116	<.001	94.1	93.0	.048	.75	[0.065-0.084]
3 Factor	329.278	116	<.001	94.1	93.0	.048	.075	[0.065-0.084]
2 Factor	338.233	103	<.001	93.1	92.0	.053	.082	[.073-.092]
1 Factor	635.374	65	<.001	.792	.751	.085	.165	[.154 - .177]

Note. χ^2 = Model Chi-Square; CFI = Comparative Fit Index; TLI=Tucker Lewis Index RMSEA = Root Mean Square Error of Approximation.

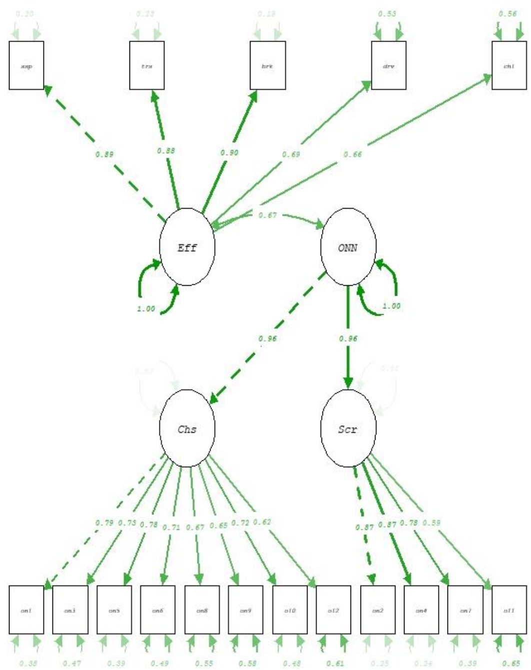
Table 11. Parameter Estimates for Second-Order Factor Model

Relation/Variable	Estimate	SE	z-value	*p*	Std
Factor Loadings					
Cohesion					
Onn1	1.00				0.790
Onn3	0.904	0.082	11.072	<.0001	0.729
Onn5	1.011	0.069	14.568	<.0001	0.783
Onn6	1.078	0.075	14.419	<.0001	0.713
Onn8	0.83	0.083	9.977	<.0001	0.672
Onn9	0.93	0.091	10.197	<.0001	0.647
Onn10	1.076	0.084	12.812	<.0001	0.723
Onn12	0.892	0.09	9.929	<.0001	0.622
Security					
Onn2	1.00				86.9
On4		0.039	26.211	<.0001	0.87
Onn7		0.059	16.692	<.0001	0.782
Onn11		0.074	11.375	<.0001	0.591
Efficiency					
Suspicious	1.00				0.892
Trespassers		0.034	30.264	<.0001	0.880
Breakins		0.031	32.417	<.0001	0.898
Drivers		0.044	19.051	<.0001	0.686
Children		0.053	16.278	<.0001	0.660
ONNEfficacy~					
Cohesion	1				0.957
Security	1.145	0.079	14.409	<.0001	0.959
Covariances					
Efficiency~ONNEfficacy	0.499	0.061	8.171	<.0001	0.668

Table 12. Extracted AVEs

Cohesion	Security	Efficiency
.502	.590	.639

Figure 4. Second Order Factor Model



2.7 Discussion

This study sought to develop and test items to determine a factor structure and conceptualize a scale that can address the construct of online neighborhood network efficacy. The findings suggest that there is a strong basis to consider online neighborhood efficacy as a latent construct to explore in future studies, particularly the relationship between the use of ONN and attitudes about social cohesion and security which manifest as factors significantly relating to ONN efficacy. Overall, findings indicated that the construct of online neighborhood network efficacy scale is based on generating perceptions of awareness, informational trust, helpfulness, and cohesiveness tied to traditional neighborly relationships combined with perceptions of neighbors' ability to protect and maintain the safety of individuals and the community through the online environment.

The exploratory factor analysis revealed three distinct factors with an adequate number of high loading indicators for cohesion, security, and efficiency. Overall, the findings indicate that there are some differences between traditional collective efficacy and online neighborhood network efficacy which may be the results of the underlying processes that occur online. All three factors suggest that social cohesion and feelings of security can be generated and measured in the online space and that it is highly salient to ONN users. For example, the two highest loadings for social cohesion and security, "My online neighbors help others in need" and "Crimes have been stopped thanks to my online neighborhood group" imply that online neighborhood network users can not only distinguish between their physical neighbors and their online neighbors, but that they also have the knowledge that the online neighbors, who they may or may not know personally, behave in ways that strengthen community relations or that deter neighborhood crime. In contrast, traditional collective efficacy measures willingness to help and/or intervene rather than actual behavior or the outcome of such behaviors. Moreover, the factor loadings for efficiency reveal that not all neighborhood incidents are related to the networks' ability to communicate neighborhood related information. Rather, only events that potentially threaten the safety of others in the community such as suspicious activity and break-ins seem to tap into this factor. This is further evidenced by the measures that did not load on the factor and which may not be characteristically considered threats to the community: car accidents and lost pets.

The CFA revealed somewhat unexpected results as it deviates from the factor structure that surfaced in the exploratory factor analysis. While the second-factor model indicates an underlying construct of online neighborhood network efficacy, only social cohesion and security emerge as interrelated dimensions of ONN efficacy. While the efficiency to communicate neighborhood threats does suggest a significant co-varying relationship with ONN efficacy, it points to a functional aspect of efficacy and supports the construct, yet it is conceptually and empirically distinct from ONN efficacy and should be treated as such.

While it is impossible to make explicit comparisons between this ONN efficacy scale and traditional collective efficacy scales, it is important to note that unlike other studies that argue for distinguishing between social cohesion and willingness to intervene as distinct constructs (Armstrong et al., 2010; Gau, 2014; Kingston, 2009), in this case I find that social cohesion and security can be treated as one single scale. These findings are analogous to the original researchers' conclusion that collective efficacy is a combination of social cohesion and willingness to intervene (Sampson et al., 1997). In the case of online neighborhood networks, it is a combination of social cohesion and security, with security being a direct outcome of the exercise of informal social control actions, an assumption of the traditional collective efficacy conceptualization. Furthermore, it coincides with Sampson's (2013) assessment that activated social ties measured as neighboring activities or reciprocated exchange, and social cohesion are interrelated dimensions of collective efficacy. The ONN efficacy scale captured both dimensions plus the unique dimension of security.

The study herewith also aligns and adds to the previous works on ONNs in a European context. Robaesyst et al (2022) found that sense of community is mainly predicted by "the amount of information shared by residents about the neighborhood (p.113)". The current analysis indicates that for ONN users, the trust placed on the information, the efficiency of the communication for creating awareness, and the relationship to neighborhood safety are key components to understanding ONN beliefs. Yet, whereas other work (Melhbaum & van Steden, 2018; van Steden & Mehlbaum, 2022) found that WhatsApp Neighborhood Crime Prevention groups stimulate social cohesion rather than crime prevention or feelings of safety, the current study suggests that across multiple platforms, ONN users may not only believe otherwise, but that not just social cohesion, but crime prevention, deterrence, and safety are principal indicators of online collective efficacy.

2.7.a Limitations

The study contains several limitations. The study is not generalizable to the population of online neighborhood network users since (1) prevalence of online neighborhood network use in the population is unknown and (2) the data stems from an internet nonprobability sample. The study was conducted with a population of online neighborhood network users; however, certain populations groups are less likely to participate in online surveys like the one administered in this study (Rittase et al., 2020). To control for underrepresentation in both the EFA and CFA samples, I sampled Black, Latinos, and Asians in a second wave of recruitment and offered a slightly higher incentive (16.7%) than for the first wave of respondents (McGrath, 2006; Singer & Ye, 2013). This resulted in a more diverse sample, decreasing the percentage of white respondents from 75% to 54% between the first recruitment and the final sample. More importantly it increased minority participation by 116%. Lastly, the findings for the efficiency factor may be related to the attempt to combine different scales, efficacy, and efficiency, into one scale. Future studies should consider integrating and testing the efficiency measures in the same scale using the same Likert-type response to examine whether the efficiency factor should indeed be operationalized as a separate scale.

2.8 Conclusion

This research significantly contributes to the interdisciplinary literature of the mechanisms occurring in online neighborhood environments, the scales available to measure types of ONN use (De Meulanere et al., 2021a), as well as support and enhance the longstanding work by collective efficacy theorists in the field of criminology. Future research should consider applying, testing, and validating the scale in studies that examine the relationship between online neighborhood network use and offline neighborhood outcomes to determine if the psycho-social mechanisms occurring online influence individual and neighborhood level outcomes such as fear and violence.

CHAPTER 3: EXAMINING THE ROLE OF ONLINE NEIGHBORHOOD NETWORKS ON FEAR OF CRIME

3.1 Introduction

Online neighborhood networks provide benefits to neighborhoods such as community participation, potential mobilization, a sense of safety and protection, and a sense of community (De Meulenaere et al, 2021b; Molinet, n.d.(a); Vogel et al, 2020; Vogel et al, 2021). Yet, there is still a question of the negative outcomes that these networks could generate on individuals who frequently use these platforms, particularly for neighborhood crime information. ONNs provide users with a slew of alerts and posts that are crowd-sourced and framed in a news-style manner that promote awareness and become a "central hub of information" for neighborhoods, but lack journalistic principles (De Meulanere et al, 2021a). Other studies indicate that these platforms are primarily conceptualized through a neighborhood security dimension where all other factors of social cohesion and community are facilitated by the platforms' abilities to engender safety, protection, and potentially deter and stop crime (Molinet, n.d.(a)). Moreover, reliance on these spaces to successfully deter crime and work productively with police has been limited and at times even contentious (Mols & Pridmore, 2019; Williams et al, 2013). Yet, the topic of whether online neighborhood networks influence fear of neighborhood crime remains underexplored.

To my knowledge, no study has attempted to isolate the effect of the type, frequency, and magnitude of online neighborhood network use on fear of neighborhood victimization. Thus, this paper addresses this issue by quantitatively examining the variation in type, frequency, and magnitude of online neighborhood network use and fear of neighborhood victimization. I apply inverse probability weights to the sample to statistically control for the confounders between

ONN use and fear, thereby addressing the self-selection bias found in non-probability sampling to calculate the effect of ONN use on fear of neighborhood victimization.

3.2 Background and Framework

3.2.a The Proliferation of Online Neighborhood Networks

ONNs are restricted social media platforms designed to organize neighborhoods and connect neighbors online based on socio-spatially defined boundaries and identity verification (Coulton et al, 2013; Higgitt & Memken, 2001; Payne, 2017; Vogel et al, 2019; Vogel et al, 2020). Neighborhood residents share information and resources about issues relevant to their neighborhood or community. ONN members primarily use the networks for either instrumental reasons such as getting help for something or expressive reasons such as sharing information relating to neighborhood events (De Meulenaere et al, 2021). ONNs can be private groups created by neighborhood residents in applications such as Facebook or WhatsApp. They are also ad-supported applications specifically designed to attract neighborhood residents to register as users and where the neighborhood parameters are mostly defined by the platforms. Examples include Nextdoor, Neighbors by Ring, Front Porch Forum, Hopplr in Belgium, and Neighbourly in New Zealand. While ONNs share many of the same characteristics as other social media platforms they are distinct in their membership protocols and delineation of neighborhoods which are determined by the platforms, the neighbors, or a combination of both (Boyd & Ellison, 2007; Vogel et al, 2020).

