Examining Collaborative Support for Privacy and Security in the Broader Context of Tech Caregiving

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Managing digital privacy and security is often a collaborative process, where groups of individuals work together to share information and give one another advice. Yet, this collaborative process is not always reciprocal or equally shared. In many cases, individuals with more expertise help others without receiving help in return. Therefore, we studied the phenomenon of "Tech Caregiving" by surveying 20 groups (112 individuals) comprised of friends, family members, and/or co-workers who identified at least one member of their group as a someone who provides informal technical support to the people they know. We found that tech caregivers reported significantly higher levels of power use and self-efficacy for digital privacy and security, compared to tech caregivees. However, caregivers and caregivees did not differ based on their self-reported *community collective-efficacy* for collaboratively managing privacy and security together as a group. This finding demonstrates the importance of tech caregiving and community belonging in building community collective efficacy for digital privacy and security. We also found that caregivers and caregivees most often communicated via text message or phone when coordinating support, which was most frequently needed when troubleshooting or setting up new devices. Meanwhile, discussions specific to privacy and security represented only a small fraction of the issues for which participants gave or received tech care. Thus, we conclude that educating tech caregivers on how to provide privacy and security-focused support, as well as designing technologies that facilitate such support, has the potential to create positive networks effects towards the collective management of digital privacy and security.

CCS Concepts: • **Human-centered computing** → *Computer supported cooperative work*.

Additional Key Words and Phrases: Privacy and Security, Technology Caregiver, Community Collective Efficacy, Self-Efficacy, Power Use

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1 INTRODUCTION

Mobile devices have placed computing technology in the hands of nearly every person in the U.S. [39]. Yet, a 2019 Pew Research study [6] found that most adults in the U.S. report having a lack of control over their data privacy and are concerned about how their digital information is being used by third-party entities. Pew Research [50] also recently uncovered that the majority of U.S. adults

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have significant knowledge gaps when it comes to their digital privacy and security. For instance, only 28% of adults surveyed could correctly identify an example of two-factor authentication, and only 24% were familiar with the concept of private browsing [50]. The report also found that younger adults (ages 18-29) were significantly more likely to answer questions about digital privacy and security correctly, compared to older adults (ages 65 and older). The lack of general knowledge around digital privacy and security, combined with the prevalent use of personal digital devices, creates a critical need for innovative approaches that fill knowledge gaps in a way that helps protect individuals from potential privacy and security threats.

As such, researchers have begun to identify the importance of social support in managing individual and collective digital privacy and security (e.g., [19, 20, 36]). Several studies have demonstrated that social influence plays an important role in gaining knowledge and also changing an individual's privacy behaviors [24, 29, 46]. Others have examined how trusted communities of family and friends can help support and oversee security and privacy management [3, 14, 48]. Much of this work relates to research that has identified how loved ones help one another with technology advice and support more generally, a concept we refer to in this paper as "tech caregiving." We build upon both of these sets of literature to examine collective security and privacy management within the concept of tech caregiving within small networks of trusted family, friends, and co-workers.

The characteristics of tech caregivers and how they give and receive support related to digital privacy and security is an under-explored and worthwhile topic of research. Tech caregiving does not require formal training, nor direct acknowledgment of the position, as people take on this role for varying reasons [49]. Yet, research has also found *technology expertise* as a prerequisite that must exist within an individual's network for such social resources and processes to be effective in security and privacy management [32]. Thus, we aim to examine the collaborative practices for managing digital privacy and security that involve asymmetric relationships between people who help (or may not help) one another manage digital privacy and security. We also study the role of tech caregivers more broadly in building *community collective efficacy for privacy and security*, which is the capacity of a community to collaboratively perform a shared task [11, 12, 32], which in our case, would be managing digital privacy and security decisions together.

- **RQ1:** *What are the unique characteristics of tech caregivers, and how do tech caregivers differ from those who act primarily as tech caregivees?*
- **RQ2:** *How does tech caregiving play a role in the formation of community collective efficacy for privacy and security?*
- **RQ3:** *How and through what means do tech caregivers provide support and advice to their networks?*

To answer these research questions, we conducted a web-based survey with 112 people between the ages of 13 and 78. Participants were recruited in 20 self-formed groups of 5-10 individuals who knew one another and had at least one person in the group who identified as a tech caregiver. Participants self-reported whether, to whom, in what capacity, and through what means they played the role of a tech caregiver or caregivee as it related to making online privacy and security decisions. To examine RQ1, we asked participants to self-report demographic information and their perceptions-based constructs that have been correlated with privacy and security outcomes in past literature: 1) *self-efficacy*: an individual's perceived personal capacity to complete a task [8], *power usage*: an individual's propensity to be a proactive technology user that explores all customization options [47], *sense of community belonging*: an individual's perceived connection to their community [12], and *community collective efficacy*: an individual's perception of the community's collective capacity to achieve a task together [32]. We present descriptive statistics and between-group mean differences on these demographic characteristics and constructs to illustrate the unique characteristics of tech caregivers versus caregivees. To address RQ2, we conducted an exploratory path analysis to examine the significant relationships between these constructs, using community collective efficacy for privacy and security as our outcome variable. For RQ3, we asked participants to report on how and through what means they provided tech support within their group and qualitatively analyzed their open-ended responses.

Overall, we found that tech caregiving was a fluid role, where some participants both gave and received tech care. We also found that many groups and individuals had more than one tech caregiver. While older adults did tend to be caregivees rather than caregivers, younger demographics were also caregivees, such as emerging adults. For RQ1, We report on the characteristics and differences between tech caregivers and caregivees to better understand these two groups and the interactions between them. For instance, we measured power usage (the extent to which users are eager to adopt and use new technologies [47]), self-efficacy (one's capacity to perform privacy and security tasks [32]), sense of community (being part of a particularly group [12], and community collective efficacy for privacy and security (the capacity and willingness to intervene on behalf of one's community [32]). We found that tech caregivers reported significantly higher levels of power usage and self-efficacy for privacy and security than caregivees. However, caregivers and caregivees did not significantly differ in terms of community belonging and community collective efficacy, suggesting that being part of the community may have bolstered their collective capacity for making privacy and security decisions as a group.

For RQ2, we found that sense of community belonging was a significant factor in predicting higher levels of community collective efficacy for privacy and security. Tech caregiving moderated the relationship between power use and community belonging, such that caregivers who gave support to more people and who had a higher score on power use had a higher sense of community belonging. Self-efficacy also positively predicted power use. For RQ3, participants reported giving and getting support primarily through text messaging and phone calls. The most common types of support given and received were troubleshooting problems and getting help setting up new devices. This finding demonstrates how privacy and security support is often implicitly embedded in more general support-related tasks, such as setting up a new technology or troubleshooting when problems occur. Interestingly, while our study was framed around tech caregiving for digital security and privacy, our qualitative results, which focused more generally on tech caregiving, demonstrate how security and privacy management is practiced implicitly during more generalized tech support, rather than as an explicit task in and of itself. Thus, a key implication of our work for the security and privacy community is to situate social support for security and privacy management within the broader context of tech caregiving. Further, our findings regarding the characteristics of tech caregivers and caregivees, as well as the kinds of technology support given and received are applicable beyond the security and privacy community.