Even though different forms of online neighborhood networks have been around since the 1990s (Carroll & Ronson, 1996), in recent years online neighborhood networks have gained significant ground in the United States and worldwide. The best-known ONN in the United States, Nextdoor, claims to have a presence in 11 countries and connect 305,000 neighborhoods worldwide. Other applications share similar popularity. Google Play ranks Neighbors by Ring as the #36 news and magazine application by number of downloads and #32 in usage. Meanwhile private neighborhood groups on Facebook and WhatsApp Crime Prevention Groups in Europe have also become popular methods of sharing exclusive neighborhood information.

3.2.b Security or Fear and Tension Production in ONNs

Qualitative researchers argue ONNs produce fear, tension, and division among its users (Kurwa, 2019; Lambright, 2019; Payne, 2017; Pridmore et al, 2019). With its launch in 2011, Nextdoor aimed to capture neighborhood audiences promoting themselves as a private social network. The platform invited members to use the tool for four different actions,“request and share local service recommendations, sell or donate items, learn more about their neighbors, and help each other in ways that benefit the entire neighborhood (Nextdoor, 2011).”

By 2012 the platform also highlighted the platform as a tool to get crime and safety information and inviting users to “join your neighbors and organize a neighborhood watch (Nextdoor, 2012).” By 2014, the platform was defending itself against practices of racial profiling and fear producing mechanisms stemming from their crime section (Asimov, 2016). In 2020, after the Black Lives Matter protests and public criticism, the platform established guidelines for reporting crime and disabled the Forward to Police feature (Waller, 2020). In 2022, the tool attempted to reduce the relevance on the crime and safety section which accounted for 20% of the posts and only refer to it as the safety section while promoting kindness and community (Holder & Aknnibi, 2022).

Meanwhile, another application on the market, Neighbors by Ring, has been criticized for seemingly crowd-sourcing fear and turning vigilantism into a hobby (Ingram & Farivar, 2021). Critics this application further contend that these platforms monetize tensions and fear (Cohen, 2021). Unlike Nextdoor, which has tried to move away from crime as a focal point, Neighbors works by applying the user's address, creating a radius, and allowing users to post anonymously about crime incidents (Neighbors.com, n.d.). Users can also upload their Ring camera videos as evidence of the event. The platform also promotes itself as a way to keep abreast and help after a disaster, or as an effective tool to find lost pets. However, their homepage appeals to social cohesion and sense of community through the act of deterring crime (Appendix A).

Some studies have found that these networks even put the platforms at odds with police and promote vigilante behavior while at the same time extending efforts to collaborate with law enforcement (Pridmore et al, 2019). Even when online neighborhood network users primarily associate these networks to social cohesion factors of trust, helpfulness, and they are facilitated by their perceived ability to deter crime, enhance awareness, and generate feelings of safety and protection (Molinet, n.d. (a)). Social cohesion then is intrinsically intertwined to security-driven behavior and outcomes.

3.2.c The Correlates of Fear

Fear of crime research focuses on three key models traditionally associated with the overarching construct: direct or indirect victimization (Skogan & Maxfield, 1981, Skogan, 1986) disorder/incivilities (Hinkle, 2005; Hinkle & Weisburd, 2008; LaGrange et al, 1992; Taylor & Covington, 1993; Wilson & Kelling, 1982), and social integration (Bursik & Grasmik 2001; Gibson et al, 2002; Hale & Taylor, 1986). Researchers find that the key variables in each model are all predictors of fear of crime, that not one model is sufficient to fully explain the mechanisms underlying fear of crime, that predictors vary by type of crime, and that other cognitive or neighborhood variables also play a role in fear (Alper & Chappell, 2012; Covington & Taylor, 1991; Lee et al, 2020; McGarrell et al, 1997; Taylor & Hall, 1986). Furthermore, the operationalization of the fear of crime measure itself also may also affect which predictors significantly influence fear of crime (Farrall et al, 1997; Hinkle, 2015). Currently, most studies integrate the three key elements of victimization, perceived disorder, and social integration in multilevel analysis to provide a better explanatory model for example, Ferguson & Mindel (2007), Franklin et al (2008), Gainey et al (2011) and McGarrell et al (1997). These and other studies also examine both individual and neighborhood level characteristics that may impact the mechanisms leading to individual fear of crime.

Neighborhood-level structural characteristics such as concentrated disadvantage, mobility, heterogeneity, and neighborhoods that report higher perceived disorder and violence have been positively associated with fear of crime (Barton et al, 2016; Brunton-Smith & Sturgis, 2011; Hinkle & Weisburd, 2008; Kilewer, 2013; Scarborough et al, 2010; Stein, 2014; Taylor & Covington, 1981). Collective efficacy, which refers to an individual belief in the neighborhood's capabilities to come together, organize and execute actions and extend it to a collective belief by community residents, has also generally been found to be a significant predictor of fear. Some researchers find that collective efficacy has a direct negative effect on individual or community-level fear of crime (Abdullah et al, 2015; Gibson et al, 2002; Yuan & McNeeley, 2017), while others find that the negative effect of collective efficacy on fear is indirect and mediated by disorder or other neighborhood characteristics such as disorder (Gainey et al, 2011). However, Brunton-Smith et al (2014) found that collective efficacy mediated the relationship between disorder and fear of crime. These mixed findings may be the result of a reciprocal feedback loop between disorder and collective efficacy (Markowitz et al, 2001). Lastly, social cohesion and trust which are both indicators of collective efficacy, have been found to be positively associated with either higher fear of or have no effect on fear (Hardyns, 2018; Roundree & Land, 1996).

The effects on fear of individual level characteristics are also nuanced. The literature suggests that the two strongest individual level characteristics are gender and age. Most findings support that women and older age groups are more fearful of crime than men and younger people (Ferguson & Mindel, 2007; Ferraro & LaGrange, 1987; Hale, 1986; Scarborough et al, 2010; Skogan, 1990; Warr, 1990). Yet, other work suggest that gender differences may be a consequence of the types of questions being asked or the crime types being examined (Chatway & Hart, 2019; Farrall et al, 2000; Reid & Konrad, 2004) while age related fear of crime may be somewhat overestimated (Ferraro & LaGrange, 1989) or may be dependent of on other dimensions of vulnerability not properly measured (Hanslmaier et al, 2018). Other work indicates that demographics and neighborhood conditions interact with women reporting more fear based perceived neighborhood disorder (Snedker, 2015).

3.2.d The Media and Fear of Crime

Media and news consumption have traditionally been positively associated with fear of crime and violence (Callanan, 2012; Chiricos et al, 1997; Chiricos et al, 2000; Romer et al, 2014; Kohm et al, 2012; Romer et al, 2003). Yet, the relationship may be dependent on type of media, type of audience, and could be moderated by neighborhood context, and vary based on demographic characteristics (Eschholz et al, 2003; Lytle et al, 2022; Weitzer & Kubrin, 2004; Williamson et al, 2019; Yamamoto et al, 2019). Those who consume passive media such as TV and radio report have been found to report higher fear than those who consume active media sources like the internet where they actively seek it out the information and/or engage with the content (Roche et al, 2016; Williamson, 2019). Furthermore, being a woman, having previously been victimized, and negative perceptions of neighborhood more significantly predict fear than media consumption (Callanan & Rosenberger, 2015). Researchers surmise that the significant association between women and fear may be generated by the overrepresentation of women as victims in entertainment media and crime news (Eschholz et al., 2003; Madriz et al, 1997; Rosenberger et al., 2023; Schlesinger et al, 1992; Weiss & Chermak, 1998). Yet, other research disputes this association finding that it is either non-significant or becomes non-significant after controlling for actual crime (Chadee et al, 2019; Doob & McDonald, 2017).

The pervasiveness of social media, its ability to spread a message in a more effective manner than traditional media, and the framing of fear discourse supported by imagery and misrepresentation could lead to increased fear (Altheide, 2013; Walby & Joshua, 2021). Yet, the relationship is as unclear and nuanced as those from traditional news consumption studies. General social media consumption has been associated with fear in some segments of the population including young adults and minorities (Intravia et al, 2017; Rosenberger et al, 2023). One study found that individuals who use various social media sites for crime news were more likely to report fear of street violence compared to those who only use traditional media (Näsi et al, 2021). However, several other studies indicate that consuming news via platforms like Facebook, Google, or Twitter is not correlated with increased fear of victimization (Hollis et al, 2021; Rosenberger et al, 2023). To further complicate matters, selective engagement of information may be an omitted mechanism in these studies. Fearful social media users may simply be selecting, engaging with, and continuously reinforcing negative and fear-related content (Merten, 2021; van der Meer, 2022; Woolley & Sharif, 2022).

While social media and fear of crime studies have primarily focused on news consumed in well-known sites like Facebook and Twitter, research focused on the association between participation in online neighborhood networks and fear of crime remains unexplored. Yet, by combining official local law enforcement bulletins while giving all citizens the ability to post about any neighborhood-related incident or event without upholding journalistic principles or any monitoring to the veracity of the information, individual online neighborhood networks act as an amalgamation of local news sources and rumor networks which are characterized by proximity and personal significance they have to the reader and connect directly with an individual's environment which could have a significant impact of their perception of crime (De Meulenaere et al, 2021a; Skogan, 1986; Tyler, 1984; Weitzer & Kubrin, 2004).

3.2.e Inverse Probability Weights and Treatment Effects

Inverse probability weights (IPW) allow researchers to create a counterfactual of the treatment group by first estimating the probability of exposure to a treatment for each individual (a propensity score) based on individual characteristics, and then calculating the inverse of those scores to equally distribute confounders across both groups (Chesnaye et al, 2022; Curtis et al, 2007; Gertler et al, 2016). This produces an unbiased or less biased estimator when calculating the average treatment effect of the exposure on the outcome.

IPW models have traditionally been used in public health studies to adjust for selection bias in research that may not be able to conduct a fully randomized controlled trial (Hernan, 2002; Lippman et al, 2011; Pezzi et al, 2016). IPWs have also been applied to evaluate the effects of criminal justice interventions such as juvenile justice involvement in adult criminal outcomes (Copeland et al, 2023), financial burden in prison reentry (Link, 2019), and day reporting center use and recidivism (Osselin et al, 2023).

Inverse probability weights then provide an opportunity to treat digital activities such as membership and participation into an online neighborhood network as a program since users voluntarily choose to register and be able to meet location requirements to be able to use the platforms. This means that we can divide into a "treated group" of ONN users and a "comparison" group of non-ONN users. The assumptions of IPW are exchangeability, consistency, positivity, and no misspecification in the model (Chesnaye et al, 2022; Cole & Hernan, 2008; Zhu et al, 2021). In this case, it means that ONN users and non-ONN users must appear similar based on observed characteristics, that an individual's potential outcome will be the one that will be observed regardless of any variation in exposure, that at every level of confounders there are both users and non-users, and the probability of being exposed cannot be equal to 0. The assumption of exchangeability is critical in IPW models. Overall, for exchangeability to be met, propensity scores need to satisfy both the common independence assumption and the common support assumption to make the groups exchangeable (Gertler et al, 2016). While the common support assumption can be tested, the common independence assumption assumes that the groups are as "good as random", but it is impossible to test with observational data since it is dependent on potential unmeasured confounders (Chesnaye et al, 2022; Gertler et al, 2016). Positivity can also be observed, while the consistency assumption is generally satisfied by creating well-defined and specific measures of exposure (Chesnaye et al, 2022; Rehkopf et al, 2016).

3.3 Current Study

This study will contribute to the media and crime literature in several ways: First, by exploring individual online neighborhood network use and perceptions of fear of neighborhood victimization. By examining the relationship between online neighborhood network use and neighborhood specific fear of crime we may be able to better understand whether spending more time using online neighborhood networks significantly predicts fearful attitudes related to neighborhood victimization. This research also contributes to social media literature by providing a comprehensive measure of online neighborhood network use specified by prevalence, frequency, and magnitude capturing both quantitative and qualitative indicators.

Lastly, the study overcomes issues of self-selection bias traditionally found in non-probability sampling by applying inverse probability weights to the sample which controls for observed confounders between use and fear to produce a less biased estimation of the effects of ONN use on fear. The main question of interest is as follows: Does individual use of online neighborhood networks increase reported fear of neighborhood victimization, independent of other neighborhood and individual-level characteristics?

I expect that 1) online neighborhood network users will be significantly more concerned about fear of neighborhood victimization than non-online neighborhood network users and 2) as visits to the ONNs and minutes spent engaging with the ONNs increase, individuals will report significantly higher fear of being victimized. Furthermore, based on the abundance of previous findings, I also expect that prior victimization, perceived disorder, and gender will significantly influence fear of neighborhood victimization.

3.4. Data and Methods

3.4.a Design

The study uses a cross-sectional survey in which the main questions focus on the multiple qualitative and quantitative ways that ONN users spend their time in the platforms along with their perceptions on online discord, neighborhood disorder, and fear. The questionnaire also includes other well-known individual covariates of fear such as prior victimization, news consumption, and demographic characteristics. Since the study seeks to compare ONN user and non-ONN users the instrument questioned non-ONN users about all these covariates except for ONN use. I draw the main ONN use questions from qualitative interviews previously conducted in Molinet (n.d.(a)) which indicated how much time and in what ways ONN users spend their time on these applications. Those findings revealed that while ONNs serve users for a variety of purposes including everything from finding lost pets to helping in tragedies yet, one of the principal ways that online neighborhood network users identified the networks was as a neighborhood watch that facilitated every other aspect of the interactions. Finally, the study also calculates propensity scores and creates weights to control for selection bias and create comparable treatment and comparison groups by calculating the probability of online neighborhood network use for each individual in the sample.

3.4.b Sample

I recruited a total of 1,371 participants between March 2023 and July 2023 via Prolific online recruitment platform. These types of online crowdsourcing recruitment platforms have been found to recruit samples like those in traditional psychology, while also providing an older more diverse participant pool (Behrend et al., 2011). Prolific has been found to have the best data quality in the online research platform field compared to both Amazon Mechanical Turk and CloudResearch (Peer et al., 2022) and the most representative sample, particularly for questions about attitudes and experience (Tang et al., 2022). To reduce social desirability bias and to avoid attracting respondents who are more likely to be engaged in online neighborhood networks (Chang & Krosnick, 2009) the survey recruitment prompt did not mention online neighborhood networks, rather described the study as one about neighborhoods.

I pre-screened everyone for eligibility based on country of residence, fluency in English, and living arrangements. Individuals who did not own or rent their own home were excluded from recruitment. Blacks and Latinos were oversampled due to low participation and non-response rates within the Prolific platform and in overall survey research (Department of Education, n.d.; Rittase et al., 2020). Within the questionnaire, I again screened respondents about living arrangements, social media use, and online neighborhood network use. Ten observations were dropped from the sample due to inadvertently providing duplicate questionnaires after conducting an oversample of Blacks and Latinos. Another ten were dropped from the sample due to low-effort response which is based on the number of answers provided and the time spent on the questionnaire. If participants spent less than 3 minutes on the survey, I reviewed their answers to assess if there was evidence of straight lining. Lastly, I dropped 25 observations due to a technical error which did not show a question to those participants, and only provided answer choices. The final sample was 1,324.

3.4.c Data Collection

I tested the questionnaire among 10 Georgia State University students and a small online sample (n=40) prior to distributing, to assess for content and measurement issues, readability, attention checks, comprehension, and length burden of the instrument. Lisa Holland, Director of the Survey Research Center, at the University of Michigan also reviewed the questionnaire. Participants reported not seeing the answer choices to two of the items in the survey. I corrected this, and the sample was given the opportunity to provide both answers separately.

The final instrument contained a total of 5 sections and 65 close-ended survey items for onn users and 54 items for non-onn users (Appendix B). I routed all respondents to answer questions about their living arrangements, social media use, online neighborhood network use, neighborhood-specific concerns about crime, perceived neighborhood disorder, victimization and reporting to the police, news consumption, and demographic information. Respondents who reported not using social media or online neighborhood network use answered items about their perceptions of neighborhood collective efficacy. Those who reported using online neighborhood networks were routed to complete the online neighborhood network efficacy and discord scales as well as more detailed questions about online neighborhood network use. The questionnaire included four attention checks for each group (users and non-users). Prior to answering the questionnaire, participants read an informed consent form which stated that continuing with the questionnaire they were acknowledging participation. I also prompted participants to provide their Prolific ID to be able to manually review each response. The median time for completing the questionnaire was close to 6 minutes.

3.4.d Dependent Variable

Neighborhood-Specific Fear of Crime I constructed the fear measure as a 6-item Likert-type scale and draws from previous work that suggest crime-specific fear of crime scales are more effective in exploring the mechanisms associated with fear (Abdullah et al, 2015; Foster et al, 2010; Rountree, 1998; Yuan & McNeeley, 2016; Yuan & McNeeley, 2017)[12] . This measure avoids a general fear of crime index that has been found to overestimate fear (Ferraro & LaGrange, 1987; Farrall et al, 1997; Rountree & Land, 1996). The scale is also adapted from the magnitude dimension of emotional-based fear used in previous studies (Farrall & Gadd, 2004; Hinkle, 2013). The measure assessed magnitude of neighborhood-specific fear of victimization by asking respondents "How concerned are you that the following will occur in your neighborhood?" and provides a 0-4 scale where 0=Not Concerned at All, 1=Slightly Concerned, 2=Moderately Concerned, 3=Very Concerned, 4=Extremely Concerned. I summed and averaged the items, where higher score reflects higher fear of criminal personal or property victimization within their neighborhood. I selected the term "concerned" rather than "fearful" to operationalize the measure since the measure aims to capture, not the immediate physiological reaction to a clear, imminent threat, but rather the anxiety of possible victimization that is related

[12] Foster, Giles-Corti & Knuiman's, 2010 (Chronbach's Alpha .93); Yuan & McNeeley, 2016; Yuan & McNeeley, 2017)

to an unclear threat (Croake & Hinkle, 2017; Croake & Knox, 1973; Hale & Taylor, 1986). Concern, synonymous with worry, is a dimension of fear but can better address the effects related to an individual's social networks and surroundings (Hale & Taylor, 1986).

3.4.e Causal Variable

Online Neighborhood Networks Use My main independent variable was operationalized as the prevalence, frequency, magnitude, and type of ONN use. First, to distinguish between online neighborhood network users and non-users, I asked respondents the following question: "Do you belong to any of the following online neighborhood networks? (Mark all that apply)" and were given a choice of size online neighborhood networks (Nextdoor, Neighbors by Ring, WhatsApp Neighborhood Group, Facebook Closed Neighborhood Group, and Front Porch Forum) as well as the possibility of entering their own answer. Respondents also had the possibility to answer, "I don't use any online neighborhood network". I coded the response choices two ways. First, as binary where 0=nonuser if they indicate they do not use any group and 1=onnuser if they indicate they belong to one or more groups. Additionally, I coded each response choice selected by respondents as a binary variable with 1=Use.

I measured frequency of use as frequency of going on to the networks and/or time spent interacting with online neighborhood network content. I adapted the measure from past social media research (Brunborg et al, 2019; Ellison et al, 2007; Heffer et al, 2018; LaRose et al, 2004; Steinfield et al, 2008), where the main independent variable is time spent and from Daly (2018) who suggests that measuring days and minutes per day of social media use provides a better measure to understand range of effects. For those who respond being online neighborhood network subscribers, they were asked "In the past week, about how many times have you visited your online neighborhood group(s)?" Next, I asked respondents "On an average week, about how many minutes do you spend visiting your online neighborhood group(s)?"

I adapted the magnitude of use measure from Ellison et al's (2007) Facebook Intensity Scale[13] which provides a more robust measure than frequency of use. I asked respondents the following three questions to determine the estimated number posts they read, publish, or respond to on an average week: "In an average week, about how many posts do you read from your online neighborhood group(s)?", "In an average week, about how many posts do you respond to your online neighborhood group(s)?" For these three questions, I collected responses as interval variables with the choices being never, 1-3 times, 4-6 times, 7-9 times, and 10 or more times. I numerically coded response categories for all three items from 0-4.

For types of use I asked participants "What do you use the online neighborhood group(s) for? (Select all that apply). Participants could choose up to 8 types of activity including connecting with other, crime information, safety information, seek advice, seek recommendations, and/or buy or sell items. I coded the response categories as binary with 1=yes.

3.4.f Explanatory Variables

Victimization Prior victimization may influence fear of crime (Gibson et al, 2002; Skogan & Maxfield, 1981). The victimization measure derives from fear of crime research that distinguishes between violence and property victimization and examines the effects of indirect victimization (Hinkle, 2012; Sampson & Raudenbush, 1999). Furthermore, it focuses on neighborhood-specific victimization to better measure the relationship between neighborhood-specific fear and victimization. First, I asked respondents "Have you reported a crime to the police in the past 6 months?" to capture any contact with police that may have dealt with a

[13] Facebook Intensity Scale demonstrated high internal consistency (Cronbach's alpha = 0.83)

victimization that was deemed a reportable crime by the individual[14]. The choice of a 6-month period is grounded in two findings: most individuals only report one victimization in a 6-month period, and it decreases the burden of survey response (Lauritsen et al, 2012). I coded responses as binary with 0=No. I routed respondents who answered yes to the question "Did this crime happen in your neighborhood?" I coded the responses as binary with 0=No. I routed respondents who answered yes, to the question "What did you report?" with the response categories: a crime that happened to me, a crime that happened to a family member, a crime that happened to a friend, a crime that happened to someone else. I combined each response with the previous two questions and created a both a numeric variable and a factor variable where 0=No report, 1=Victimization to someone other than respondent outside neighborhood, 2=Victimization someone else inside neighborhood, 3=Friend victimized inside neighborhood, 4=Family victimized inside neighborhood, 5=Personal victimization outside neighborhood, and 6=Personal victimization inside neighborhood.

Neighborhood Disorder Longstanding evidence links neighborhood disorder with fear of crime (Gainey et al, 2011; Gau et al, 2014; Gibson et al, 2002; Hardyns et al, 2018; Hinkle, 2013; Hinkle & Weisburd, 2008; Markowitz et al, 2001; Skogan, 1990; Zhao et al, 2015 among others). Moreover, individuals do not differentiate between disorder and actual crime (Gau & Pratt, 2008; Wickes et al, 2017). Therefore, I adapted a composite 6-item measure of physical and social disorder from scales used in large scale studies (Bolger & Bolger, 2019; Scarborough et al, 2010; Wickes et al, 2017)[15] to examine whether perceived disorder reduces the effects of

[14] I approached the measure in this manner rather than directly asking about victimization for a few reasons: First, 1 in 5 victims do not report because they do not think the crime to be serious enough. Others do not report because they deal with it in a personal way (Department of Justice, 2012). Reporting is also correlated with victim-offender relationship. Individuals are more likely to report when they do not know the offender. Lastly, sexual assault victims are less likely to report their crime due to feeling guilt or shame (Thompson et al, 2007). The question was worded in a way where they did not have to immediately disclose their victimization which could lead to non-response, rather giving the opportunity to first answer whether they report something or not.