2 BACKGROUND

In this section, we first unpack the concept of tech caregiving and synthesize the related work in this space. We then relate this concept to the domain of digital privacy and security to demonstrate how our work contributes to this broader research domain.

2.1 Providing Technology Support for the People We Care About

While the term "tech caregiving" appears to be relatively new [1, 2], the idea that people give support and advice about technology to the people they care about is not a novel concept. Early work by Dourish et al. [23] found that many people ask friends and family for technological help rather than seeking out professional support. A cohesive theme in the HCI literature has been the focus on providing tech care in family-based settings. For instance, Correa et al. [15] showed how children take on the job of influencing their parents' use of technology and become internet guides in their families, especially for older adults who were not raised in a digital environment or were not exposed to these technologies through school or peers. Similarly, Kiesler et al. [30] explored the process by which a family member with comparatively higher technical skill, most often a teenager, became what they described as the 'family guru,' the person in the family to whom the rest of the family turned for technical help, and found that they benefited from their roles. The family guru influenced how the household adopted technology and represented an important link between households and computer support. For instance, Grinter et al. [27] explored how two-adult family households set up and supported complex networking technologies and discovered one member of the household took on the role of "system administrator". Poole et al. [41] studied users' (i.e., 'helpers') motivation for giving technology assistance and found that many provided technical support primarily out of a sense of obligation to people for which they cared (e.g., elderly parents or children). Helpers assisted others in everyday technology support, such as computer or internet use, but reported that while providing help was initially satisfying, that feeling faded as problems became mundane and free time became scarce. Although tech caregiving has been shown to provide benefits for those who receive help [16], as well as those who provide help, it presents some unique challenges in terms of a sustained motivation for continuous and sustained care. We seek to expand upon this work by examining the informal community of caregivers and caregivees specifically in the domain of privacy and security.

A trend in the tech caregiving literature, especially as it relates to providing oversight for digital privacy and security, is that it tends to focus predominantly on the need to provide support to older adults. For instance, Zhao et al. [53] created a novel interface where elders could use a simple remote control to trigger a request to a 'helper', who would then perform computer-based tasks, such as placing a Skype call for them. Their approach significantly reduced frustration levels of the older adults and overall time to complete the task. Similarly, Mendel and Toch [35, 37] proposed a framework for providing social help to older adults for managing their privacy and security in mobile contexts. They found that relatives were the support group most likely to be motivated to help and that familiarity with the older relative's preferences was key to providing meaningful support. More recently, McDonald et al. [34] studied how older adult couples made consensual choices together about safety settings for online activities in a way that accounts for cognitive decline, autonomy, and collaborative management of shared assets. These studies make it clear that older adults need and can benefit from technology support and oversight, particularly when it comes to digital safety, privacy, and security. Indeed, Gen X and Older Millennials are more likely to provide tech support, while older adults are more likely to be on the receiving end of tech care [49]. Yet, a potential limitation of this framing is an over-emphasis on providing tech care to older adults could lead to gaps in providing tech care more generally to others who could also benefit from it. Therefore, we contribute to this literature by studying a wider range of people (e.g., parents, children, older adults, friends, co-workers, etc.) who may provide and/or benefit from the tech care of another. Further, we contribute to the growing body of literature on informal tech support provided by and given to loved ones for the purpose of protecting their online privacy and security.

2.2 Using a Community-based Approach for Managing Digital Privacy and Security

In the field of digital privacy and security, much research has focused on raising individuals' awareness of security and privacy threats and protective behaviors through mechanisms such as improved security and privacy notices, training tools, or developing user-friendly security systems [4, 5, 52]. However, a recent study [50] found that users often face difficulty managing many security and privacy tasks on their own and may benefit from seeking advice from others. Therefore, networked privacy researchers have shifted attention to studying collaborative and community-based approaches to help people manage their digital privacy and security together [19, 21].

A number of researchers have identified ways that people already take such a collaborative approach [7, 38]. For example, Rader et al. found that people learn about security from the informal stories they hear from friends and family [42, 43]. Redmiles et al. [44] also found that people trust and adopt privacy advice when it comes from trusted colleagues, family members, and friends. People then pass that knowledge onto others in their networks, such as the stories told to them by others [42]. Das observed that technology users often communicate with their friends and family to learn about privacy threats and preventative strategies [19], and pass along security warnings to others whom they care about. Thus, social influence can have an important impact on people adopting privacy and security practices. Mendel et al. [36] examined how the source of security information affected the behavioral intention of technology users to change their privacy behaviors. Their study revealed that people with low self-efficacy on privacy matters were more open to adopting privacy practices when their social network influences them. Das et al. [20, 21] found evidence that an individual can be motivated to adopt a security feature merely by viewing how many of their friends used that feature, which is referred to as social proof. Similarly, Tabassum et al. [48] sought to understand users' perspectives about privacy and trust in connection to sharing smart home devices with individuals living outside of the home and discovered that smart device owners took a community-based approach to the safety and care of their home. Altogether, a collaborative approach to privacy and security management can be beneficial based on the members who make up the community [13] and their relationship with each other.

Despite this evidence that social processes influence users' security and privacy behaviors, few researchers have examined frameworks or interventions to utilize such processes for aiding decision making. One exception is the work by Chouhan et al. [14], which proposed a community oversight model of groups of users collaboratively supporting each other in privacy and security management. They examined this model in a formative study of the features of a mobile application that would allow users to support others in their community in mobile app privacy and security decisions. Participants regularly conceptualized their community as trusted friends, family, and co-workers who could help them with their decisions. Thus, we build upon this notion of community to examine how such groups of users with differing technology knowledge can share and receive support related to digital privacy and security.

3 METHODS

To examine our research questions of tech caregiving, we conducted a survey study, recruiting small communities of users where at least one identified as a tech caregiver. We drew upon the concepts of community from Chouhan et al. [14] to target small groups of trusted users who know each other. We now describe our recruitment, survey design, and data analysis methods in detail.

3.1 Study Overview

To study the collaborative and often asymmetrical process of tech caregiving, we recruited small (5-10 individuals), self-organized groups of people who knew each other personally and identified at least one of the group members as a "tech caregiver", someone who helps other people they know maintain or troubleshoot technology issues, such as helping them with the privacy and security of their digital devices. Groups' members could be of any age, but participants under the age of 18 were required to obtain consent from their parent, who had to participate in the study with them. To ensure some level of technology use, we also required that participants own a smartphone. The study was presented to the participants as an effort to understand how they discuss online privacy and security management. We also stated that the purpose of the study was to help our team develop a smartphone app for friends and family members to collectively manage their online privacy and security. After participants were screened for eligibility and consented to participate in the study, they were individually directed to complete a web-based survey administered through Qualtrics. An individual's survey responses were not shared with the members of their group. Upon at least five members of the group completing the survey, participants were each compensated with a $10 Amazon gift card. The study was approved by the Institutional Review Boards (IRBs) of the universities who administered the study. Data collection began in August 2019 and completed in May 2020. It took participants approximately 20 minutes to complete the survey.