[15] Wickes et al's scales that combines physical and social disorder indicated high reliability at both the individual and neighborhood level as well as strong factor loading.

ONN use on my dependent variables. Like previous work, this measure does not distinguish between actual crimes and disorder. Respondents rated each item as 0=Not a problem at all to 3=A big problem, from a list of disorder/incivilities/crimes (property problems, traffic problems, begging, prostitution, drugs, public drinking, loud parties). I summed and averaged all response items where higher score perceived higher neighborhood disorder.

Online Discord Scale Analysis of the qualitative interviews done prior to the questionnaire (Molinet, n.d.(b)) revealed a theme of animosity or discord in the online networks that affected individual perceptions of the networks, their engagement with them, and suggested concerns for the effects of online discord on neighborhoods. To test whether negative online discord influences fear and efficacy, I asked respondents "Still thinking about your online neighborhood group(s), please select the response best describes the extent to which the following happen" along with the following 3-items (1) My neighbors fight online (2) My neighbors complain online, and (3) There is negativity in my online neighborhood group(s). Respondents rated each item on a scale of 0-4 where 0=Don't Know, 1=Not At All 2= To a Little Extent, 3=To Some Extent, and 4=To a Large Extent. I summed and averaged the scale. Higher score reflected higher perceived online discord.

General News Consumption The questionnaire included general questions about respondents' news consumption since media consumption in general is positively associated with fear of crime (Chiricos et al, 1997; Weitzer & Kubrin, 2004). I asked respondents the following three questions: "On an average week, how often do you watch the news?", "On an average week, how often do you listen to news?", and "On an average week, how often do you read news?" Response categories were never, 1-2 days a week, 3-4 days a week, 5-6 days a week, and daily. I coded each variable as a numeric variable as 0-4 where 0=Never.

Social Ties The strength of social integration may affect individual perceptions of fear (Gates & Rohe, 1987; Gibson et al, 2002; Hale & Taylor, 1986). To test this from the online neighborhood perspective, I asked respondents "About how many people do you <u>personally know</u> from your <u>online neighborhood group(s)?"</u> with the following response categories: "I don't personally know anyone", "1-3 persons", "4-6 persons", "7-9 persons", and "10 or more persons". I coded the measure was coded as a numeric variable where 0=None to 4=10 or more.

Individual Level Characteristics The following individual level characteristics included in the study have been found to be predictors of fear of crime: home ownership, length of residence, gender, age, race, marital status, education, and household income (Baumer 1978; Skogan & Maxfield, 1981; Taylor & Hale, 2017; Weinrath & Gartrell, 1996). I coded all individual level characteristics except age as numeric and categorical variables.

I coded home ownership was coded as 1=Owner. For length of residence, I asked respondents "About how many years have you lived in your neighborhood?" with open-ended response. Gender response categories included male, female, trans/gender non-conforming/non-binary and other, where 0=Male and 1=Female/Other. I coded age as a continuous variable. I coded marital status as 1=Married. I coded education as 1=High School or less, 2=Some college 3=Bachelors, 4=Graduate Degree. I coded Race/Ethnicity as 1=White, 2=Black 3=Latino, 4=Asian, 5=Other.

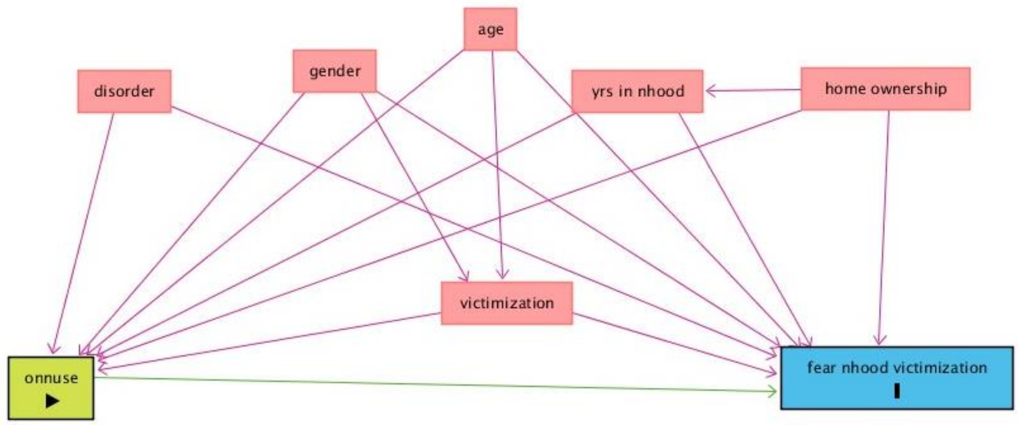
3.4.g Analytic Approach

I applied a two-step approach to analyze the outcome for my dependent variable of fear of neighborhood crime. First, I examined whether the use of online neighborhood networks is associated with (1) neighborhood-specific fear of crime between ONN users and non-ONN users. Next, I examined whether higher use of online neighborhood networks is associated with neighborhood-specific fear of crime among the sub-sample of ONN users. I dropped a total of 30 observations were dropped from the second part of the analysis due to missing data that were deemed missing at random.

3.4.h Inverse Probability Weight Model

Due to the lack of prior research regarding the prevalence and characteristics of online neighborhood network use in the population, I draw from fear of crime theory and an abundance of prior fear of crime research as well as social media research, to determine which variables would act as observed confounders between ONN use and fear. The confounders initially chosen for the IPW model were disorder, victimization, gender, age, home ownership, years in neighborhood, and news consumption. Previous works theorizes that disorder, prior victimization, gender, and age are important predictors of fear of crime (Ferraro & LaGrange, 1987; Ferguson & Mindel, 2007; Hale, 1986; Hinkle, 2005; Hinkle & Weisburd, 2008, McGarrell et al, 1997; Skogan, 1986; Skogan & Maxfield, 1981; Taylor & Covington, 1993, among others). Home ownership and years living in neighborhood are also considered confounders since while the findings are not always consistent, some research suggests a positive association between residential stability and fear (Donelly, 1989; Gainey et al, 2011; Lee et al, 2022). I theorized that these variables may also determine ONN use since perceiving disorder or having been victimized may lead individuals to join an ONN to keep up to date with potentially dangerous situations in their neighborhood. Women consume more social media than men (Duggan, 2013). Older and established neighborhood residents may be more likely to be ONN users based on the social integration and community support it provides (De Meulanere et al 2023, Molinet, n.d.(a)); Vogel et al, 2021). The directed acyclical graph (DAG) (Figure 5) depicts the variables that theoretically act as confounders between ONN use and fear. This DAG is used with the purpose of building inverse probability weights to control for theorized confounders between fear and online neighborhood network use.

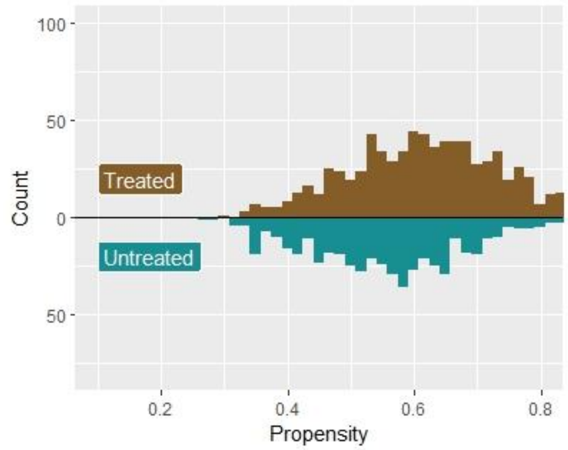
Figure 5. Directed Acyclical Graph for Theorized ONN Use and Fear Confounders



Before building the model to compare ONN users and non-users, I conducted a descriptive analysis of the entire sample as well as correlational analysis for the theorized key variables of ONN use (e.g., victimization, disorder, ownership, years in neighborhood, gender, and news consumption) to determine whether any of these key variables were highly correlated and needed to be dropped from the analysis. Next, I conducted t-tests with each variable to examine whether the mean differences in our key variables between both groups were significant.

To test the assumptions of exchangeability I plotted one histogram (Figure 6) to examine the distribution of the propensity scores before applying the weights. I also assessed the co-variate balance among the variables and standardized the absolute mean differences using both a matching model and a propensity score model. The positivity assumption is met since both groups use the internet so the probability of being exposed to the treatment does not equal zero.

Figure 6. Distribution of Propensity Scores Before Adding Weights



After determining the key variables to use for the weights, I created a dataset with inverse probability weights with ONN use as the treatment and use the weights to conduct a log-linear regression to examine the effect of online neighborhood use on reported fear of crime between users and non-users applying the weighted scores. The IPW model (Equation 1) specifies the dependent variable of fear in log form.[16]

Equation 1

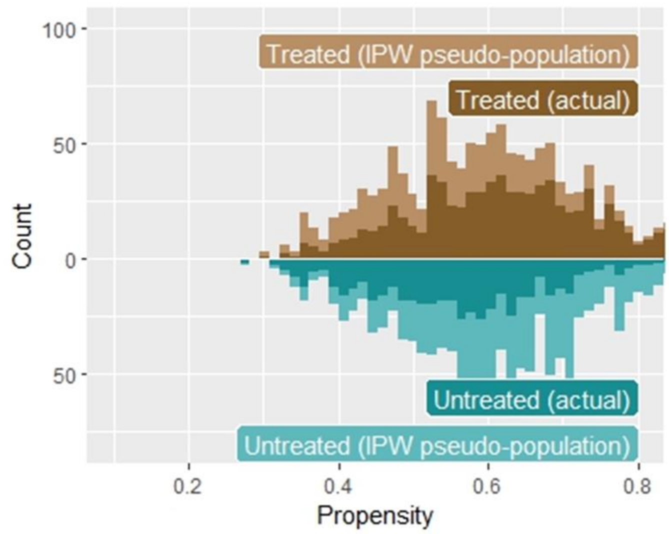
$$log(fear) = \beta_0 + \beta_{1}x_1 + \beta_k x_k + \epsilon$$

In Eq.1 β_0 represents the constant term of the regression and β_1 is the parameter to be estimated for my independent variable of onnuse. The β_k coefficients are interpreted as the proportionate change in fear resulting from the change from non-use to use.

After building the weights, I graphed a second histogram comparing the distribution of propensity scores between the treated group and the untreated group before the weights and after applying the weights to confirm that the groups would be more comparable after the weights (Figure 7).

[16] The log form of fear was specified since pre-analysis indicated that residuals were not normally distributed.

Figure 7. Propensity Score Distribution Before and After Adding Weights



3.4.i. Log-Linear Regressions for Variation in ONN Use

The second stage of the analysis examines the effect of online neighborhood use on neighborhood specific fear of crime. For the first outcome, I analyzed the independent variable of online neighborhood use as minutes spent online and visits per month to the groups with the expectation that both measures of online neighborhood use will influence fear of neighborhood-specific crime. I first tested a linear specification model for linear assumption violations. An analysis of the distribution of the residuals indicates that a linear regression will not fit the data. Therefore, the basic specification for "fear" is a log-linear specification, where the dependent variable is the natural log of its values, and my independent variables are linear. Eq.2 shows a basic specification for the fear models. In Eq.2, x_1 through x_k represent the independent variables; β_0 represents the constant term of the regression and β_1 through β_k are the parameters to be estimated for my independent variables. The β_k coefficients are interpreted as the proportionate change in fear resulting from a one-unit change in one of the independent variables.

Equation 2

$$\log(fear) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$$

I then estimated three sets of regressions with two of the operationalized measures of frequency of use, minutes per day on online neighborhood networks and visits per month to online neighborhood networks: (1) An unweighted regression model that does not control for the possible confounders between online neighborhood use and fear, (2) a weighted regression model which applies the inverse probability weights from the original sample and does not contain the individual effects of each of the variables included in the weights, (3) a weighted regression model which applies both the inverse probability weights and the individual residual effects of each of the variables used to estimate the weights.

I used an iterative approach for building the final models. First, I estimated a regression of the dependent variable on one or more key or focal independent variables. Then, to test the robustness of the effects of these initial focal variables, I introduced other ONN-related covariates, and finally, I included the control variables.

For example, I estimated the first model with two continuous measures of online use: visits and minutes. I sampled the effects of these variables in linear and quadratic forms. In a second set of fear regressions, I included three other measures of use: reading, responding, and publishing as categorical variables. Then, I included victimization, disorder, and other neighborhood participation variables. And finally, I estimate a set of regressions that adds to the control variables to the first three sets of regressions. Across specifications, I am interested in understanding the joint or shared variance among the ONN measures and other covariates, or the extent to which the effects of ONN use measures are relatively independent of the effects of other variables.

3.5 Findings

3.5.a Between Group Fear

Table 13 presents the descriptive characteristics for both ONN users and non-users. Missing data for the categorical variables, gender, and news consumption was less than 1% while missing data for years in neighborhood, age, and income accounted for about 1.7%. No other variables suffered from missing data. Over half of the sample are online neighborhood network users (59%). 57% of the sample also own their own home and have been residentially stable, with a mean of 9 years living in the neighborhood. The sample was also composed of older respondents with an average age of 40 years. People who identified as men made up 47% of the sample, while people who identified as women or other gender made up 53% of the sample. While more than half of the sample was white (58%), minorities still made up a sizeable number comprised of 15% Blacks, 17% Latinos, and 10.6% another race/ethnicity.

Unmarried individuals accounted for 54% of the sample. A large majority of the sample had not reported any kind of crime to the police in the past 6 months (90%). Of those who did report a crime, only a small group (4%) indicated that they reported a victimization that happened to them either outside or inside their neighborhood. Overall, reported fear of neighborhood crime was not exceedingly high (m = 2.12, s.d=1.03) and perceived disorder was also relatively low (m=1.90, s.d.=.74). Most respondents are also non-news consumers or light news consumers with 54% indicating they watch the news 2 days or less a week and 70% spend 2 days or less reading the news, and 67% reading news 4 days or less a week.

Next, Table 14 provides a comparison of summary statistics for ONN users. Compared to non-ONN users, ONN users include more homeowners (63%), more women (56%), and more married people (56%). The average age was the same for both groups. In terms of neighborhood characteristics, ONN users indicated a higher average level of fear of neighborhood crime (m=2.32, s.d.=1.07), perceived disorder (m=1.99 s.d.=0.76), than their counterparts.

Personal victimization both outside and inside the neighborhood was about the same for both groups and initially looked like there was no significant differences.

The differences in fear, disorder, and victimization between both groups were tested to examine whether they were significant. Figure.8, Figure 9, and Figure 10 provide the results of two-sample t-tests conducted to examine mean differences in perceived disorder and fear. ONN users reported significantly higher levels of fear ($t(1277.16) = -8.97$, $p<.0001$) and perceived disorder ($t(1225.89)= -5.32$, $p<.0001$) than non-ONN users. Furthermore, while minimal, there was a significant difference in victimization between ONN users and non-users ($t(1238.51) = -1.97$, $p<.05$). Since perceived disorder and victimization are known correlates of fear these results indicate a strong basis to include both variables as confounder of use and fear to isolate the effect of disorder on fear as previously theorized.

Next, Figure 11 graphs the results of the covariate balance assessment for unadjusted, matching, and propensity scores for all possible confounders for ONN use and fear between ONN users and non-users. Both matching and propensity scores significantly improve the balance between the treatment group (ONN users) and the comparison group (non-ONN users), with propensity scores providing the lowest standardized mean difference for all possible confounding variables between the two groups with all mean differences below the .10 threshold (Austin, 2011). This suggests that using inverse probability weights to examine the effects of ONN use on fear is the best method to control for use and fear confounders. The variance ratio of all variables except the media consumption variables in the propensity score models were also close to 1 which indicates that the variance of the samples after balancing are similar.

Table 13. Sample Summary Statistics

Continuous Variable	M SD Min Max
age	40 13 18 80
yrs_nhood	9 9 0 60
fear	2.12 1.03 1.00 5.00
disoder	1.90 0.74 1.00 4.00
Categorical Variable	**N | %**
home:own	1,324 | 57%
home:rent	1,324 | 43%
onnuse=yes	755 | 59%
race:white	761 | 58%
race:black	193 | 15%
race:latino	221 | 17%
race:asian	122 | 9.2%
race: other	18 |1.4%
gender: male	618 | 47%
gender:female|other	698 | 53%
education: hs	140 | 11%
education: some college	406 | 31%
education: ba	549| 41%
education: grad	229 | 17%
income:<50K	427 | 32%
income: 50-80K	349 | 26%
income: 80K-110K	204 |15%
income: 110K>	322 | 24%
married	615|46%
not married	709 |54%
vic:noreport	1,197 | 90%
vic:outsidenhood	19 | 1.4%
vic:nhoodsomeonelse	33 | 2.5%
vic:nhoodfriend	17 | 1.3%
vic:nhoodfamily	6 | 0.5%
vic:outsidepersonal	6 | 0.5%
vic:nhoodpersonal	46 | 3.5%
watchnews: none	320 | 24%
watchnews: 1-2	403|30%
watchnews: 3-4	217|16%

Table 13. Sample Summary Statistics (continued)

watchnews: daily	262|20%
listennews: none	558 | 42%
listennews1: 1-2	370 | 28%
listennews2: 3-4	183 |14%
listennews3: 5-6	87 | 6.6%
listennews4: daily	125 | .4%
readnews: none	121| 9.1%
readnews:1-2	363 | 27%
readnews:3-4	272 | 21%
readnews:5-6	163 |12%
readnews:daily	404 | 31%
1n | N % ; Mean SD Minimum Maximum	

Table 14. ONN Users' Summary Statistics

Continuous Variable	**M SD Min Max**
age	40 13 18 77
yrs_nhood	11 15 0 99
fear	2.32 1.07 1.00 5.00
disorder	1.99 0.76 1.00 4.00
discord	2.90 0.90 1.00 5.00
Categorical Variable	**N | %**
home:own	491 |63%
home:rent	294 | 37%
race:white	433 | 55%
race:black	125 | 16%
race:latino	133 | 17%
race:asian	76 | 9.7%
race: other	13 | 1.7%
gender: male	338 | 43%
gender:female|other	443 | 56%
education: hs	63 | 8.0%
education: some college	217 | 28%

Table 14. ONN Users' Summary Statistics (continued)

education: ba	360 | 46%
education: grad	145 | 18%
income:<50K	198 | 25%
income: 50-80K	211 | 27%
income: 80K-110K	128 | 16%
income: 110K>	238 | 30%
married	406 | 52%
not married	379 | 48%
vic:noreport	694 | 88%
vic:outsidenhood	14 | 1.8%
vic:nhoodsomeonelse	24 | 3.1%
vic:nhoodfriend	16 | 2.0%
vic:nhoodfamily	4 | 0.5%
vic:outsidepersonal	5 | 0.6%
vic:nhoodpersonal	28 | 3.6%
watchnews: none	170 | 22%
watchnews: 1-2	239 | 30%
watchnews: 3-4	148 | 19%
watchnews: 5-6	69 | 8.8%
watchnews: daily	158 | 20%
listennews: none	294 | 37%
listennews1: 1-2	234 | 30%
listennews2: 3-4	133 | 17%
listennews3: 5-6	48 | 6.1%
listennews4: daily	75 | 9.6%
readnews: none	61 | 7.8%
readnews:1-2	211 | 27%
readnews:3-4	171 | 22%
readnews:5-6	105 | 13%
readnews:daily	236 | 30%

Figure 8. Mean Differences in Fear

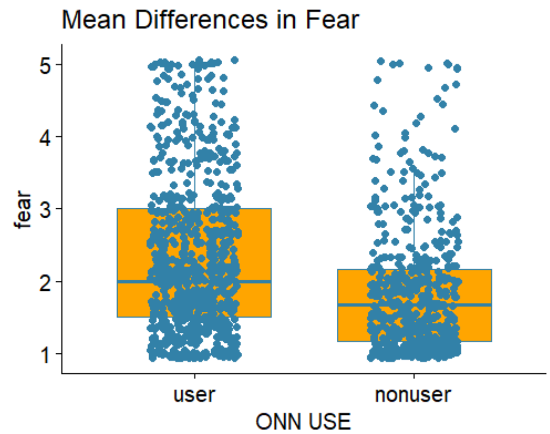


Figure 9. Mean Differences in Disorder

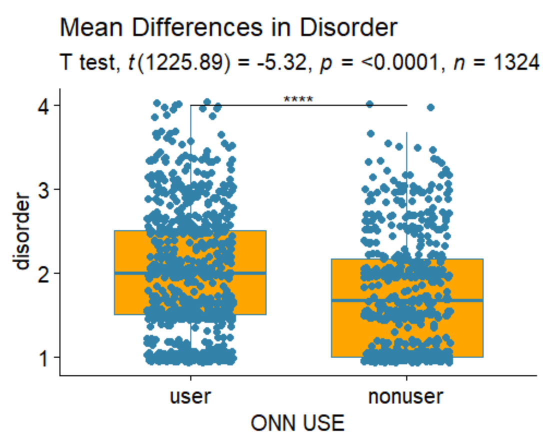


Figure 10. Mean Differences in Victimization

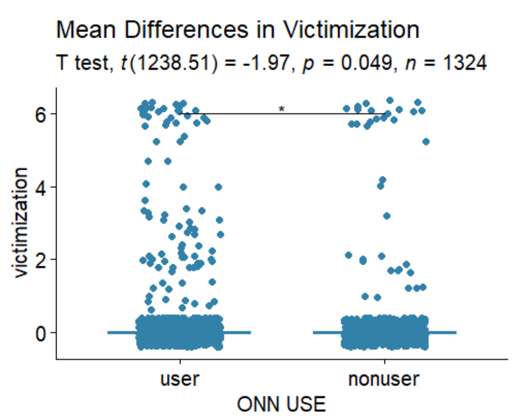
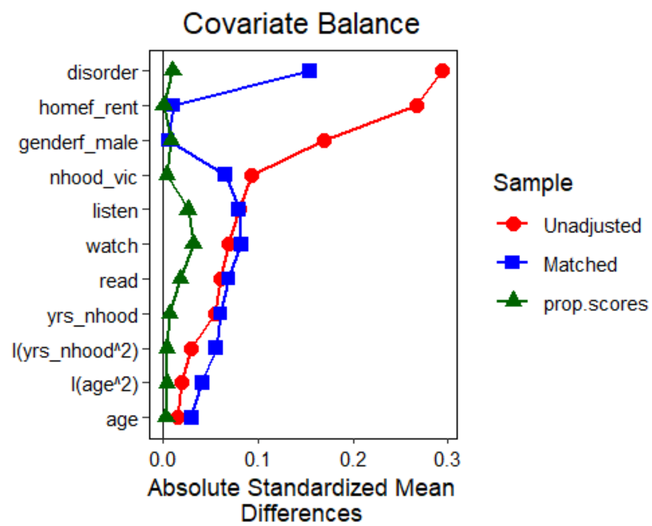


Figure 11. Covariate Assessment with Unadjusted, Matched, and Propensity Scores Balancing



The news consumption variables also presented the highest standard mean differences even after balancing. The model used to generate propensity scores also suggests that news consumption is not a significant predictor of ONN use. The combined results of the covariate balance assessment and the spurious relationship between ONN use and news consumption indicate that these should be dropped from the IPW model. All other possible confounding variables remain in the propensity score models as these resulted in being significant predictors of ONN use either individually or jointly[17].