3.2 Survey Design

The survey was sub-divided into the following sections: 1) characterizing the nature of the relationships between group members, 2) the types of advice given or received, as well as the means through which this communication was facilitated, 3) community-level factors (i.e., sense of community belonging and community collective efficacy), individual-level factors (i.e., self-efficacy and power use), and 4) demographic information (i.e., age, gender, education level, and income). We describe each of these sections in more detail below. The full survey can be found in the supplemental materials.

3.2.1 Relationships between Group Members. We first ask each group member to describe the interpersonal relationship (e.g., friend, family member, etc.) between themselves and each of the other members in the group, as well as the proximity to others in terms of their home residence. Then, we asked each participant to classify the other members of their group as a tech caregiver (gives tech advice to me) or caregivee (receives tech advice from me). Participants were able to select either option or both options simultaneously, which would indicate a reciprocal relationship. Participants were also asked which topics they typically discuss when they interact with one another and were given the option to select as many of the following that were applicable: entertainment such as games and music, news and alerts, or privacy and security. Examples of activities in each of these categories were described in the survey.

3.2.2 Types of Advice Given and Received. Next, we asked open-ended questions regarding the types of advice or help participants gave or received from other members of their group, as well as how they currently reached out to members in their group to coordinate these efforts. We framed these open-ended questions more generally, to learn more about the kinds of support respondents were participating in, and how that occurred. We asked the the following questions:

- *For those that you receive tech support from, please describe the type of advice or help you get from your tech caregiver in the space below. (Could include things like setting up new devices, considering app settings on a smartphone, or fixing problems that come up with a specific device.)*
- *If you have technology issues, how do you currently reach out to your tech caregiver for help?*
- *For those that you provide tech support to, please describe the type of advice or help you provide. (Could include things like setting up new devices, considering app settings on a smartphone, or fixing problems that come up with a specific device.)*
- *When people have technology issues, how do they currently reach out to you for help?*

3.2.3 Community-level Factors: Community Collective Efficacy and Sense of Community Belonging. Next, we measured several pre-validated constructs related to salient community-level and individual-level factors (included in supplemental materials). *Community collective efficacy* refers to mutual trust and solidarity among community members, as well as the willingness to intervene on behalf of the common good [12]. Carroll et al. defined community collective efficacy as an extension of an individual's self-efficacy [8]. This scale measures the capacity of a group or community in performing a shared task collaboratively. We utilize a pre-validated version of this construct to measure each group's perceived collective capacity to manage privacy and security together [32], which was previously used in a study of privacy and security support for older adults. Individual items were phrased as a challenge or achievement in privacy and security management, in a collective capacity (e.g. "Our community can provide information for people with different interests and needs when it comes to online privacy and security decision-making."). The composite score of this scale was used to examine an individuals' perception of community capacity to manage privacy and security together.

Carroll's research [11] also revealed that an individual's community collective efficacy is highly correlated with his or her *sense of community belonging*. A sense of community has been described as "the sense that one was part of a readily available, mutually supportive network of relationships upon which one could depend and as a result of which one did not experience sustained feelings of loneliness" [45]. In this survey, we utilized Carroll's community belonging scale to measure this construct where each of the variables were used to help us to understand the participant's feelings on how much they matter to each other. Participants were presented the scale items as statements and were asked to rate each on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree), consistent with the way these questions have been presented in previous work.

3.2.4 Individual-level Factors: Self-Efficacy and Power Use. Bandura defined *self-efficacy* as one's perceived capacity to perform a task [8]. In our study, self-efficacy was adapted from Bandura's self-efficacy scale [8] by limiting the scope of the survey to digital privacy and security (e.g., "I think I am the kind of person who would learn to use best practices for good online privacy and security decision-making."). We were interested to understand how the individual-level factors were related to the community-level factors, particularly community collective efficacy, in the context of tech caregiving.

In addition to self-efficacy, we measured *power usage*, which is defined as the degree to which an individual is a power user of technology [47]. Sundar created a scale [47] to describe one's level of power usage of those who are more likely to explore all possible customization with their technology, which is applied in our study to examine each users' comfort with technology features. We phrased some items of Sundar's scale with modern technological devices, i.e., we used 'smartphone' instead of 'PDA'. These constructs were also measured on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

3.2.5 Demographic Information. Demographic information (i.e., age, gender, education level, and income) was also gathered to help us examine the differing characteristics between tech caregivers and caregivees (RQ1).

3.3 Data Analysis Approach

First, we categorized participants as either caregivers or caregivees. If they offered care to more individuals than they received care from, they were categorized as tech cargivers. Those who received more care than they gave were categorized as caregivees. In a few (N=5) cases, participants gave and received an equal amount of technology support. We categorized these participants as caregivers. We then investigated any demographic differences between caregivers and caregivees using chi-square tests. Next, we verified the construct validity of our measures using Cronbach's alpha [17] and created sum-scores to represent each construct. We then conducted Shapiro–Wilk tests and found that the sum-scores of the constructs were not normally distributed ($ps < .01$). Therefore, we performed a non-parametric test (2-group Mann–Whitney U-test) to identify significant differences between caregiver and caregivee groups.

For RQ2, we conducted analysis in MPLUS using a saturated path model [33] which is useful for identifying significant relationships between model constructs in an exploratory fashion (i.e., when no prior hypotheses are posited) [26]. We modeled all direct, moderating, and mediating effects of tech caregiving on and between all of our constructs. As shown in Figure 1, non-significant paths were trimmed from the model. As to not reduce the statistical power of the model given our modest sample size [22], we chose to retain the numerical value (i.e., the number of group members for whom a participant provided tech care), rather than the dichotomous variable (i.e., tech caregiver vs. tech caregivee). Since our DVs were not normally distributed, we used a MLR estimator which is robust to non-normality. We graphed statistically significant moderating effects identified in our model, and included non-significant, yet interesting, trends we observed in the data as part of our discussion on future research directions worthy of additional exploration.

To answer RQ3, we conducted a thematic qualitative analysis [9] to understand how tech caregivers offer advice and support to their social networks. First, we familiarized ourselves with the data to generate initial codes and understand the variance within the interview responses. During this process, we took note of common themes that emerged from responses. The final codebook was divided into two categories: 1) the types of advice group members received or offered, which was sub-divided into seven separate codes (i.e., troubleshooting, device setup/new device explanation, settings, suggestions, new application setup/explanation, security, and other), and 2) the different modes of communication the participants used to share this advice or support, which was divided into six codes (i.e., text message, phone, face-to-face, messaging apps, video/video share, and email). Given the open-ended nature of the responses, participants often gave more than one type of advice and/or modes of communication; therefore, these responses were double-coded, making the final count in each category often greater than the total number of participants. Next, we describe how we recruited the participants who took part in our study.

3.4 Participant Recruitment

We recruited a total of 112 participants that were associated with 20 different groups of caregivers and caregivees. For the most part, all invited members of each group responded and completed the survey. We recruited participants through word-of-mouth, fliers shared with local community organizations and posted at local businesses, and university-based listservs. For instance, members of our research team contacted community organizations, such as parent-teacher associations of local high schools and neighborhood associations, and shared fliers with leaders of these groups to share with their members. Fliers were also posted on public bulletin boards in local shops and in the public library. We also emailed the undergraduate and graduate listservs of a large Computer Science Department in the Southeastern United States. Our rationale was that Computer Science majors would likely be part of the demographic of tech caregivers.

As shown in Table 1, we characterized the groups based on their composition (i.e. family, friends, coworkers, and others), the size of the group (ranging from 5 participants to 9 participants), and the number of tech caregivers (ranging from 1 to 4) in each group. Most (40%, N=8) of our groups were composed of friends only, 15% (N=3) of groups were family only, and another 25% of our groups (N=5) were comprised of both friends and family members. Only N=6 (30%) of the groups had only 1 caregiver, while the remaining had 2 or more. When group members were asked the proximity of their residence in relation to others in the group, 5 groups (25%) contained a majority of group members who lived in the same house, while 7 groups (35%) had a majority that lived in different towns from one another.

Table 1. Characteristics of groups

	N	*%*
Total no. of groups	*20*	*100*
Composition		
Friends Only	8	40
Friends and Family	5	25
Family Only	3	15
Coworkers/Team members	2	10
Other	2	10
Size of Group		
5 members	13	65
6 members	5	25
7 members	0	0
8 members	1	5
9 members	1	5
No. of Tech Caregivers		
1 Caregiver	6	30
2 Caregivers	11	55
3 Caregivers	1	5
4 Caregivers	2	10
Proximity of Majority of Group Members		
Same House	5	25
Same Neighborhood	2	10
Same Town	5	25
Out of Town	7	35
Combination	1	5

4 RESULTS

We first present our results by describing the characteristics of the tech caregivers versus caregivees (RQ1). Then, we explore the role tech caregivers play in the formation of community efficacy for privacy and security (RQ2). Finally, we conclude our results by describing the different ways tech caregivers and caregivees coordinate the process of giving and receiving technology support (RQ3).

4.1 Characteristics of Tech Caregivers vs. Tech Caregivees (RQ1)

We first characterize our participants based on their demographic characteristics, then highlight the ways in which tech caregivers differ from caregivees.

4.1.1 Demographic Characteristics. Table 2 summarizes the gender, age groups, education, and income of our participants sub-divided by whether they predominantly acted as tech caregivers or caregivees. Out of the 112 who participated in our survey, N=41 (37%) were classified as tech caregivers, and N=71 (63%) were classified as tech caregivees. Among the 41 tech caregivers, N=5 (4%) equally received and provided support to others in their network. Our sample was nearly gender-balanced (46% female and 54% male), but tech caregivers tended to be male (66%), while caregivees were both female (52%) and male (47%). However, this gender difference between tech caregivers and caregivees was not statistically significant $\chi^2(1) = 2.354, p = 0.124$ (we excluded the gender group of 'other' from this analysis due to low N in that group).

Table 2. Sociodemographic Characteristics of Participants

Role	Tech Caregivers		Tech Caregivees		Total	
N	41		71		112	
	n	%	*n*	%	*n*	%
Gender						
Female	14	34	37	52	51	46
Male	27	66	33	47	60	54
Other	0	0	1	1	1	1
Age						
13-17	1	2.4	7	9.9	4	3.6
18-24	30	73.2	37	52.1	71	63.4
25-34	8	19.5	6	8.5	14	12.5
35-44	1	2.4	2	2.8	3	2.7
45-54	0	0	10	14.1	10	8.9
55-64	1	2.4	1	1.4	2	1.8
65+	0	0	8	11.3	8	7.1
Education						
Primary School	0	0	2	3	2	2
High School	19	46	29	41	48	43
College	14	34	23	32	37	33
Masters	8	20	14	20	22	20
Doctoral/Professional	0	0	3	4	3	3
Annual Household Income						
Less than $24,999	14	34	8	11	22	20
$25,000-49,999	2	5	12	17	14	13
$50,000-74,999	5	12	16	23	21	19
$75,000-$100,000	12	29	14	20	26	23
More than $100,000	8	20	21	30	29	26

While the majority (63%) of our participants were between the ages of 18-24, this demographic was also the largest group of tech caregivers (73%). Only N=2 (5%) of tech caregivers were over the age of 35. In contrast, caregivees were primarily in the age range of 18-24 (52%) but in contrast to caregivers, 27% were also above the age of 45. This suggests a somewhat bi-modal distribution of caregiving to the younger and older members of a group. The 5 tech caregivers who equally gave and received tech support were all (100%) under the age of 25. To study if there were differences in terms of being a caregiver across the age-groups, we categorize ages by teens (13 to 17), younger adults (below 35), middle-aged adults (35 to 54), and older adults (above 55). Compared to middle-aged adults, younger adults were significantly more likely to be caregivers than caregivees ($p = 0.006$), and older adults were marginally more likely to be caregivees (only marginally significant—$p = 0.075$), $\chi^2(3) = 61.038, p < 0.0001$.

Table 2 also describes the education and household income of participants. Tech caregivers were not different than caregivees in terms of completed education (below college vs. college vs. above college), $\chi^2(2) = 0.065, p = 0.968$. For all tech caregivers and tech caregivees, their annual household incomes all ranged from less than $24,999 to more than $100,000. Overall, we found that the group with the lowest income level was significantly more likely to be a caregiver rather than a caregivee compared to other groups ($p = 0.010$), $\chi^2(4) = 11.680, p = 0.019$.

4.1.2 Mean Differences between Caregivers and Caregivees. Table 3 summarizes the Cronbach's alpha, means, and standard deviations of each of the constructs measured in the survey. All Cronbach's alphas were greater than 0.70, which suggests good internal consistency of our measures. Next, we tested for between-group differences based on these constructs and whether a participant was categorized as a tech caregiver versus caregivee. The means and standard deviations of the constructs for the caregiver and the caregivee groups are reported in Table 4.