Table 15 provides the model comparison between the naïve model and the IPW model. Without adjusting for confounders, the naïve model indicates that those in the "treated" group

[17] While age and years living in neighborhood both in linear and quadratic form were not individually significant in ONN use, joint significance testing indicated that they were jointly significant, so they were retained in the model, while any of the combined media consumption variables were not jointly significant, so they were dropped from the model. The decision to drop these variables is also in accordance with previous literature that has produced mixed findings on the effects of media consumption on fear. To be included in the weights, media consumption should be a confounder for fear and use, yet there is no evidence that media consumption is significantly related to onn use and there is only weak evidence that it is significantly related to fear of crime.
Alternate IPW models were run to determine if including the media consumption variables and/or the categorical variables of race/ethnicity, income, and education would significantly change the results of the IPW model. The results were the same, around 21% higher fear among ONN users.

(ONN users) have a 27% increase in fear that can be explained by ONN use. However, the naïve model does not adjust for the introduced selection bias on observed confounders.

By contrast, the IPW model which adjusts for self-selection into the groups of users and non-users, indicates that the “treated” group of ONN users have a 22% increase in fear neighborhood-specific victimization that can be explained by ONN use after adjusting for the observed confounders among the groups (home ownership, years in neighborhood, perceived disorder, victimization, age, and gender). Moreover, this means that regardless of the time spent or visits made to ONNs, choosing to participate in ONNs will lead individuals to report higher fear than those who do not choose to belong to ONNs.

Table 15. Naïve vs IPW Model for ONN Use and Fear

	Naïve Model	**IPW Model**
Intercept	.49890***	0.52207***
t-stat	25.69221	29.9109
p.val	<.0001	<.0001
std.err	.01942	0.01745
onnuse	.23858***	0.19869***
t-stat	9.46923	8.0489
p.val	<.0001	<.0001
std.err	.02520	0.02469
Num.Obs.	1271	1271
R2	-2.003	0.049
R2 Adj.		0.048
AIC	3158.8	3166.9
BIC	3174.3	3182.3
Log.Lik.	-762.188	-790.628
F	89.666	64.785
RMSE	0.49	0.44

3.5.b Understanding Use among ONNs

Compared to other social media, most ONN users do not spend a lot of time visiting or engaging with ONN groups (Table 16). Over half the sample visits only about 5 times per week (m= 4.9, s.d.=7.3) and they spend an average of 30 minutes a week (m=30, s.d.=52). Most could be considered passive or "lurkers", meaning that they read posts but either don't respond or publish or do so on a limited basis. In fact, 54% of respondents read 1-6 posts a week. Yet, 88% reported responding to 3 or less posts a week, and 89% reported publishing 3 posts or less a month. Most users belonged to only one ONN (65%). The three ONNs most users belonged to were Nextdoor (64%), Facebook private neighborhood group (34%), and Neighbors (23%). Lastly, there were no significant differences in use among race or gender with Blacks spending slightly more time than other races (Figure 12 & Figure 13).

Figure 12. ONN Users Distribution of Visits by Race

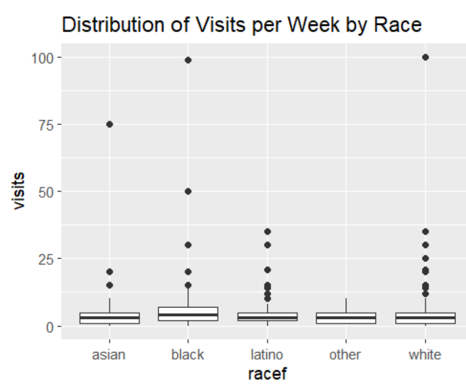
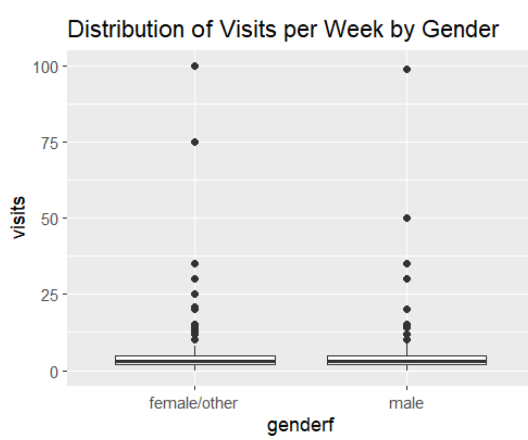
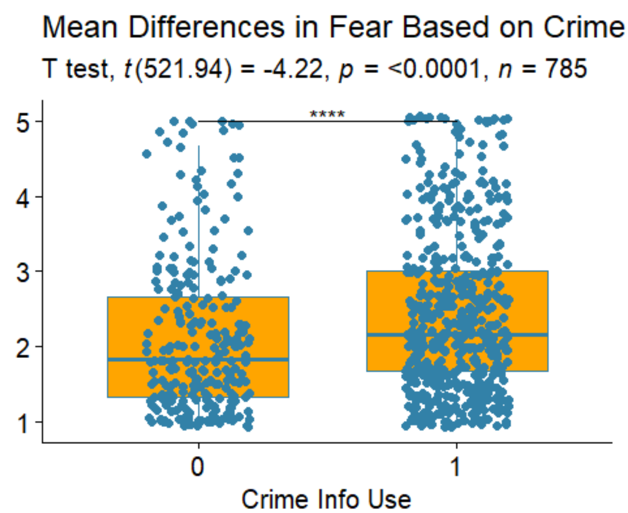


Figure 13. ONN Users Distribution of Visits by Gender



Types of activity varied among users with most reporting using the ONNs for neighborhood news (86%) and 67% of those sampled reported using the platforms for crime information. Results of a two-sample t-test indicated that those using the ONNs specifically for crime information reported significantly higher levels of fear ($t(521.94) = -4.22$, $p<.0001$) than those who do not use the platforms for crime information (Figure 14)[18].

Figure 14. Mean Difference in Fear Based on ONN Use for Crime Information



3.5.c Fear Among ONN Users

Table 17 presents two unweighted regression models. The first two models include the uncontrolled effects for the first ONN use variables of visits per month and the second model includes the effects of minutes per week on site. It suggests that while independently, visits per month to the site is not significantly related to fear of neighborhood crime, minutes spent on site is significant.

[18] A Bartlett's Test of Sphericity was also conducted to assess variance among the groups. P.value >.05 so the null hypothesis that the variance is the same for both groups cannot be rejected.

Table 16. ONN Use Summary Statistics

Continuous Variable	**M SD Min Max**
visits	4.9 7.3 0.0 100.0
minutes	30 52 0 1,000
Categorical Variable	**N | %**
neighbors	181 | 23%
fb_onn	270 | 34%
whatsapp_onn	77 | 9.8%
frontporch	13 | 1.7%
other_onn	19 | 2.4%
onn_groupstotal	
1	514 | 65%
2	204 | 26%
3	55 | 7.0%
4	9 | 1.1%
5	2 | 0.3%
6	1 | 0.1%
readp	
0	15 | 1.9%
1	205 | 26%
2	201 | 26%
3	129 | 16%
4	235 | 30%
respondp	
0	409 | 52%
1	285 | 36%
2	59 | 7.5%
3	10 | 1.3%
4	22 | 2.8%
publishp	
0	462 | 59%
1	235 | 30%
2	53 | 6.8%
3	19 | 2.4%
4	16 | 2.0%

Model 2 indicates that for every one-minute spent on ONNs, there is a .13% linear increase in fear of neighborhood victimization. Furthermore, a test of joint significance indicates that visits and minutes per week are jointly significant, and this effect holds across all other models. Model 2 also suggests that there is a very small non-linear relationship between use and fear and minutes spent with ONNs nullify the effect of visits. However, this non-linear relationship becomes non-significant after I introduce other neighborhood variables.

The third model provides the unweighted results for fear regressed on visits and minutes per week on site and introduces types of use variables (Model 3). While neither number of posts read or responded to have any significant association to fear, publishing posts was positively associated with fear. For each category of publishing posts reported fear increased by 6%. However, the largest effect stems from using the platforms for crime information. The use of ONNs specifically for crime information is associated with nearly a 18% increase in reported fear of neighborhood victimization ($t=4.776$, $p<.001$).

Table 18 examines two models. Model 1 includes the neighborhood variables of personal victimization, disorder, social ties, years in neighborhood, homeownership, and level of ONN discord. While social ties and ONN discord did not hold a significant association to fear, personal victimization, years in neighborhood, home ownership, and disorder all were significant predictors of fear. However, while the first 3 variables only produced a small effect, disorder had a large, sizeable effect on reported fear. For every 1-unit increase in perceived disorder, reported fear significantly increased by 19% ($t=8.511$, $p<.0001$). Despite these effects, controlling for neighborhood variables did not reduce the effects of minutes spent, and only reduced the effects of publishing by less than 1% and the effects of using the ONN for crime information by 2% ($t=4.401$, $p<.0001$).

Table 17. Unweighted Regression for Visits and Minutes Per Week

	Model 1	Model 2
Intercept	0.707***	0.631***
	34.653	25.384
	<.001	<.001
	'(0.020)'	'(0.025)'
visits	0.006**	0.008+
	2.593	1.699
	0.01	0.09
	'(0.003)'	'(0.005)'
I(visits^2)		-0.0001*
		-2.02
		0.044
		'(0.00007)'
minutes		0.003***
		4.663
		<.001
		'(0.0006)'
I(minutes^2)		-0.000002**
		-2.716
		0.007
		'(0.0000008)'
Num.Obs.	753	753
R2	0.009	0.058
R2 Adj.	0.008	0.053
AIC	2052.6	2020.2
BIC	2066.5	2047.9
Log.Lik.	-467.442	-448.21
F	6.724	11.563
RMSE	0.45	0.44

Next, Model 2 includes a full model which accounts for significant demographic characteristics[19]. Publishing, using ONN for crime information, and perceived disorder continue to hold the strongest association to increased fear. However, race also becomes a significant predictor of fear with being Black, Latino, or Asian positively associated with higher reported fear than White.