Table 3. Internal Consistency (Cronbach's Alpha) and descriptive statistics of key constructs. Items were measured on a 5-point Likert scale coded from 1 (strongly disagree) to 5 (strongly agree)

Construct	No. items	α	*M*	*SD*
Community Collective Efficacy	7	0.89	29.019	4.852
Community Belonging	8	0.89	35.960	4.512
Self Efficacy	5	0.95	19.65	5.244
Power Usage	22	0.83	82.857	12.154

Table 4. Mann–Whitney U-test of Caregiver and Caregivee Responses to Key Constructs

Characteristics	Tech Caregiver		Tech Caregivee		w-value	p-value
	M	*SD*	*M*	*SD*		
Community Collective Efficacy	29.083	3.937	28.942	5.235	1239.5	0.719
Community Belonging	36.777	4.057	35.544	4.682	960.5	0.133
Self Efficacy	20.585	5.572	19.078	5.160	1016 **	.007
Power Usage	90.073	8.406	79.118	11.902	648 ***	< 0.001

*p<.05; **p<.01;***p <.001

As shown in Table 4, tech caregivers reported significantly higher levels of self-efficacy for privacy and security ($p = .007$) than caregivees. Furthermore, tech caregivers report significantly higher levels of power use ($p < .001$). However, community belonging and community collective efficacy scores were not significantly different across the two groups ($ps = .133$, .719).

4.2 Tech Caregivers and Community Collective Efficacy for Privacy and Security (RQ2)

As described in our Methods section, we ran a saturated path model to explore the direct, moderating, and mediation effects between our model constructs. We modeled tech caregiving based on the numeric value of people to whom a caregiver provided support. Figure 1 shows the final model, where most of the non-significant paths were trimmed from the model except three, which are represented with dashed lines. The path between power use and community belonging was retained due to the significant moderating effect of number of tech caregivees. We kept the two other non-significant paths in the model because they contributed to the model fit and have a p-value below 0.1. However, these two paths need additional study with more statistical power to be confirmed. The fit measures suggest a robust fit for this model. Chi-square test suggests that there is not any significant misfit between the estimated and observed correlation matrix ($\chi^2(8) = 13.288, p = 0.1694$). Likewise,

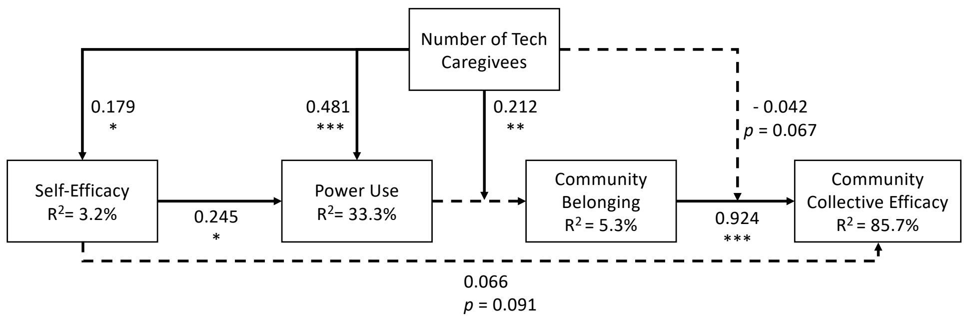
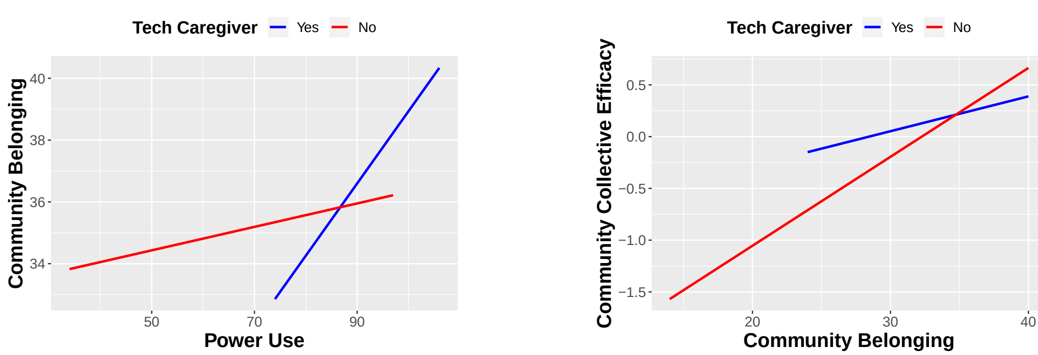


Fig. 1. The path model

RMSEA suggests an insignificant misfit of 0.077 (p = 0.238). Lastly, CFI = 0.976 and TLI = 0.947 are above acceptable thresholds [28].

In our path analysis, we confirmed our earlier findings that tech caregivers who provided tech care to more people had higher self-efficacy ($p = .031$) and reported higher levels of power use ($p < .001$). In addition, participants who reported higher self-efficacy also had a higher score on power use ($p = .020$). In addition, our results show that community belonging positively predicted community collective efficacy ($p < .001$). Next, we report on the significant moderation effects of providing tech care.



(a) The effect of PU on CB is significantly moderated by the number of tech caregivees one has.

(b) The effect of CB on CCE may* be moderated by the number of tech caregivees one has.

Fig. 2. Interaction effects from Figure 1. *The moderation effect in Fig. 2b did not reach significance.

The number of tech caregivees significantly moderated the relationship between power use and sense of community belonging. As shown in Figure 2a, being someone who predominantly acted as a tech caregiver strengthened the relationship between power use and sense of community belonging ($p = .008$). In other words, tech caregivers who were also power users had a stronger sense of community belonging than tech caregivees and tech caregivers who were not power users. We also found a trend where caregivees with a strong sense of community belonging report higher levels of community collective efficacy than tech caregivers (see Figure 2b). This effect, however, did not reach a significant threshold ($p = .067$) but would be useful to explore further in a future study with a larger sample size.

4.3 The Ways in Which Tech Caregivers Provide Support (RQ3)

In this section, we present a descriptive account of relationships between group members, the most common types of advice and support tech caregivers gave, and caregivees received. Then, we identify the different ways caregivers and caregivees facilitated this communication. Table 5 shows the distribution of our codes divided based on the responses provided by tech caregivers versus caregivees. As mentioned earlier, double-coded responses translated into column sums equalling greater than 100%. Also, since these percentages did not differ significantly by group, we present our qualitative findings for tech caregivers and caregivees together.

4.4 Relationships between Group Members

Participants classified the other members of their group as a tech caregiver (gives tech advice to me) or caregivee (receives tech advice from me) wherein it was possible to select either option or both options simultaneously. We observed 196 relationships between participants where one group member reported receiving tech advice from another. Among those, 26 (13%) were reciprocal relationships, wherein participants affirmed that they receive advice from one another. Another way that we qualified relationships was by asking about the topics they discussed on a one-on-one or small group basis with other group members, namely topics related to entertainment, news and alerts, or privacy and security matters, where participants were able to select as many topics as were applicable. In total, participants reported 1,206 interactions and on average, participants each reported 10 interactions (Md. = 11; Min. = 0; Max. = 24). Of those interactions reported, 47% were related to entertainment, 33% were related to news and alerts, and 20% were related to privacy and security.

Table 5. Communication Among Groups.