Finally, Table 19 provides a side-to-side comparison of a full unweighted model and two models that include inverse probability weights. The weighted regression results are analogous to the unweighted model with the minutes spent on ONNs, publishing posts, and using ONNs for crime information continue to hold their effects on reported fear. Even after adding weights and individually controlling for the weight variables, using ONNs for crime information neighborhood significantly increases reported fear of neighborhood crime by 15% ($t=4.298$, $p<.001$). Meanwhile, the effects of victimization and disorder, and the demographic variables of race hold their significance.

3.6 Discussion

This paper examines the role of online neighborhood network use in reported fear of neighborhood-specific victimization. The current study contributes to media and crime literature in three ways. First, it seeks to understand the influence of ONN use on fear of neighborhood crime. Likewise, the current study devises a 3-dimension measure of prevalence, frequency, and magnitude specific to ONN use inspired by various quantitative and qualitative measures found in social media and ONN research (Brunborg et al, 2019; De Meulanere et al, 2021; Ellison et al, 2007; Heffer et al, 2018; LaRose et al, 2004; Steinfield et al, 2008). Finally, the current study applies a causal methodology approach by treating ONN use as a program in which individuals

[19] A third model with news consumption variables was estimated but was excluded from presentation as it did not yield any significant findings. Table 6, Model 2 provides estimates only for race, the only demographic variables that was significant.

select into. Using inverse probability weights as a tool to correct estimates is gaining popularity in both criminal justice and social media research (Copeland et al, 2023; Link, 2019; Lohmann & Zagheni, 2023; Osselin et al, 2023; Tiwasing, 2021; Yu et al, 2022). However, to my current knowledge, this study is the first to attempt to correct for the non-random selection characteristics to isolate the effect of using a particular type of social media to explain fear of neighborhood crime.

Like previous traditional and social media studies the mechanisms by which ONN use influences fear is complicated. The findings here highlight two important key issues. First, as evidenced by the between group analysis, using ONN does seem to have some influence on fear. But based on the subsequent analysis is not so much as matter of time spent but rather how that time is spent that drives fear.

While visits and minutes to site had little to no effect on fear, using ONN for crime information and publishing posts did. This is analogous to findings in neighborhood watch participation studies. To many users, online neighborhood networks represent a digital, large-scale neighborhood watch and those who participate in neighborhood watches have been found to hold more fearful attitudes toward violent victimization (Zhao et al, 2002).

The second important issue is that like previous work on the correlates of fear, perceived neighborhood disorder is still the largest predictor of fear of crime with prior victimization also having some significant influence (Hinkle, 2005; Hinkle & Weisburd, 2008; LaGrange et al, 1992; Skogan & Maxfield, 1981, Skogan, 1986; Taylor & Covington, 1993; Wilson & Kelling, 1982). This points to an exacerbated and reciprocal relationship. Users who perceive their neighborhood as disordered are fearful may lead them to use ONNs to stay informed and to communicate with other about their perceived level of disorder and crime, which leads them to publish content specifically about what they either witness or heard about, which in turn heightens concerns about neighborhood victimization. This pattern is analogous to what other suggested occur through disorder, indirect victimization, and the rumor network (Skogan, 1990; Skogan & Maxfield, 1986). Unlike other work however the findings here did not indicate that social integration, measured here as personally knowing people in the ONNs, is significantly associated with fear (Gates & Rohe,1987; Gibson et al, 2002; Skogan & Maxfield, 1981; Wilcox Rountree & Land, 1996; Yuan & McNeeley, 2017; Zahnow & Tsai, 2021). This may be since in the online environment the content and delivery of information is more important than who delivers the content.

This also leads to questions of the mechanisms of online collective efficacy and whether developing a sense of collective efficacy online would mediate the relationship between use and fear. The findings here suggest that like previous studies, an integrated model of use and fear is needed to thoroughly explain the dynamics of online interactions and individual perceptions of neighborhood crime (Ferguson & Mindel; 2007, Franklin et al, 2008; Gainey et al, 201, & McGarrell et al, 1997 among others).

3.6.a Limitations

The study contains several limitations. The cross-sectional nature of the study makes it impossible to disentangle the directionality between ONN use and disorder among ONN users. The study is also not generalizable to a larger population since the sample is drawn from a population of internet users. Prolific users may be more likely to use the internet and more likely to use ONNs. Furthermore, certain populations groups are less likely to participate in online surveys like the one administered in this study (Rittase et al., 2020). To control for underrepresentation I oversampled Black, Latinos, and Asians and offered a slightly higher incentive than for the general population of respondents (McGrath, 2006; Singer & Ye, 2013).

The study also did not control for frequency of viewing violent media which has previously been associated with fear in women. However, that relationship has been consistently found to be non-significant after controlling for other variables (Chadee et al, 2019; Doob & McDonald, 2017).

Lastly, the study does not control specific types of ONNs. There may be differences in fear perceptions between those who belong to one ONN over another. Recently, Nextdoor has made an effort to minimize negative content including crime posts and focus more on social cohesion, while applications like Ring and Citizen promote the personal safety aspect of their tool. Yet, 67% of the current sample cited using ONNs for crime-safety information which may be driving use away from some platforms to another. Six percent of participants in the study cited Citizen as an ONN. This study does not consider Citizen an online neighborhood network, and the features in Citizen are qualitatively different from other ONNs like Nextdoor and Facebook neighborhood groups. However, respondents' citing Citizen as an ONN, does provide insight into what users consider what an ONN is and the use of any application that refers to the individual's surroundings.

3.7 Directions for Future Research

This research lays the groundwork for the further exploration of the mechanisms and outcomes related to use of online neighborhood networks and their contributing role in individual and neighborhood differences in collective efficacy, fear, and response to neighborhood crime. This work also highlights several unanswered questions such as: (1) What is the role of online collective efficacy in fear of neighborhood victimization? (2) How does online neighborhood network communication contribute to fear of victimization among persons and communities of color? and (3) What is the role of online neighborhood networks in neighborhood social control actions, police response, and violence? Furthermore, while social ties were not a significant predictor of fear in this study, it is possible that the social network dynamics in an online neighborhood network could influence fear and collective efficacy among users. My future agenda consists of finding answers to these questions through an encompassing line of inquiry consisting of qualitative, quantitative, and mixed method studies.

First, using previously collected data through a cross-sectional questionnaire with collective efficacy questions for non-ONN users and online efficacy questions for ONN users, I will examine whether there are significant differences in individual collective efficacy between ONN users and non-ONN users. Next, following the same methods and fear data in the current study I will examine whether online collective efficacy acts as a mediator between use, disorder, and fear of neighborhood victimization.

Conducting non-probability sampling in neighborhoods to get a non-biased prevalence estimate of the use of these platforms is also necessary to better understand the relationship between ONN use and neighborhood-level outcomes. Thus, I will develop a neighborhood-level study that consists of applying the ONN efficacy scale to assess whether online collective efficacy influences fear of victimization at the neighborhood-level. This quantitative study will include primary data collection via a randomized sampling of ONN neighborhood groups from the two largest ONNs available, Nextdoor and Neighbors, in multiple cities. ONN groups can serve as a proxy for neighborhoods as well as capture the cognitive-based perceptions of neighborhoods. This proposed work will include neighborhood-level characteristics such as crime rate, household income, digital access in homes, and poverty level data collected from the

American Community Survey. Ideally, this initial study will be part of a longitudinal analysis to better disentangle the relationship between the key variables.

The current study also indicated significantly higher levels of fear of neighborhood victimization for every race and ethnicity other than Whites. What is unclear is whether online neighborhood networks contribute to this fear by posts that may frame individuals of a specific race or ethnicity as perpetrators and are viewed as perceived threats to the neighborhood, or whether the neighborhoods these individuals live in are more disordered, leading to more negative or more crime-related posts which could in turn enhance fear. For this topic, I will develop a mixed-method study that includes a systematic content analysis of crime-related posts and interviews with ONN users belonging to these groups and who identify as a racial and/or ethnic minority to assess if and which posts are associated with individual fear via a multi-stage sampling of online neighborhood groups and users.

This research aimed to better capture the influence that online neighborhood networks have on fear of neighborhood victimization, yet an examination of the ONN features that facilitate and produce incident reporting and social control actions was outside the scope of this work. Therefore, a comprehensive examination of the causal effects of online neighborhood network features such as the use and sharing of surveillance video and the availability of law enforcement bulletins and alerts in individual and neighborhood response to crime would help to better explain what contextual elements lead individuals to report incidents or take actions. To examine the effects of ONN surveillance and communications in decision-making, I will conduct a randomized survey experiment via an online-survey platform consisting on vignettes to analyze response to a variety of scenarios and individuals including posts containing surveillance videos and posts relying on eyewitness testimonyand posts relying on 3rd party accounts to address how the use of sharing of personal surveillance technology within online neighborhood networks contributes to decision-making, incident-report and other social control actions.

While ONNs have historically touted their work with law enforcement, the relationship has not been a positive one (Mols & Pridmore, 2019). To explore the topic of online neighborhood network practices and policing, I will be designing a mixed-method study consisting of focus groups with law enforcement officers tasked with interacting or monitoring ONN groups to gauge the advantages and challenges to police response to neighborhood incidents. The findings from this first stage of the study can be used as the basis to conduct a content analysis of crime-related posts in ONNs that lead to police response. This work will contribute to understanding the way in which these platforms can be more successfully used by community leaders and law enforcement to intervene, communicate, and collaborate with citizens *online,* to empower *offline* actions and reduce fear, an effort that has been traditionally attempted with community policing but has demonstrated mixed results (Crowl, 2017; Weisburd et al, 2021).

Lastly, to address whether certain individuals within ONNs are influential in shaping perceptions of fear and collective efficacy, I will conduct a social network analysis of various ONN groups via respondent driven sampling to identify key players whose activities within the ONNs. This study can serve as a follow-up study from the neighborhood-level study via an initial subsample of the participants and then operationalized through respondent-driven sampling. Neighborhoods are not limited by strict spatial barriers anymore. The popularity of online neighborhood networks calls for the need to integrate them as part of the explanatory criminological models examining neighborhood crime and safety.