N	98		87	
Characteristics	Getting Support		Giving Support	
	n	%	*n*	%
Types of Advice/Support				
Troubleshooting	45	46	36	41
New Device Setup/Explanation	40	41	31	36
Settings	17	17	19	22
Suggestions	16	16	16	18
Direct Support	14	14	14	16
Security	6	6	2	2
Other	7	7	6	7
Mode of Communication				
Text Message	47	48	43	49
Phone	46	47	38	44
Face-to-Face	22	22	25	29
Messaging apps	15	15	13	15
Video/Video share	11	11	12	14
Email	9	9	7	8

4.4.1 Types of Advice/Support Given/Received. The most common type of advice participants discussed was troubleshooting (received N=45 (46%); gave N=36 (41%)). Troubleshooting involved problem-solving unexpected issues on an as-needed basis, when participants were unfamiliar with the device or software that they were trying to use:

> *"Troubleshooting issues for devices I am less familiar with, such as Apple (macOS) and Linux devices"* - P12, Male, Age 20, Group 66, Getting Support

The next most common type of advice was assisting with device setup or explaining how to use a new device (received N=40 (41%); gave N=31 (36%)). This support helped participants to understand what a new device was used for, and how to get started using it. Participants also mentioned supporting one another to ensure the set up of their new devices was secure and they were not at risk of security or privacy concerns. This was the most common support needed by caregivees ages 65+ (N=5, 63%). For instance, one participant stated:

> *"Setting up my iWatch, adjusting my settings for sports and check my heart. The girls make sure my accounts don't get locked up and make sure I can unlock everything if necessary."* - P50, Group 10, Male, Age 69, Getting Support.

The third most common type of advice participants exchanged was on the topic of their devices' settings (received N=19 (22%); gave N=17 (17%)). This was slightly different than the previous category as the settings did not appear to be for new devices, but existing ones. The participants discussed the options available to them to customize the settings on their devices to fit their preferences, as well as securing their settings to maintain their privacy. Participants also stated they received or gave support about various types of suggestions (received N=16 (16%); gave N=16 (18%)), such as what type of phone to buy next, what apps they should or should not download, and what specific settings are most useful. For example:

> *"Just like the support I receive, my support will usually come in the form of suggestions of apps or settings to try out."* -P13, Group 66, Male, Age 20, Giving Support

Another type of caregiving mentioned was giving and receiving direct support (received N=14 (14%); N=14 (16%)), which involved caregivers directly helping caregivees, such as by downloading apps and setting them up, managing account settings, and assisting with use of technology. The following quote is from a participant whose tech caregivers set up and adjusted an app they wanted to use frequently:

> *"P48 and P49 manage my accounts in its entirety now. Its too much for me to remember how to login on every internet site. I like to get a new phone every other year to keep up with technology. P48 typically finds one that I like and sets it up with me. P49 always adjusts my Bible app for me on wednesday and saturday night so I can just go straight to the pastors notes. If we are having praise and worship outside, one of them usually has to print my sheet music."* - P51, Female, Age 71, Group 10, Getting Support

Finally only a few participants mentioned more technical security advice (received N=6 (6%); N=2 (2%)), which included the support of their device security, network security, and internet security.

4.4.2 Modes of Communication. The participants of our study used different modes of communication to give and receive support, whether it be through various forms of technology or physically face-to-face as described in Table 5. Participants used text messaging (received N=47 (48%); gave N=43 (49%)) and phone calls (received N=46 (47%); gave N=38 (44%)) as their most frequent forms of communication regarding tech caregiving.

> *"I text or call the girls. I used to call Apple support but they weren't helpful."* - P50, Male, Age 69, Group 10, Getting Support

Phone calls were the most common way of communicating with tech caregivers (N=6, 75%) among participants over the age of 65. The following quote explains why this participant chose to call for support.

> *"I would usually call them to better explain my issue and better understand their help."* - P110, Female, Age 21, Group I, Getting Support

Participants did not always use technology to communicate with their group members; they also spoke to one another face-to-face (received N=22 (22%); gave N=25 (29%)). These encounters often happened when group members lived in the same household (e.g., parents and children), or, since they had personal relationships, spent time with one another in-person.

Messaging apps were also mentioned (received N=15 (15%); gave N=13 (15%)), which included social media apps such as Facebook Messenger, and other online discussion platforms such as GroupMe or Discord. The messaging apps were not used by any participants over the age of 55 and were primarily used (N=23, 83%) by participants that were under the age of 25, who were also more likely to use these apps in their day-to-day lives. Participants less frequently used video/video share (received N=11 (11%); gave N=12 (14%)), such as FaceTime or Skype video. Video share was included in this category as some participants mentioned sharing the contents of their screen to their group members through an online program (such as TeamViewer) to receive and offer their support visually. However, only participants under the age of 25 utilized this method:

> *"If needed by sharing their screen either through a program like discord or teamviewer."* - P25, Group 63, Male, Age 20, Giving Support

The participants were able to contact the other members in their tech caregiving group for support through a combination of different modes of communication, and they often used more than just one. However, a consistent theme in these modes of communication is that they were not integrated into the technologies in which caregivees were seeking support, but instead through whatever platforms were regularly used by group members for communication. Therefore, coordination had to occur informally outside of the technology platforms they were discussing.

5 DISCUSSION

The aim of our study was to examine the phenomenon of tech caregiving for digital security and privacy, examining whether and how such care can contribute to a collective ability to manage security and privacy among small groups of trusted people. Overall, we did find evidence that people give and receive care that was related to security and privacy management, but that was a part of a broader range of support related to an individual's devices and settings. Thus, while our measures are still specific to security and privacy, many of our results can contribute to the more general literature on tech care, with deeper understanding of the characteristics of caregivers and caregivees, the kinds of support given and received, and the modes in which it is given. Below, we further discuss our findings with respect to our original research questions, then continue with the implications and limitations of our study.

5.1 Tech Caregiving Roles and Impacts on Communities

5.1.1 Unique Characteristics of Tech Caregivers and Caregivees. One of our novel findings was that the role of caregiver or caregivee was more fluid than we expected; respondents could play both roles, and both give and receive tech care. We also confirmed Chouhan et al.'s results [14] that family, friends, and co-workers are members of a user's trusted community for giving and receiving this care. In studying participants' socio-demographic characteristics for RQ1, we found several ways that tech caregivers' differed from tech caregivees. We found that older adults tend to be tech caregivees, whereas younger adults are more likely to be tech caregivers. These results confirm findings from prior literature [15, 18, 25, 30] that older adults tend to need care and younger generations often tend to be the key person to provide tech support to their families. However, our results also show that younger people benefit from tech caregiving as many of the tech caregivees in our sample were emerging adults.

On the other hand, we found little evidence of any significant difference between tech caregivers and tech caregivees in terms of gender. Franz et al. [25] similarly reported that age rather than gender was a significant factor in providing or seeking tech support. Therefore, tech caregiving research needs to encompass all ages, rather than focusing on just the young or old, as same-aged peers can also support one another.

Yet we did not find any significant difference between the two in terms of the community-level factors (i.e., community belonging and community collective efficacy). It is possible that caregivers can act as equalizers and their presence in the groups is sufficient to contribute to the groups' community-level factors. Further research is needed to investigate this possibility.

5.1.2 Tech Caregivers Role in Community Collective Efficacy. We utilized a path model to investigate the relationship among our individual and community measures. Our primary findings affirmed that community belonging was the only factor that predicted the community collective efficacy out of all the variables. This is similar to Carroll et al.'s study [12] in another domain, who found a strong correlation between community belonging and community collective efficacy.

Yet, there were still relationships amongst other variables. Interestingly, the number of tech caregivees that tech caregivers assisted played a central role and related to all of our constructs (self-efficacy, power use, and community belonging), except for community collective efficacy. Tech caregivers who helped more tech caregivees reported higher self-efficacy and power usage. One explanation is that people relied more heavily on those with more proficiency. It is also possible that their tendency to help more individuals would expose them to more trouble shooting situations and therefore increase their technology competencies and power use. Furthermore, we found that power users who provide care to more caregivees experience a higher sense of community belonging. Again, there could be multiple explanations for this. Those with higher community belonging may be willing to help more people. Alternatively, being asked for help by more people could lead to a greater sense of community for the caregiver.

Our study highlights the importance of community belonging when building community collective efficacy for privacy and security. Therefore, to better understand the dynamics behind community collective efficacy, future research should seek other factors that contribute to building a strong sense of community belonging or community collective efficacy. One possible way to increase community belonging is to encourage tech caregivers to help a larger number of tech caregivees in their groups. Another possible way is to make sure that community members have strong ties to one another, such as engaging groups to carry out shared computing-related tasks. We believe further research with populations of more varied levels of tech expertise and community engagement will be useful to get an in-depth insight into the correlations among all these factors.

Additionally, the majority of our participant groups reported more than one tech caregiver, and thus future work should explore whether having multiple caregivers further modulates the effects found in our model. As a post-hoc analysis, we modeled the number of caregivers a caregivee has in addition to the effects reported in Figure 1. The only significant effect we found was that having more caregivers moderates the relationship between self-efficacy and power use ($b = 0.292, p < .001$), such that having more tech caregivers strengthens the positive relationship between these two variables. Thus, now that our work uncovered that a multi-tech caregiver phenomenon exists, we encourage further exploration as to whether having multiple tech caregivers can lead to better privacy and security outcomes.

In general, future studies should consider a larger sample size to increase the the power for detecting more nuanced effects. For example, we explored the 3-way interaction between tech caregiving, self-efficacy, and community collective efficacy as shown in Figure 3. While we did not have enough power to detect statistical significance for this 3-way interaction effect, the patterns in this graph are noteworthy. First, the relationship between self-efficacy and community collective efficacy is generally positive for both tech caregivers and caregivees on both sides of the graph. This makes logical sense. Similarly, on the left side of Figure 3, we see what would be expected from an individualistic perspective; when operating as individuals (i.e, low community belonging), tech caregivers have higher levels of self-efficacy and relatively higher levels of community collective efficacy than caregivees. However, on the right, this pattern flips. When participants act collectively (i.e., reporting a strong sense of community belonging) tech caregivees actually report higher levels of community collective efficacy than tech caregivers, even when they report low levels of self-efficacy. In a sense, it seems like having a sense of community in a network with someone who acts as a tech caregiver could bolster the confidence levels of caregivees in making collective decisions about digital privacy and security while essentially bringing down the collective average for tech caregivers. Greater statistical power could confirm the significance of these relationships.

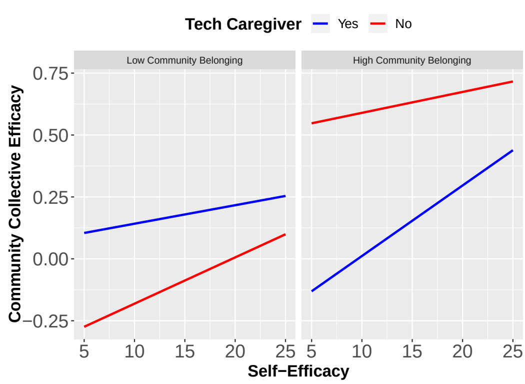


Fig. 3. The three-way interaction (non-significant)

5.1.3 *Provision of Support by Tech Caregivers.* In RQ3, our findings gave us a broad understanding of how tech caregivers and tech caregivees communicate with each other. Tech caregiving is not continuous, and support for security and privacy is not separate. Caregiving appears to happen at particular moments, especially during set-up or when problems occur The fact that participants may not continuously ask for support for their everyday technology use could be attributed to multiple sources, such as caregivers' growing reluctance to provide constant support [3], or caregivees' hesitation to bother caregivers [51]. Previous research [3, 41] has found that participants' motivation to provide help to others wanes over time. Thus, our findings point to the need for additional research on methods to ensure tech caregivers' sustained engagement over time.

Further, we learned from our results that tech caregivees seek support and advice through a variety of communication modes, but they most commonly provided tech caregiving through phone calls and text messages. Since tech caregiving groups were not predominantly family members who lived together physically, the participants had to rely on communicating through technology and they were not always able to have face-to-face interactions. Therefore, we need further studies to improve the quality of tech care by designing in-system support mechanisms (e.g., mobile phones, computers, applications) that facilitate these types of seamless communication support. It is important to consider the form the new facilitation takes, as the participants' age affected what mode of communication they used the most. Since the older population most frequently used their phones or face-to-face interactions, while younger participants used other communications, like messaging apps and video share, it is important to design mechanisms that users of all ages will be comfortable using. Paul and Stegbauer [40] explained the growing digital divide between the older and younger generations. As suggested by their research, it is essential to offer tools tailored to specific generations to avoid gaps in tech caregiving to particular age groups.

5.2 Implications for Supporting Tech Caregiving

In this subsection we discuss the implications of our results for tech caregiving, which we believe may be applicable beyond the domain of security and privacy care.

5.2.1 Enhance Community Belonging. Our work highlights the importance of community belonging in the collaborative management of privacy and security, and confirms this finding from other studies. This suggests the potential usefulness of mechanisms that strengthen the community, either prior to tech care or as a part of tech care. We recommend that tools designed to support tech care also work to build community belonging among members, or target groups of users that have established strong bonds. Future research will be needed to examine how to build community as a part of tech care. For example, previous research has shown that when local communities engage with one another using online social networks, community belonging is an outcome of these interactions [31]. By supporting tech care through more visible, group-level interactions, rather than offline 1-on-1 conversations, community belonging may be similarly impacted.

5.2.2 Facilitate In-Technology Support. As seen in Table 5, the primary mode of communication to give and get support utilized text and phone. Due to this finding, we recommend that in-technology support be used when possible to better facilitate tech caregiving rather than having to coordinate through other means. This will involve utilizing the communication technologies users are most familiar with. Additionally, our findings suggested that tech caregiving was not a phenomenon that was exclusive to older adults. Therefore, we need to build technologies that can support a diverse range of tech caregivees, potentially integrating with existing virtual conferencing platforms where we could not only allow audio/video calls, messaging, and computer screen sharing but also offer remote control ability.