Table 18. Unweighted Regressions with Type of Use and Neighborhood Variables

	Model 1	Model 2
Intercept	0.561***	.145*
	13.676	2.085
	<.001	0.047
	'(0.041)'	(0.069)'
visits	0.006	0.007
	1.172	1.1415
	0.242	0.157
	'(0.005)'	'(0.005)'
I(visits^2)	-0.00009	-0.00001
	-1.356	-1.611
	0.175	0.108
	'(0.00006)'	'(0.00006)'
minutes	0.002***	0.002**
	3.582	2.828
	<.001	0.005
	'(0.0006)'	'(0.0006)'
I(minutes^2)	-0.000001+	-0.000001
	-1.861	-1.459
	0.063	0.145
	'(0.0000008)'	(0.0000007)'
readp	-0.021	-0.026
	-1.418	-1.853
	0.157	0.064
	'(0.015)'	'(0.014)'
respondp	0.002	0.002
	0.069	0.065
	0.945	0.948
	'(0.025)'	'(0.024)'
publishp	0.057*	0.050*
	2.391	2.223
	0.017	0.026
	'(0.024)'	(0.026)'
crimeinfo	0.163***	0.140***
	4.776	4.401
	<.001	<.0001
	'(0.034)'	'(0.032)'
known		-0.024
		-1.892

Table 18. Unweighted Regressions with Type of Use and Neighborhood Variables (continued)

discord		0.019
		1.132
		0.258
		'(0.017)'
nhood_vic		0.031**
		2.665
		0.008
		'(0.012)'
disorder		0.175***
		8.511
		<.0001
		'(0.020)'
yrs_nhood		0.005*
		2.795
		0.005
		'(0.002)'
homefrent		.087**
		2.602
		0.009
		(0.033)'
Num.Obs.	756	756
R2	0.093	0.22
R2 Adj.	0.083	0.207
AIC	2006.7	1902.1
BIC	2053	1971.5
Log.Lik.	-435.861	-378.551
F	9.528	16.121
RMSE	0.43	0.4

Table 19. Side to Side Comparison: Unweighted vs Weighted Results

	Model 1	**Model 2**	**Model 3**
Intercept	-0.045	0.376***	-0.026
	-0.436	4.589	-0.252
	0.663	<0.001	0.801
	'(0.104)'	'(0.082)'	'(0.104)'
visits	0.005	0.005	0.005
	0.927	0.97	0.931
	0.354	0.333	0.352
	'(0.005)'	'(0.005)'	'(0.005)'
I(visits^2)	-0.00007	-0.00008	-0.00007
	-1.092	-1.105	-1.061
	0.275	0.27	0.289
	'(0.00007)'	'(0.00007)'	'(0.00007)'
Mins p.week	0.001*	0.002**	0.001*
	2.281	2.871	2.049
	0.023	0.004	0.041
	'(0.0006)'	'(0.0007)'	'(0.0006)'
Mins,nonlinear	-0.0000007	-0.000001	-0.0000006
	-0.915	-1.318	-0.793
	0.361	0.188	0.428
	'(0.0000008)'	'(0.0000008)'	'(0.0000008)'
readp	-0.022	-0.023	-0.021
	-1.498	-1.475	-1.432
	0.135	0.141	0.153
	'(0.015)'	'(0.015)'	'(0.015)'
respondp	-0.006	0.005	-0.012
	-0.232	0.186	-0.48
	0.816	0.853	0.631
	'(0.024)'	'(0.026)'	'(0.025)'
publishp	0.049*	0.077**	0.066**
	2.163	3.157	2.813
	0.031	0.002	0.005
	'(0.023)'	'(0.024)'	'(0.023)'
crimeinfo	0.139***	0.148***	0.138***
	4.334	4.404	4.298
	<0.001	<0.001	<0.001
	'(0.032)'	'(0.034)'	'(0.032)'
ONN people known	-0.017	-0.023+	-0.022
	-1.281	-1.65	-1.614
	0.201	0.099	0.107

Table 19. Side to Side Comparison: Unweighted vs Weighted Results (continued)

	'(0.013)'	'(0.014)'	'(0.013)'
ONN discord scale	0.034+	0.058**	0.027
	1.96	3.263	1.537
	0.05	0.001	0.125
	'(0.017)'	'(0.018)'	'(0.017)'
nhood_vic	0.033**		0.031*
	2.823		2.511
	0.005		0.012
	'(0.012)'		'(0.012)'
disorder	0.165***		0.170***
	7.968		7.924
	<0.001		<0.001
	'(0.021)'		'(0.021)'
yrs_nhood	0.003		0.003
	1.643		1.482
	0.101		0.139
	'(0.002)'		'(0.002)'
age	0.002		0.002
	1.61		1.56
	0.108		0.119
	'(0.001)'		'(0.001)'
watch	0.006	0.01	0.006
	0.467	0.746	0.48
	0.64	0.456	0.631
	'(0.012)'	'(0.013)'	'(0.012)'
listen	0.005	0.005	0.004
	0.413	0.37	0.299
	0.68	0.712	0.765
	'(0.013)'	'(0.014)'	'(0.014)'
read	0.004	0.009	0.005
	0.345	0.695	0.434
	0.73	0.487	0.664
	'(0.012)'	'(0.013)'	'(0.012)'
incomef50-80K	-0.003	-0.084+	-0.01
	-0.065	-1.932	-0.233
	0.948	0.054	0.816
	'(0.043)'	'(0.043)'	'(0.043)'
incomef80K-110K	0.004	-0.05	0.005
	0.077	-0.956	0.103

Table 19. Side to Side Comparison: Unweighted vs Weighted Results (continued)

	0.939	0.339	0.918
	'(0.051)'	'(0.053)'	'(0.051)'
incomefmissing	0.125	0.011	0.105
	0.838	0.069	0.68
	0.402	0.945	0.497
	'(0.149)'	'(0.161)'	'(0.154)'
incomefOver 110K	-0.026	-0.131**	-0.03
	-0.54	-2.709	-0.619
	'(0.048)'	'(0.049)'	'(0.049)'
homefrent	0.074*		0.074*
	2.025		2.054
	0.043		0.04
	'(0.036)'		'(0.036)'
race:black	0.157***	0.184***	0.160***
	3.511	3.943	3.6
	<0.001	<0.001	<0.001
	'(0.045)'	'(0.047)'	'(0.045)'
racef:hispanic	0.083*	0.100*	0.091*
	1.975	2.306	2.169
	0.049	0.021	0.03
	'(0.042)'	'(0.043)'	'(0.042)'
race:asian	0.224***	0.258***	0.232***
	4.196	4.553	4.261
	<0.001	<0.001	<0.001
	'(0.053)'	'(0.057)'	'(0.054)'
race:other	0.12	0.037	0.109
	0.963	0.269	0.834
	0.336	0.788	0.404
	'(0.124)'	'(0.136)'	'(0.130)'
genderffemale/other	0.021		0.024
	0.682		0.79
	0.495		0.43
	'(0.031)'		'(0.031)'
educationfgrad	-0.024	-0.001	-0.017
	-0.586	-0.023	-0.408
	0.558	0.982	0.683
	'(0.042)'	'(0.044)'	'(0.042)'

Table 19. Side to Side Comparison: Unweighted vs Weighted Results (continued)

educationfhs	0.086	0.096	0.091
	1.443	1.547	1.542
	0.149	0.122	0.124
	'(0.060)'	'(0.062)'	'(0.059)'
educationfsome college	0.002	-0.008	-0.006
	0.064	-0.211	-0.15
	0.949	0.833	0.881
	'(0.037)'	'(0.039)'	'(0.037)'
maritalfnot married	0.000003	-0.005	-0.004
	0.0001	-0.13	-0.124
	1	0.896	0.901
	'(0.034)'	'(0.035)'	'(0.034)'
Num.Obs.	751	751	751
R2	0.263	0.164	0.257
R2 Adj.	0.231	0.135	0.225
AIC	1886.9	1965.1	1888.4
BIC	2039.4	2089.9	2040.9
Log.Lik.	-356.115	-414.08	-369.741
F	8.263	5.692	8.03
RMSE	0.39	0.41	0.39

Appendix A. List of Facebook Groups Initially Contacted for Recruitment

Facebook Groups	Request Result	Date Posted
Friendly Marietta City Neighborhood Group	Posted*	10/24/2022
What’s Happening in Mableton and Austell Ga.	Posted*	10/17/2022
What's Happening in Cobb County	Posted*	10/17/2022
Cobb County Homeschooling Families	Posted*	10/24/2022
Cobb Marietta Bulletin Board	Posted*	10/17/2022
Black & Brown Parents of Cobb County	Posted*	10/24/2022
West Cobb Life	Posted *	10/24/2022
What's Happening in Kennesaw, GA	Posted *	10/24/2022
Smyrna/Vinings Neighborhood Group	Never Replied	
MOMS Club of Acworth, GA	Never Replied	
Friends for the East Cobb Park	Never Replied	
Backyard Chickens Alliance of Cobb County	Never Replied	
Smyrna, Mableton, Marietta and vinings Hispanic Parents	Never Replied	
Mableton Residents and Business News	Never Replied	
Cobb County Fire and Emergency Services retirees group	Never Replied	
Senior Citizens Council of Cobb County	Never Replied	
Friends of Mableton	Never Replied	
Mableton Business Group	Never Replied	
Mableton Moms	Never Replied	
Mableton News and Discussion	Never Replied	
East Cobb Homeschoolers	Never Replied	
East Cobb Women in Business	Never Replied	
Concerned Citizens of East Cobb	Never Replied	
East Cobb Moms	Never Replied	
East Cobb Mom Exchange	Never Replied	
Cobb Parents for Safe Schools	Never Replied	
Cobb County Georgia Branch NAACP	Never Replied	
East Cobb Working Moms	Request Denied	
Wheeler 2027 Parents	Request Denied	

Appendix B. Original Variables

My online neighbors provide information I can trust
My online neighbors care about our community
My online neighbors share resources that keep me safe
My online neighbors come together to help in tragedies
My online neighborhood group(s) is my primary source of information for my neighborhood
My online neighbors provide information that helps protect me
I do not trust my online neighbors
My online neighbors care about our property values
My online neighbors share information that keeps me safe
Crimes have been stopped thanks to my online neighborhood group
My online neighbors share helpful recommendations
I know what is going on in my community thanks to my online neighbors
There is too much negativity in my online neighborhood group(s)
My online neighborhood group is like a community within a community
I don't have a reason to distrust my online neighbors
My online neighbors respect each other
My online neighbors help others in need
My community is safer thanks to my online neighborhood group
All my online neighbors do is complain online
My online neighbors lookout for suspicious activity
My online neighbors fight too much online
My online neighborhood group(s) is like a large neighborhood watch
Everyone can safely share their views in my online neighborhood group
My online neighbors watch out for each other
My online neighborhood group is the first line of defense for anything happening around me
My online neighbors come together to protect each other
My online neighbors do not get along
My online neighborhood group is the most efficient way to alert neighbors about- Suspicious Activity
My online neighborhood group is the most efficient way to alert neighbors about Lost Pets
My online neighborhood group is the most efficient way to alert neighbors about Break-Ins
My online neighborhood group is the most efficient way to alert neighbors about - Unsafe Drivers
My online neighborhood group is the most efficient way to alert neighbors about Trespassers
My online neighborhood group is the most efficient way to alert neighbors about Missing Children
My online neighborhood group is the most efficient way to alert neighbors aboutCar Accidents

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VITA

Marie T (MariTere) Molinet is a recipient of the 2CI Fellowship in Evidence-Based Policy. MariTere also holds a B.A. in Broadcast Journalism, an M.A. in Psychology, and a M.A. in Latin American Studies. This background grounds her as an interdisciplinary scholar who successfully merges theories and research from various fields. Her interests focus on crime and victimization from a social psychology perspective. Her mixed-methods dissertation explores the online social processes and mechanisms that can generate and sustain online neighborhood network (ONN) efficacy as well as fear of neighborhood crime. Through her research, she collected both qualitative and quantitative data to explore (1) how individuals conceptualize online collective efficacy, (2) developing and validating an online neighborhood network efficacy scale, and (3) to examine the relationship between ONN use, fear, and collective efficacy.

She previously collaborated in the program evaluation for the My Journey Matters program in Atlanta, GA and is co-authoring several papers with Dr. William J. Sabol on the topics of foster care and police response to harm. MariTere is also working with Dr. Timothy Brezina on papers relating to female offenders' self-efficacy and motivations for committing economic crimes. Before pursuing an academic career, MariTere was an international media executive for over 15 years. MariTere is also an active volunteer with several groups and organizations such as the Juvenile Diabetes Research Foundation, Criminal Justice Association of Georgia, the Emory Peach Bowl Mock Trial Invitationals, and has served as a peer reviewer with the journal *Criminology*.