5.2.3 Support Reciprocity and Multiple Relationships. A novel finding of our study is the varied relationships between caregiver and caregivee: community members may help more than one person, a person may have more than one caregiver, and caregiving can even be reciprocal. Most of the groups (N=14, 70%) reported that they had two or more tech caregivers, and although the majority of tech caregiving relationships were asymmetrical in terms of receiving support, we found that 13% of these relationships were reciprocated, wherein two participants received tech support from one another. Another insight from our work is that while most tech caregivees are not able to reciprocate tech support, the questions that they raise to tech caregivers may provide opportunities for them to learn more about technology and gain further expertise. We believe that this may be another form of a mutually beneficial relationship. A further area to explore is how current tech caregivees could, by learning through interactions with tech caregivers, become tech caregivers themselves and offer their assistance using the knowledge they have gained. Based on these insights, it is important to be mindful of the potential for these relationships. Tools should not merely consist of uni-directional information sharing, but rather more fluid exchanges of support.

These results also suggest that making the caregiving of a community more visible to its members beyond just the two people involved in a particular exchange may allow users to find additional caregivers with different expertise, and users could offer support to more people within their trusted networks. This could also serve to further enhance community belonging.

5.3 Implications for Privacy and Security Information Sharing in Communities

The goals of our work are to examine community-based approaches to support users in collectively managing their security and privacy. Yet, in their open-ended response regarding the kinds of tech care they gave, respondents did not discuss much support specific to security and privacy, despite the focus of the entire survey. However, security or privacy management would be a component of much of the care that participants did mention, such as setting up a new device or application and modifying settings. Thus, we believe an important implication of our work for the security and privacy community is to examine how to support and motivate attention to security and privacy as part of the larger process of tech caregiving. One way to support privacy and security tech care is to find ways to call attention to these issues, through nudges or reminders, during the process of tech care. Another is to find ways for tech caregivers to specifically communicate around security and privacy issues with their caregivees. The mobile application proposed by Chouhan et al. for community members to actively discuss and oversee privacy and security issues is an example of this [14], and our results indicate that this example could be even more beneficial if integrated into general tech care in some way. Another means is to ensure that tech caregivers have the knowledge and skills to initiate care regarding security and privacy. We can find ways to educate or train tech caregivers on how to have conversations on digital privacy and security, and provide assistance for specific types of security or privacy issues. This would be further enhanced if caregivers can support other caregivers in this regard.

Many of our study participants describe engaging with a tech caregiver when setting up a device for the first time or if there is a problem encountered, but few described patterns of ongoing maintenance. Yet, we believe that security and privacy may need more regular attention that caregivees may not be as aware of or feel they need help with. For example, new types of cyber attacks emerge regularly that caregivees may need to be alerted of, a firmware update improving security may warrant the need to update a device quickly, or a user may have privacy concerns arise that they are not sure can be addressed. Caregivees may also feel overly confident that they are secure after set-up or an issue is resolved, and not consider requesting additional care. Based on this, we recommend that tools that support collaborative privacy and security create mechanisms to nudge tech caregivers to sustain support beyond set up in order to ensure engagement in advice sharing on an on-going basis. However, past work has indicated that motivation to support others in security and privacy management may wane over time [3], and thus research needs to examine incentives that can help caregivers with sustained and long term care around security and privacy.

5.4 Limitations and Future Work

We would like to highlight limitations of our work that should be addressed in future work. First, our sample was skewed toward younger technology users, likely a sampling bias of recruiting college-aged tech caregivers. Further, we found that while tech caregivers in our study reported higher scores on the power user scale than tech caregivees, both groups demonstrated relative comfort with technology. Future research with more varied populations could help understand the influence of different demographic variables and technical expertise on the individual and community-level factors we studied.

Second, we explicitly recruited 5-10 people who knew one another and had at least one person in their group who identified as a tech caregiver. One limitation of this is that each group in our study may not represent a "complete set" of a trusted community members, as the term "community" often has loaded meanings and fuzzy boundaries [10]. Yet, this sampling method was chosen intentionally because we wanted to understand the community-oriented mechanisms of tech caregiving as defined by our participants, similar to prior privacy work [14, 48]. However, had we recruited groups more generally, we would have been able to study how groups without a tech caregiver compare to groups with one or more tech caregivers. For example, do groups without tech caregivers have significantly lower levels of community collective efficacy than groups who have tech caregivers among their members? This would be a worthy area of exploration in future work. Additionally, we did not account for multi-caregiver networks that could involve caregivers having expertise in different areas and future work may expand into this topic to better understand how this could affect the dynamics of the communities. Finally, future work could also explore the impacts in makeup of one's tech caregiving community, as group of co-workers may support each other differently, with different outcomes, than more informal groups of friends and family.

Another potential limitation of our study was that we allowed participants to self-identify as the tech caregiver, caregivee, or both, in relation to other members of their group. We used this classification in the statistical models presented in this paper. Yet, we noticed that an individual's perceptions did not always match up with their group members' perceptions. Therefore, future research should try to understand why there may have been discrepancies in perceptions of caregiving and caregivee relationships, as well as how these different roles interact with one another. For example, when several caregivers are present, do they interact with each-other? What are the determinant factors for caregivees approaching a specific caregiver? Future studies can contribute to the literature by investigating such research questions.

Finally, an additional limitation is that while the study emphasized privacy and security at the macro-level, the lack of actual discussion about these topics in our micro-level qualitative results was an important and interesting finding of this research. We were concerned that asking only about the privacy and security issues would overly prime the participants in their responses. Yet not asking directly about privacy and security caregiving activities in the open-ended questions may have instead caused a response bias towards general technological issues (e.g., troubleshooting, settings) rather than about privacy and security. Thus, a deeper exploration of the kinds of security and privacy tech care would also be a useful extension of this work. We also believe new methods to capture the transactional process of giving and receiving care would be helpful to deepen our understanding of tech care, particularly related to security and privacy. For instance, a daily diary study may overcome issues with recall bias and give more accurate accounts of day-to-day giving and receiving of tech care.

6 CONCLUSION

Tech caregiving is an important phenomenon of giving and receiving technical support from a trusted community of friends and family. We believe that this phenomenon is useful to examine in the context of social support for security and privacy management. Thus, in this paper, we have examined the perceived capacity of small groups supported by tech caregivers to collectively manage digital privacy and security. Our results highlight unique characteristics of tech caregivers and methods that are employed in small groups to give and get support from them. Overall, our results also illustrate the important role that community belonging plays in supporting community collective efficacy of privacy and security. Based on our findings, we believe focus on supporting and educating tech caregivers may be useful to investigate social privacy and security interventions. We contribute our work as an extension of the discussion on social cybersecurity and collaborative management of privacy and security.

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